



HAL
open science

Technological Approach for Early and Unobtrusive Detection of Possible Health Changes toward Better Adaptation of Services for Elderly People

Firas Kaddachi

► **To cite this version:**

Firas Kaddachi. Technological Approach for Early and Unobtrusive Detection of Possible Health Changes toward Better Adaptation of Services for Elderly People. Other [cs.OH]. Université Montpellier, 2018. English. NNT: 2018MONT047 . tel-02138134

HAL Id: tel-02138134

<https://theses.hal.science/tel-02138134v1>

Submitted on 23 May 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

THÈSE POUR OBTENIR LE GRADE DE DOCTEUR DE L'UNIVERSITÉ DE MONTPELLIER

En Informatique

École doctorale I2S

Unité de recherche CNRS-LIRMM

Technological Approach for Early and Unobtrusive Detection of Possible Health Changes toward Better Adaptation of Services for Elderly People

Présentée par Firas Kaddachi

Le 3 décembre 2018

Devant le jury composé de

Christine AZEVEDO, Directrice de Recherche, LIRMM Montpellier, France

Émilie GUETTARD, Médecin, Clinique Beau Soleil Montpellier, France

Sumi HELAL, Professeur, Université de Lancaster, Royaume-Uni

Nazim AGOULMINE, Professeur, Université d'Évry-Val d'Essonne, France

Hamdi ALOULOU, Maître Assistant, Université de Monastir, Tunisie

Bessam ABDULRAZAK, Professeur Associé, Université de Sherbrooke, Canada

Philippe FRAISSE, Professeur, Université de Montpellier, France

Mounir MOKHTARI, Professeur, Institut Mines-Télécom Paris, France

Présidente du Jury

Examinatrice

Rapporteur

Rapporteur

Co-Encadrant

Co-Encadrant

Co-Directeur de Thèse

Directeur de Thèse



UNIVERSITÉ
DE MONTPELLIER

**For my beautiful family Maha and Yassine
For my precious parents Ali and Habiba
For my beloved parents Nejib and Hinda**

Contents

Acknowledgement	9
Abstract	10
Résumé	11
Chapter 1 Introduction: PhD Thesis Context, Objectives and Contributions	13
1.1 Context and Objectives	14
1.1.1 Early Health Change Detection	15
1.1.2 Unobtrusive Health Change Detection	15
1.2 Problem Statement and Contributions	15
1.2.1 Problem Statement	16
1.2.2 Methodological and Technical Contributions	16
1.2.3 Medical Relevance Validation	18
1.3 European Project City4Age	19
1.3.1 City4Age Strategy and Objectives	19
1.3.2 City4Age Deployment Sites	20
1.4 Author Publications	20
1.5 Thesis Structure	21
Chapter 2 State of the Art: Psycho-Geriatric and Technological Health Change Detection Approaches	23
2.1 Behavior Definitions and Models	24
2.2 Behavior Change Initiation and Maintenance Models	25
2.3 Psycho-Geriatric Health Change Detection Approaches	27
2.3.1 Short Emergency Geriatric Assessment (SEGA)	28
2.3.2 Mini Mental State Examination (MMSE)	28
2.3.3 Geriatric Depression Scale (GDS)	29
2.3.4 Instrumental Activities of Daily Living (IADL)	29
2.3.5 Autonomie Gerontologique et Groupes Iso-Ressources (AGGIR) . .	31

2.3.6	Get Up And Go (GUGO)	31
2.3.7	Mini Nutritional Assessment	31
2.3.8	Behavioral Pathology in Alzheimer’s Disease (BeAd)	32
2.3.9	Neuropsychiatric Inventory (NPI)	32
2.3.10	Quality of Life Scales (QoL)	33
2.3.11	Pain Assessment Scales	33
2.3.12	Agitation Assessment Scales	33
2.3.13	Psycho-Geriatric Assessment Limitations	34
2.4	Technological Health Change Detection Approaches	34
2.4.1	Short-term Health Change Detection	34
2.4.2	Retrospective Health Change Detection	35
2.4.3	Population-scale Health Change Detection	36
2.4.4	Intrusive Health Change Detection	37
2.4.5	Simulation-based Health Change Detection	38
2.5	Conclusion and Discussion	38
 Chapter 3 Methodology: Translating Geriatric Needs via Internet of Things Technologies		42
3.1	Investigated Geriatric Needs	43
3.1.1	Geriatrician Needs	44
3.1.2	Nursing Home Needs	45
3.1.3	Caregiver and Family Member Needs	46
3.1.4	Elderly People Needs	46
3.1.5	Geriatric Need Comparison and Translation	47
3.2	Analyzed Health Change Indicators	48
3.2.1	Activity of Daily Living (ADL) Indicators	49
3.2.2	Mobility Indicators	50
3.2.3	Cognitive Indicators	50
3.2.4	Social Life Indicators	51
3.2.5	Nutritional Indicators	52
3.2.6	Emotional Indicators	52
3.3	Employed Unobtrusive Monitoring Technologies	53
3.3.1	Environmental Sensors	53
3.3.2	Sensor-Enhanced Devices	55
3.3.3	In-Phone-Embedded Sensors	56
3.4	Selected Health Change Metrics	57
3.5	Validation Approach	58

3.6	Conclusion and Discussion	59
Chapter 4	Implementation: ChangeTracker Service for Online Behavior Analysis and Continuous Change Detection	60
4.1	Developed Data Processing Algorithms	62
4.1.1	Time At Home Algorithm	63
4.1.2	Visit Detection Algorithm	65
4.1.3	Wake-up and Sleep Time Detection Algorithm	66
4.1.4	Weighted Toilet Entry Algorithm	67
4.1.5	Weighted Sleep Interruption Algorithm	68
4.1.6	Weighted Movement Number Algorithm	69
4.2	Evaluated and Adapted Change Detection Techniques	70
4.2.1	Z-Score Change Detection Technique	72
4.2.2	Bootstrap Change Detection Technique	73
4.2.3	CUSUM Change Detection Technique	74
4.2.4	SD-Band Change Detection Technique	76
4.2.5	PELT Change Detection Technique	77
4.2.6	Naive Bayes Classifier Change Detection Technique	77
4.2.7	Bayesian Change Detection Technique	78
4.2.8	ULSIF Change Detection Technique	79
4.2.9	One-Class SVM Change Detection Technique	80
4.2.10	Affinity Propagation, K-Means and Mean Shift Change Detection Techniques	81
4.3	ChangeTracker Service Implementation Architecture	82
4.3.1	Model Layer for Data Acquisition and Storage	83
4.3.2	Controller Layer for Data Processing and Change Detection	85
4.3.3	View Layer for Data Visualization and Change Notification	87
4.4	Ambient Assisted Living Platform UbiSMART	90
4.4.1	HomeDesc Service for Sensor Network Modeling and Configuration	92
4.4.2	SensLog Service for Raw Data Visualization	93
4.4.3	Life Service for Real-Time Activity Recognition	94
4.5	Conclusion and Discussion	95
Chapter 5	Validation: Real Deployments and Experimental Results	97
5.1	Recruitment Process and Data Collection	99
5.1.1	Local Medical Partners and Experimental House	99
5.1.2	Validation Environment and Technological Solutions	102

5.1.3	Medical Participant Profiles and Analysis Indicators	105
5.2	Early Health Change Detection Examples	113
5.2.1	Detected Health Changes for Participant A	113
5.2.2	Detected Health Changes for Participant B	115
5.2.3	Detected Health Changes for Participant C	117
5.2.4	Detected Health Changes for Participant D	119
5.2.5	Detected Health Changes for Participant E	120
5.2.6	Detected Health Changes for Participants F and G	122
5.2.7	Detected Health Changes for Participants H and I	124
5.2.8	Detected Health Changes for Participants J and K	126
5.2.9	Detected Health Changes for Participants L and M	127
5.2.10	Detected Health Changes for Participants N and O	129
5.2.11	Detected Health Changes for Participants T and U	130
5.2.12	Detected Health Changes for Participants V, X and Y	132
5.3	Health Change Cause Investigation and Medical Relevance Validation	134
5.3.1	Personal, Context and Medical Information Collection	135
5.3.2	Possible Health Change Cause Categories and Rates	137
5.3.3	Health Change Detection Ontology	139
5.3.4	Change Detection Technique Performance Evaluation	141
5.4	Conclusion and Discussion	146
	Conclusion and Future Work	147
	List of Figures	152
	List of Tables	154
	List of Listings	156
	List of Algorithms	157
	Appendix	158
	References	173

Acknowledgement

I greatly thank my supervisors for their helpful support, constructive encouragement and significant feedbacks. Bessam Abdulrazak is not only my scientific supervisor, but also my scientific father. I learn from his large experience how to create and justify new scientific contributions. Hamdi Aloulou is not only my scientific and technical supervisor, but also my dear friend. I learn from his considerable experience how to propose reliable technological solutions and publish meaningful scientific content. Nursing home managers Brigitte Choquet and Pascale Jeanne are friendly welcoming people. I learn from their geriatric experience how to communicate with elderly people and better understand their needs.

Emilie Guettard is a friendly person. I learn from her medical experience how to interpret technological observations and investigate useful results. Philippe Fraisse is a very kind and caring person. I learn from his smart feedbacks how to develop accurate algorithms and improve scientific presentations. Mounir Mokhtari has huge experience in proposing convincing business models. I learn from him how to collaborate with international partners and manage large-scale projects.

I gratefully offer my doctor degree to my precious parents Ali and Habiba. They create the man inside me and see their life dreams come true through me. I humbly offer my PhD achievement to my beloved parents Nejib and Hinda. They always stand by me and believe in the day when I become real doctor. I kindly offer my success to my beautiful family Maha and Yassine with love. They are meaning of my life and make it more beautiful than words.

I specially thank my brothers Seyf and Achraf. I wish their dreams come true and live happily ever after. I gratefully thank my brother Nabil and sister Nihel. I wish them best life moments in the warmth of their love. I kindly thank my grandparents Hsan and Nejia. They are a blessing from God in our life. Thanks for all my family members and life friends for their sincere feelings and sweet memories.

PhD work is part of the European project City4Age that received funding from the Horizon 2020 research and innovation program under grant agreement number 689731.

Abstract

Aging process is associated with serious **decline in physical and cognitive abilities**. Aging-related health problems present growing burden on public health and economy. Nowadays, **existing geriatric services** have limitations in terms of **early detecting possible health changes** toward better adaptation of medical assessment and intervention for elderly people. Bridging the gap between these geriatric needs and existing services is a major enabler to improve their impact. In this thesis, **proposed technological approach** employs **unobtrusive Internet of Things (IoT) technologies** for **long-term** behavior monitoring and early detection of possible changes. **Proposed methodology** identifies **geriatric indicators** that can be monitored via unobtrusive IoT technologies, and are associated with physical and cognitive problems. This thesis develops **data processing algorithms** that convert raw sensor data into geriatric indicators. These geriatric indicators are analyzed on a daily basis, in order to early detect possible changes. This thesis **evaluates and adapts** further **statistical, probabilistic and machine-learning techniques** for long-term **change detection**. Adapting these techniques discards transient deviations, and retains permanent changes in monitored behavior. **Real 3-year deployments** in nursing home and individual houses validate proposed approach. **Medical clinic geriatrician** and **nursing home team** validate **medical relevance of detected changes**.

Résumé

Les capacités physiques et cognitives diminuent considérablement à cause du vieillissement. Les problèmes de santé liés au vieillissement présentent une grande charge pour la santé publique. Aujourd'hui, les services gériatriques ne sont pas suffisants pour détecter les problèmes de santé dans les premiers stades de leur évolution, dans le but d'améliorer l'évaluation et l'intervention médicale des personnes âgées. Traduire ces besoins gériatriques à travers les services existants est essentiel pour améliorer leur impact. Dans le cadre de ma thèse, je propose une approche technologique qui utilise des technologies non-intrusives pour analyser le comportement des personnes âgées sur de longues périodes et détecter des possibilités d'évolution de maladies physiques ou cognitives. Des références gériatriques internationales me permettent d'identifier des indicateurs de changement de comportement qui peuvent être suivis à travers de technologies non-intrusives sans interférer avec le comportement naturel des personnes âgées. J'analyse ces indicateurs en considérant plusieurs dimensions spatio-temporelles, et utilisant des techniques de détection de changement qui différencient les changements transitoires et continus dans le comportement suivi. Je valide mon approche proposée à travers un déploiement réel de 3 ans dans une maison de retraite et des maisons individuelles.

Je propose une méthodologie de détection précoce et non-intrusive des possibilités de changement dans l'état de santé. Des entretiens personnels avec les personnes âgées, les membres de la famille, les médecins gériatres et les infirmières de la maison de retraite me permettent d'identifier leurs besoins gériatriques. Les parties prenantes de mes services proposés ont besoin d'une information fiable à propos des changements possibles dans l'état de santé le plus tôt possible, sans suivre les personnes d'une manière intrusive. Afin de traduire ces besoins gériatriques, je propose une approche technologique qui utilise des technologies non-intrusives pour suivre les personnes âgées pendant des semaines et des mois, et identifier des changements possible dans leur comportement fortement liés à des problèmes physiques ou cognitifs.

Mon service web ChangeTracker implémente ma méthodologie. ChangeTracker analyse le comportement des personnes âgées en ligne et détecte des changements possibles chaque

jour. Je développe des algorithmes qui convertissent les données de capteurs brutes en données inférées en relation avec l'état de santé de la personne suivie. Des techniques de détection de changement (par ex., des techniques statistiques, probabilistes et d'apprentissage) distinguent les changements temporaires et continus dans le comportement de la personne.

Une validation réelle de mon approche a lieu dans 3 villes françaises Montpellier, Lattes et Occagnes. Les résultats expérimentaux de 25 participants valident ma détection précoce et non-intrusive des changements de santé. Les 25 participants vivent seuls à domicile ou dans une maison de retraite. Dans mon cas d'étude, j'installe des capteurs de mouvement dans chaque chambre de la maison et des capteurs de contact sur chaque porte principale. Ces capteurs collectent mes données de suivi pendant 3 ans. Mes algorithmes analysent ces données, calculent des indicateurs gériatriques significatifs, et détectent des changements possibles en corrélation avec l'état de santé.

Chapter 1

Introduction: PhD Thesis Context, Objectives and Contributions

Contents

1.1	Context and Objectives	14
1.1.1	Early Health Change Detection	15
1.1.2	Unobtrusive Health Change Detection	15
1.2	Problem Statement and Contributions	15
1.2.1	Problem Statement	16
1.2.2	Methodological and Technical Contributions	16
1.2.3	Medical Relevance Validation	18
1.3	European Project City4Age	19
1.3.1	City4Age Strategy and Objectives	19
1.3.2	City4Age Deployment Sites	20
1.4	Author Publications	20
1.5	Thesis Structure	21

Physical and cognitive abilities considerably decline during aging process. **Early detection** of aging-related health problems is a major enabler to improve geriatric assessments and interventions. Nowadays, **geriatric methods** have limitations in terms of following-up elderly people behavior on a daily basis. **Proposed technological approach** in this thesis employs unobtrusive technologies for long-term behavior monitoring and early detection of possible changes. **European project City4Age** adopts proposed approach and provides validation case studies. This chapter presents thesis context, problematic and contributions.

1.1 Context and Objectives

World population is aging [1]. Elderly people aged 60 years and over are 600 million in 2000 and will be 2 billion by 2050 [2]. Oldest subgroup including elderly people aged 80 years and over represents 3.3% in 2000 and will represent 8% by 2050 [3]. **Physical and cognitive decline** is much more common with age, and considerably affects quality of life of elderly people. Frailty refers to increased risk of dependence in managing activities of daily living [4]. It affects a quarter to a half of elderly people aged 85 years and over [5]. Dementia refers to long-term decline in cognitive abilities as result of aging-related diseases (e.g., Alzheimer, Parkinson and Bipolar Disorder) [6]. Without early detection of Alzheimer disease, it is expected that Alzheimer patient number will be 4 times higher in 2050 more than 2002 [7].

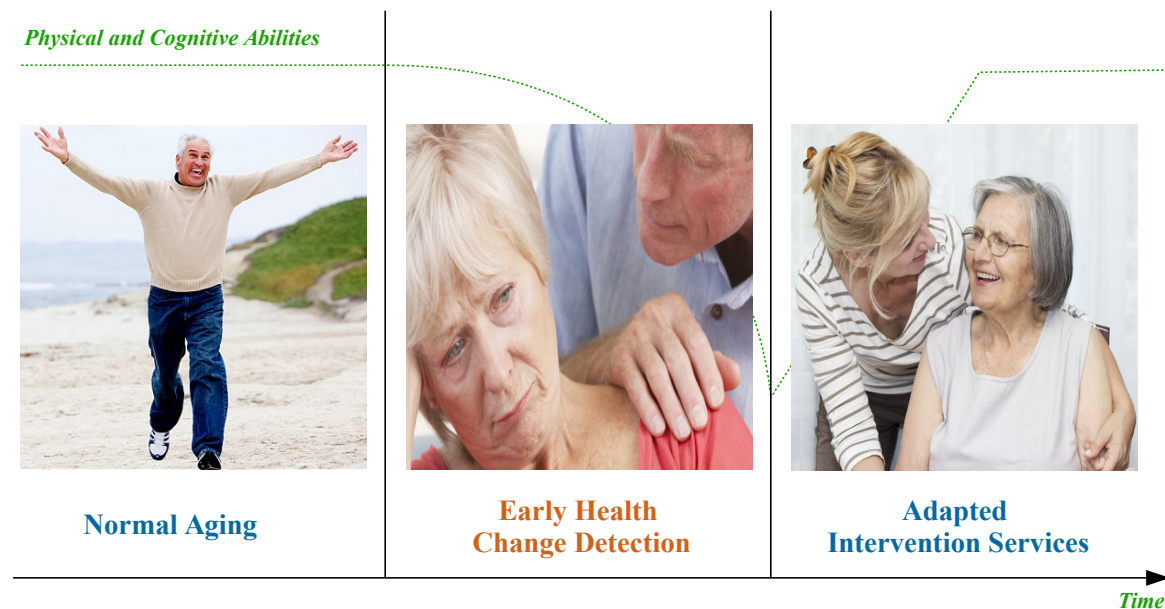


Fig. 1.1 Positive Impact of Early Health Change Detection on Intervention Services for Elderly People

Early detection of aging-related health problems is a keystone for more **effective assessment** and **intervention services** (Fig. 1.1). Nowadays, geriatric methods mainly rely on interviews, and are insufficient to detect possible health changes **as early as possible**. **Proposed approach** translates these geriatric needs via **unobtrusive** Internet of Things (IoT) technologies. It targets **long-term** behavior monitoring and **early** detection of possible changes in health status.

1.1.1 Early Health Change Detection

Elderly people experience diverse physical and cognitive health problems [8]. Geriatricians often investigate health changes with **medical scales** and **questionnaires** by relying on **subjective** and **incomplete** patient feedbacks [9]. Elderly people can not recall all past events at assessment time. Geriatrician visits are once or twice per year, and accessibility to healthcare services is often inconvenient for elderly people [10]. Classical geriatric methods are therefore insufficient to follow-up health status on a daily basis [11]. This leads to missing 75% of possible health changes among elderly people [12].

Early detection of aging-related health problems is essential to provide opportunity for **proactive intervention** by effectively treating them and reducing their influence [13]. This allows to prevent, slow down or restore detected health decline, and help elderly people overcome autonomy loss if it's inevitable [14]. Elderly people have more chance to treat diseases in early stages of their evolution, regain affected functions and reduce disease impact on their independent living.

1.1.2 Unobtrusive Health Change Detection

Geriatricians are interested in integrating **Internet of Things (IoT)** technologies to early detect possible health problems. These technologies provide **new objective observations** of daily living [15]. New smart technologies deployed at home and in city enrich medical observations and enhance medical assessment. They follow-up activities of daily living outside geriatrician's office [16]. Monitoring technologies provide new objective observations of daily living that complete classical medical observations.

IoT-enhanced services continuously monitor elderly people behavior in the environment of their choice. This helps to remain as independent as possible at home and enhance healthy aging in place [17]. Nowadays, it is convenient to use **unobtrusive** IoT technologies that are embedded in the environment or in objects of daily living. Elderly people have **lower acceptance** to **intrusive** cameras and microphones that affect individual privacy [18]. They hardly use **wearable** technologies that require additional operating efforts [19].

1.2 Problem Statement and Contributions

Proposed methodology in this thesis targets effective translation of geriatric needs by employing unobtrusive monitoring technologies (*e.g.*, environmental sensors and sensor-enhanced devices) for early detection of possible changes in health status [20–24].

1.2.1 Problem Statement

Existing geriatric and technological health change detection approaches have limitations in terms of:

- **manually** analyzing elderly people behavior and detecting possible changes. Geriatricians use scales and questionnaires to follow-up health status and investigate possible physical and cognitive problems.
- detecting health changes in **short-time** periods. Existing technological approaches analyze snapshots of behavior in specific time periods, such as identifying falls during day and wandering at night. They do not target long-term changes that require weeks and months to emerge.
- detecting health changes after their occurrence. Existing technological approaches **retrospectively** review monitoring data after change occurrence. They do not analyze data online for early change detection.
- detecting changes at **population scale**; i.e., comparing populations with or without target diseases for change detection. These technological approaches do not analyze behavior at temporal scale for personal change detection.
- employing **intrusive** technologies that require manual operating efforts and affect individual privacy. Nowadays, elderly people have low acceptance rate to wearable technologies, online-based questionnaires, cameras and microphones.
- testing analysis algorithms on **artificial** monitoring data. These technological approaches do not validate medical relevance of detected changes in real deployments.

1.2.2 Methodological and Technical Contributions

Proposed methodology in this thesis **translates geriatric needs** of geriatricians, nursing homes, caregivers, family members and elderly people. Bridging the gap between these geriatric needs and proposed approach is a major enabler to improve its impact [25, 26]. Real stakeholder requirements are enriching classical medical assessments, taking care of relatives living alone, feeling safe at home without intrusive monitoring and linking nursing homes with isolated elderly people.

This thesis translates geriatric needs by identifying **geriatric indicators**, that are extracted from validated geriatric references and can be monitored via **unobtrusive technologies**. Geriatric indicators are essential complex tasks of daily living requiring spatio-temporal

orientation, construction, calculation and attention [27–35]. They are highly related to long-term changes in physical and cognitive health. Geriatric indicators include activities of daily living, mobility, cognition, social life, nutrition, mood and emotions.

Table 1.1 Proposed Methodological Contributions

Contribution	Key Idea
Long-term Change Detection	Proposed approach analyzes overall behavior over long periods, in order to detect long-term changes in health status. These long-term changes require weeks and months to emerge, and are difficult to detect due to normal continuous variation in human behavior.
Early Change Detection	Proposed approach continuously analyzes monitoring data on a daily basis, in order to early detect possible changes. This proactive change detection provides opportunity for daily assessment and subsequent intervention.
Person-centered Change Detection	Proposed approach analyzes elderly people behavior at temporal scale, in order to detect person-centered changes compared to past habits. This enables individual assessment and personalized intervention.
Unobtrusive Behavior Monitoring	Proposed approach selects unobtrusive IoT monitoring technologies that are embedded in our real environment or in objects of daily living. These technologies do not interfere with natural behavior of elderly people and do not change their daily habits.
Real Validation	Proposed approach relies on deployments in naturalistic settings following-up real elderly people behavior over long period. Real deployments validate medical relevance of detected changes.

Unobtrusive monitoring technologies follow-up geriatric indicators without interfering with natural behavior of elderly people (Table 1.1). Integrating these technologies in the environment and in objects of daily living avoids changing personal daily habits. Environmental technologies like movement, door and bed sensors discretely collect information on activity patterns, sleep habits and go out frequency. Sensor-enhanced oven follows-up preparing meals, and sensor-enhanced medicine box checks taking medicines. In-phone-embedded sensors like GPS, accelerometer and step detector in association with city beacons notify about social activities in diverse points of interests.

Developed **data processing algorithms** in this thesis continuously compute geriatric indicators over long period (Table 1.2). These algorithms consider diverse dimensions, such as time, place, number and duration. Analysis dimensions quantify way and manner of executing monitored activities; e.g., time and place specify when and where monitored

activities are executed, number quantifies occurrence of monitored activities, and duration measures execution period. This thesis evaluates and adapts further **change detection techniques** that receive computed indicators as input, and provide possible changes as output. Change detection techniques analyze data on a daily basis, in order to early detect long-term changes; e.g., sleep interruptions increase during anxiety periods, shopping becomes less frequent because of mobility impairments, toilet entries increase as result of urinary infection and duration of preparing meals increases due to cognitive problems.

Table 1.2 Proposed Technical Contributions

Contribution	Key Idea
Online Data Processing Algorithms	Developed data processing algorithms convert sensor observations into geriatric indicators. Despite the basis information collected by unobtrusive sensors, data processing algorithms extract health change indicators, such as activity level, sleep interruptions, toilet entries, received visits and time out of home using movement and contact sensors.
Accurate Change Detection Techniques	Evaluated and adapted change detection techniques detect possible changes in monitored indicators. Statistical, probabilistic and machine-learning techniques apply different filters on deviations, and detect changes with different granularity. They have limitations in terms of single change-point detection and sensibility to outliers. Adapting these techniques by defining moving reference phase and moving window of transient deviations enables multiple long-term change detection.
Useful Change Detection Service	Developed web-based service ChangeTracker provides elderly people, family members and geriatricians with online behavior analysis and continuous change detection. Users examine daily evolution of geriatric indicators and easily identify possible changes. They have detailed information about health status before and after change occurrence. This completes medical diagnosis and enables early intervention.

1.2.3 Medical Relevance Validation

Medical clinic geriatrician Dr. Émilie Guettard [36] and **nursing home team** [37] validate **medical relevance** of technological observations. Medical clinic "Beau Soleil" does not only help with recruitment process, but also provides medical interpretations of detected changes. After obtaining ethical approval, Dr. Émilie Guettard conducts initial **interviews**

with participants. These interviews enable **health status diagnosis** at experimentation begin. Patients consult medical clinic geriatrician each 2 months, and earlier under request. Further interviews occur 6 months and 12 months after monitoring begin, in order to review health status and investigate possible **change causes**. Participants V, X and Y are actually Parkinson patients of Dr. Émilie Guettard (see sub-section 5.2.12 for more information). She identifies changes in toilet entries, time out of home and activity level, that are associated with mobility impairments and treatment side effects.

Nursing home team consists of **nurses, geriatricians and psychotherapists**. They continuously **record medical observations** using tablets. These electronic health records include hospitalizations, mobility problems, memory troubles, anxiety periods, prescribed treatments, social habits and nutritional programs. **Correlating medical observations with technological observations** is essential to validate medical relevance of detected changes. Participants A-I and L are nursing home residents (see section 5.2 for more information). Nursing home team identifies increases in sleep interruptions during anxiety periods, decreases in activity level due to mobility impairments, and increases in toilet entries because of urinary infection.

1.3 European Project City4Age

European project City4Age uses **urban sensor data** to provide adaptable services for elderly people. It targets recognition of early signs of **frailty** and **mild cognitive impairments**, and development of tailored **interventions** [38–40]. **Real deployments** in 6 international cities Madrid (Spain), Athens (Greece), Singapore (Singapore), Montpellier (France), Lecce (Italy) and Birmingham (England) employ City4Age technological solutions, collect real data and validate City4Age strategy and objectives. European project City4Age provides **validation case studies** for **this thesis**, and additionally investigates intervention services.

1.3.1 City4Age Strategy and Objectives

City4Age targets activation of **urban communities** to integrate **IoT technologies** in existing **healthcare services**. Cities play an important role in collecting more data on elderly people behavior. This enables early risk detection through continuous behavior change analysis, and effective intervention design (Fig. 1.2). City4Age project manages **monitoring data** flows collected through IoT technologies both at home and public spaces, identifies relevant **risky behaviors**, develops IoT-enhanced **intervention** services, and **evaluates proposed services** based on stakeholder feedbacks.

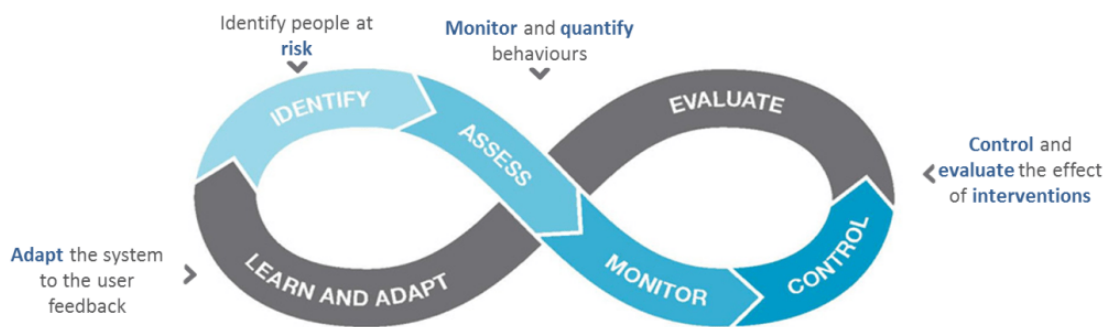


Fig. 1.2 European Project City4Age Strategy and Objectives [38]

1.3.2 City4Age Deployment Sites

Real deployments in 6 international cities Madrid (Spain), Athens (Greece), Singapore (Singapore), Montpellier (France), Lecce (Italy) and Birmingham (England) provide City4Age with real data collection (Table 1.3). Medical clinics, geriatric organizations, friendship clubs, senior care centers, nursing homes, city councils and governmental services help with **recruitment process**.

Table 1.3 European Project City4Age Deployment Sites [38]

City	Focus	Technology	Intervention
Madrid	Using means of transport	Public transport card, phone sensors	Physical exercise recommendations
Athens	Friendship club engagement	Phone application	Cultural activity recommendations
Singapore	Indoor and outdoor activities	Movement, door sensors, city beacons	SMS and email change notifications
Montpellier	Indoor and outdoor activities	Movement, door sensors, city beacons	SMS and email change notifications
Lecce	Outdoor activities	Smart watch, city beacons	Social, cultural activity recommendations
Birmingham	Physical activity data	Smart watch, city beacons	Physical exercise recommendations

1.4 Author Publications

This work and results are published in diverse journals, conferences and book chapters.

- **Journals**

Kaddachi, F., Aloulou, H., Abdulrazak, B., Fraise, P., & Mokhtari, M.. "Long-term Behavior Change Detection Approach through Objective Technological Observations toward Better Adaptation of Services for Elderly People". In *Health and Technology*. September 2018.

Kaddachi, F., Aloulou, H., Abdulrazak, B., Fraise, P., & Mokhtari, M.. "Early and Unobtrusive Detection of Possible Health Changes toward Better Translation of Geriatric Needs". In *Pervasive and Mobile Computing*. Submitted 2018.

- **Conferences**

Kaddachi, F., Aloulou, H., Abdulrazak, B., Bellmunt, J., Endelin, R., Mokhtari, M., & Fraise, P. "Technological Approach for Behavior Change Detection toward Better Adaptation of Services for Elderly People". In *proceedings of HEALTHINF*. February 2017.

Kaddachi, F., Aloulou, H., Abdulrazak, B., Fraise, P., & Mokhtari, M.. "Unobtrusive Technological Approach for Continuous Behavior Change Detection Toward Better Adaptation of Clinical Assessments and Interventions for Elderly People". In *proceedings of ICOST*. August 2017.

Kaddachi, F., Aloulou, H., Abdulrazak, B., Fraise, P., & Mokhtari, M.. "Technological Approach for Early and Unobtrusive Detection of Possible Health Changes toward More Effective Treatment". In *proceedings of ICOST*. July 2018.

Aloulou, H., Endelin, R., Mokhtari, M., Abdulrazak, B., Kaddachi, F., & Bellmunt, J. "Detecting Inconsistencies in Rule-Based Reasoning for Ambient Intelligence". In *proceedings of ICECCS*. November 2016.

Aloulou, H., Endelin, R., Mokhtari, M., Abdulrazak, B., Kaddachi, F., & Bellmunt, J. "Activity Recognition Enhancement Based on Ground-Truth: Introducing a New Method Including Accuracy and Granularity". In *proceedings of ICOST*. August 2017.

- **Book Chapter**

Urosevic, V., Kovacevic, A., Kaddachi, F., & Vukicevic, M.. "Temporal Clustering for Behavior Variation and Anomaly Detection from Data Acquired Through IoT in Smart Cities". In *Recent Applications in Data Clustering*. IntechOpen. August 2018.

1.5 Thesis Structure

Chapter 2 presents **state of the art** health change detection approaches. Nowadays, geriatricians mainly rely on psycho-geriatric scales and questionnaires to analyze elderly people

behavior and investigate possible changes. These classical geriatric methods are insufficient to monitor patients on a daily basis. Geriatricians need IoT-enhanced services to acquire new objective observations of daily living. IoT-enhanced services continuously support geriatricians and elderly people. This chapter presents existing behavior change definitions and models, psycho-geriatric and technological health change detection methods.

Chapter 3 discusses **proposed methodology** for early and unobtrusive detection of possible health changes. Proposed approach identifies essential geriatric needs of elderly people, geriatricians, family members, caregivers and nursing home. These stakeholders need to receive reliable information about possible health changes in early stages of their evolution without intrusive behavior monitoring. In order to translate these geriatric needs, proposed technological approach employs unobtrusive technologies for long-term behavior monitoring.

Chapter 4 introduces **implementation approach**. It presents developed ChangeTracker Service for online behavior analysis and continuous change detection. This chapter provides detailed information on **data processing algorithms** that compute geriatric indicators and metrics. Evaluated and adapted **change detection techniques** analyze computed indicators online and identify long-term changes.

Chapter 5 presents real **validation**. Real deployments in 3 French cities Montpellier, Lattes and Occagnes validate proposed technological approach. In total, 25 elderly people living alone at home or nursing home participate in experimentation. Movement sensors deployed in each room and door sensors installed at main house entries collect monitoring data during 3 years. Medical clinic geriatrician and nursing home team validate medical relevance of technological observations.

Chapter 2

State of the Art: Psycho-Geriatric and Technological Health Change Detection Approaches

Contents

2.1	Behavior Definitions and Models	24
2.2	Behavior Change Initiation and Maintenance Models	25
2.3	Psycho-Geriatric Health Change Detection Approaches	27
2.3.1	Short Emergency Geriatric Assessment (SEGA)	28
2.3.2	Mini Mental State Examination (MMSE)	28
2.3.3	Geriatric Depression Scale (GDS)	29
2.3.4	Instrumental Activities of Daily Living (IADL)	29
2.3.5	Autonomie Gerontologique et Groupes Iso-Ressources (AGGIR)	31
2.3.6	Get Up And Go (GUGO)	31
2.3.7	Mini Nutritional Assessment	31
2.3.8	Behavioral Pathology in Alzheimer’s Disease (BeAd)	32
2.3.9	Neuropsychiatric Inventory (NPI)	32
2.3.10	Quality of Life Scales (QoL)	33
2.3.11	Pain Assessment Scales	33
2.3.12	Agitation Assessment Scales	33
2.3.13	Psycho-Geriatric Assessment Limitations	34

2.4	Technological Health Change Detection Approaches	34
2.4.1	Short-term Health Change Detection	34
2.4.2	Retrospective Health Change Detection	35
2.4.3	Population-scale Health Change Detection	36
2.4.4	Intrusive Health Change Detection	37
2.4.5	Simulation-based Health Change Detection	38
2.5	Conclusion and Discussion	38

Early detection of possible **health problems** improves medical assessments and enables proactive intervention [13]. Aging-related health problems generate **long-term changes** in way and manner of behavior execution, such as possible instabilities, variations, impairments, declines, increases or improvements [41]. Whereas existing models target **behavior change initiation and maintenance**, **behavior change detection** enables better fulfillment of both objectives. Behavior change detection determines when to initiate behavior changes, and which services to select. Nowadays, geriatricians use **psycho-geriatric scales and questionnaires** to analyze behavior and investigate possible changes. These psycho-geriatric approaches are insufficient to monitor patients on a daily basis [9]. Geriatricians adopt **technological approaches** to acquire objective observations of daily living [11]. Technological observations early detect possible health changes [15]. This chapter introduces existing behavior change definitions and models. It presents existing psycho-geriatric and technological health change detection approaches.

2.1 Behavior Definitions and Models

Behavior is a range of actions, inactions and beliefs made by individuals, organisms, systems or artificial entities [41]. It provides outputs from the organism to the environment, and changes organism's relationship to its environment. Behavior is a response to internal (*i.e.*, organism itself) or external (*i.e.*, other organisms and physical environment) stimuli or inputs.

From sociological point of view, behavior refers to inter-individual interactions (*i.e.*, two or more organisms) [42]. It can be influenced by family structure, work or school environment relationships, health conditions and psychiatric issues.

Economists recognize behavior as processes consumers go through or reactions they have toward purchasing or consuming products or services [43]. It is influenced by internal factors, such as attitudes, needs, motives and preferences. External factors have also significant influence, such as marketing activities, social, economical and cultural aspects. Consumer Decision Making (CDM) model presents consumer behavior as response to internal and

external needs, followed by search for information (*e.g.*, retrieve memory, read reviews or reports, and ask friends) [44]. Consumers evaluate alternatives by comparing price and quality, before purchasing products and acquiring purchase experience.

In the medical field, behavior refers to persons' beliefs and actions regarding their health [45]. Health behavior is influenced by social, cultural and physical environments, and has large impact on quality of life. Positive health behaviors promote healthy life, such as avoid snacks, eat breakfast early, exercise regularly, maintain a desirable weight, moderate alcohol intake, not smoke and sleep 7-8 hours per night [46]. Negative health behaviors are associated with higher morbidity (*i.e.*, disease incidence rate) and mortality (*i.e.*, death rate). Health behaviors are early indicators for population health and predict future burdens of health risks.

Table 2.1 Existing and Proposed Behavior Definitions and Models

Category	Key Idea
Psychology [41]	Behavior is a range of actions, inactions and beliefs, that respond to internal and external stimuli or inputs.
Sociology [42]	Behavior refers to inter-individual interactions. It can be influenced by family structure, and work or school environment relationships.
Economy [43, 44]	Behavior consists of processes consumers go through or reactions they have toward purchasing or consuming products or services.
Health [45, 46]	Behavior refers to persons' beliefs and actions regarding their health. Positive health behaviors promote healthy life. Negative health behaviors are associated with higher morbidity and mortality. Health behaviors are early indicators for population health and predict future burdens of health risks.
Proposed Definition	Behavior refers to the way and manner individuals perform actions and inactions.

Existing definitions consider behavior as a response to internal or external factors, such as intentions, desires, social interactions and marketing activities (Table 2.1). However, individuals respond differently to these factors; *e.g.*, being hungry stimulates individuals to prepare meals with different duration, frequency and difficulty. Therefore, proposed definition considers behavior as the way and manner individuals perform actions and inactions.

2.2 Behavior Change Initiation and Maintenance Models

Existing models predict the amount of effort individuals require for behavior change initiation and maintenance. Initiating and maintaining behavior changes is related to individuals'

perception of their own ability to perform demanding or challenging tasks (*e.g.*, face exam and undergo surgery) [47]. Individuals' prior success in those tasks or related tasks, their psychological state and outside sources of persuasion are key factors for behavior change initiation and maintenance.

Table 2.2 Existing Behavior Change Initiation and Maintenance Models

Model	Key Idea
Health Belief Model [48]	Individuals' belief about health problems and perceived benefits of actions is key factor for changing behaviors.
Trans-theoretical Model [49]	Initiating and maintaining behavior changes require five steps: pre-contemplation, contemplation, preparation, action and maintenance.
Health Action Process Approach [50]	Behavior change refers to two continuous processes: goal setting and goal pursuit
Theory of Reasoned Action [51]	Behavior changes are determined by intentions (<i>i.e.</i> , considering behavior's consequences before performing the particular behavior).
Theory of Planned Behavior [51]	Both the amount of control an individual possesses over behavior, and the strength of intentions as key factors for changing behaviors.
Learning Theories [52]	Individuals learn complex behaviors by modifying simpler behaviors through imitation and reinforcement.
Social Cognitive Theory [53]	People observe behavior and the consequences of that behavior, they remember the sequence of events and use this information to guide subsequent behaviors.
Social Learning Theory [54]	Behavior changes are function of individual's exposure to certain behavior and their acquaintances.

In the medical field, behavior change refers to abandoning health-compromising behaviors (*e.g.*, drink, smoke and over-eat), and maintaining health-improving behaviors (*e.g.*, physical exercise, weight control, preventive nutrition and dental hygiene). Health Belief Model (HBM) suggests that individuals' belief about health problems and perceived benefits of actions plays important role in adopting health-promoting behaviors [48]. Trans-theoretical Model (TTM) proposes five steps toward initiating and maintaining new behavior changes [49]. In the first step, individuals have not thought about changing their behaviors. Then, individuals begin thinking about changing particular behaviors. Afterwards, they prepare

their plans for behavior change. In the fourth step, individuals adopt and perform new behaviors. Finally, they consistently conserve their new behaviors.

From psychological point of view, Health Action Process Approach (HAPA) recognizes behavior change as two continuous processes: goal setting and goal pursuit [50]. While goal setting is related to factors that motivate behavior change, goal pursuit consists in planning and performing intended change. Theory of Reasoned Action (TRA) confirms that behavior changes are determined by intentions (*i.e.*, considering behavior's consequences before performing the particular behavior) [51]. Personal attitude and social pressure (*i.e.*, the way society perceives same behavior) have major influence on individual intentions. Theory of Planned Behavior (TBA) considers both the amount of control an individual possesses over behavior, and the strength of intentions as key factors for changing behaviors [51].

In the education field, learning theories explain initiation and maintenance of complex behaviors by modifying simpler behaviors through imitation (*i.e.*, reproducing learned behaviors) and reinforcement (*i.e.*, positive rewarding factors that strengthen future behaviors, like wanting and liking, desire and pleasure) [52].

Social Cognitive Theory (SCT) explains behavior changes by social interactions [53]. People observe behavior and the consequences of that behavior, they remember the sequence of events and use this information to guide subsequent behaviors. Social Learning Theory (SLT) considers behavior changes as function of individual's exposure to certain behavior and their acquaintances [54]. This reinforces either socially acceptable or socially unacceptable behaviors [55].

Whereas existing models target behavior change initiation and maintenance (Table 2.2), detection of behavior change enables better fulfillment of both objectives. In deed, behavior change detection allows to make better decisions of when to initiate behavior changes, and which services to select for behavior change initiation and maintenance.

2.3 Psycho-Geriatric Health Change Detection Approaches

Psycho-geriatric scales and questionnaires analyze elderly people behavior and detect possible health changes (Table 2.3). Geriatricians and formal caregivers study question replies and task executions, such as "How many falls did you have in the last 6 months?" [27], "Please make a sketch of two intersecting polygons!" [28], "Have you dropped many of your activities and interests?" [29] and " Do you perform your activities of daily living independently (A), not spontaneously or not totally or not correctly or not frequently (B), only with help (C)?" [30]. These scales compute psycho-geriatric scores evaluating physical, emotional, nutritional, social and cognitive abilities.

Table 2.3 Comparison of Psycho-Geriatric Scales

	SEGA	MMSE	GDS	IADL	AGGIR	GUGO	MNA	BeAd	NPI
Activities of Daily Living	✓			✓	✓			✓	✓
Mobility	✓				✓	✓			
Cognition	✓	✓		✓	✓		✓	✓	✓
Social Life	✓			✓	✓		✓	✓	✓
Nutritional Status	✓				✓		✓		
Mood and Emotions	✓		✓					✓	✓

2.3.1 Short Emergency Geriatric Assessment (SEGA)

Short Emergency Geriatric Assessment (SEGA) evaluates frailty of elderly people [27]. Frailty refers to increased risk of dependence in managing activities of daily living [4]. It affects a quarter to a half of elderly people aged 85 years and over [5]. Trained caregivers use this scale by giving corresponding questions to elderly people and their informal caregivers. SEGA considers frailty-related indicators, such as falls, nutrition, memory, vision, audition, social support and financial situation. Each indicator has three possible values and corresponding scores. Total score is the sum of all partial scores: 0-8 (quite frail person), 9-11 (frail person), 12-26 (very frail person):

- Age: less than 74 (0), between 75 and 84 (1), more than 85 (2)
- Falls (during last six months): none (0), once (1), many (2)
- Mobility (getting up and walking): independently (0), only with help (1), unable (2)

2.3.2 Mini Mental State Examination (MMSE)

Mini Mental State Examination (MMSE) targets cognitive changes, such as orientation problems, attention difficulties and language troubles [28]. Trained caregivers conduct MMSE test based on questions and tasks given to elderly people. MMSE takes into consideration cognitive indicators, such as orientation, learning, attention, calculation, recall and construction. It analyses cognitive abilities based on questions replies and task executions, and rates them. Total score is the sum of all partial scores. Lower scores refer to more severe cognitive impairments:

- What is the current date (year, season, month, day of month, day of week)? (5)

- Repeat three given words (3), repeat the same words after some minutes (3)
- Count down from 100 by reducing 7 each time (5)

2.3.3 Geriatric Depression Scale (GDS)

Geriatric Depression Scale (GDS) investigates changes in mood and emotions [29]; e.g., feeling sad and that one's life is empty is associated with possible depression. Elderly people reply to emotional questions evaluating their mood and depicting possible anxiety and depression. Higher total scores refer to more severe depression:

- Do you feel that you are sad?: yes (1), no (0)
- Do you feel that your life is empty?: yes (1), no (0)
- Do you feel that you are happy almost all the time?: yes (0), no (1)
- Do you feel that your situation is desperate?: yes (1), no (0)

2.3.4 Instrumental Activities of Daily Living (IADL)

Instrumental Activities of Daily Living (IADL) identifies changes in activities of daily living that are associated with autonomy loss [30]. Trained caregivers rate IADL scale based on question replies of elderly people and their informal caregivers. IADL focuses on activities of daily living, such as using telephone, using means of transport, taking medicines and managing personal finances. Each situation has four possible outcomes and corresponding scores. Total score is the sum of all partial scores. Higher total scores refer to more severe dependency problems:

- Using telephone: on one's own initiative (1), only dial some known numbers (2), can answer the phone but can not make a call (3), never uses the phone (4)
- Using means of transport: independently (1), only with someone else (2), only with taxi or car and with assistance (3), never goes out (4)
- Taking medicines: independently (1), occasionally forgets to take them (2), only with help (3), unable (4)
- Managing personal finances: independently (1), occasionally forgets to pay important bills (2), only with help (3), unable (4)

Table 2.4 Examples of Psycho-Geriatric Scales

Scale	Focus
SEGA [27]	Evaluation of frailty based on falls, nutrition, memory, vision, audition, social support and financial situation
MMSE [28]	Evaluation of cognitive abilities based on orientation, learning, attention, calculation, recall and construction
GDS [29]	Evaluation of mood and emotions based on depression
IADL [30]	Evaluation of autonomy based on using telephone, means of transport and managing personal finances
AGGIR [31]	Evaluation of autonomy based on changes in position, movement indoors, hygiene, dressing, cooking, nutrition, medicines, household, technologies, movement outdoors, means of transport, free time and shopping
GUGO [32]	Evaluation of mobility based on getting up, walking to a mark 3m away, turning around and sitting again
MNA [33]	Evaluation of nutrition based on eating, weight, mobility, autonomy, medicines, protein intake, water consumption
BeAd [34]	Evaluation of behavioral impairments based on hallucinations, aggressiveness, affection, anxiety, phobia
NPI [35]	Evaluation of behavioral impairments based on delusions, agitation, depression, euphoria, indifference, abnormal motor behavior, nighttime behaviors, appetite
QUALIDEM [56], ADRQL [57]	Evaluation of quality of life based on relationship with caregivers, positive, negative feelings, agitation, positive self-awareness, social relationships, spacial orientation, activities
ALGOPLUS [58], DOLOPLUS [59]	Evaluation of pain based on speech, movement, cry, tears, body position, communication, social life.
CMAI [60], PAS [61]	Evaluation of agitation based on unaggressive abnormal vocalization, motor agitation, aggressiveness and resisting care

2.3.5 Autonomie Gerontologique et Groupes Iso-Ressources (AGGIR)

Autonomie Gerontologique et Groupes Iso-Ressources (AGGIR) investigates autonomy changes [31]. Trained caregivers collect information based on questions given to elderly people or their informal caregivers. AGGIR considers autonomy indicators, such as changes in position, movement indoors, hygiene, dressing, cooking, nutrition, medicines, household, technologies, movement outdoors, means of transport, free time and shopping. Each indicator has three possible codes (*e.g.*, Changes in Position: only with help (C), not spontaneously or not totally or not correctly or not frequently (B), independently (A)). AGGIR includes an algorithm that computes final score based on partial codes. Final score quantifies dependency level by associating elderly people to autonomy groups:

- Group 1: total dependence
- Group 2-5 : partial dependence
- Group 6: total independence

2.3.6 Get Up And Go (GUGO)

Get Up And Go (GUGO) targets motor behavior changes [32]. Trained caregivers ask elderly people to get up, walk and turn around, in order to analyze task execution and identify possible mobility impairments. After sitting on a chair, elderly people must get up, walk to a mark 3 meters away, turn around and sit again in 20 seconds. Each position change has zero or negative score (zero is the best partial score). Total score is the sum of partial scores. Lower total score refer to more severe mobility impairments:

- Get up: senior falls backwards (-4), only with help (-2), only after two or three tries (-1), gets up spontaneously (0)
- Walk: normal (0), zigzag (-1)
- Turn around: normal (0), only after executing successive steps (-3)

2.3.7 Mini Nutritional Assessment

Mini Nutritional Assessment (MNA) investigates nutritional changes, such as eating difficulties, weight loss and protein intake insufficiency [33]. Trained caregivers rate MNA based on information collected from elderly people and their informal caregivers. MNA focuses on nutritional indicators, such as eating, weight, mobility, autonomy, medicines,

protein intake and water consumption. Each indicator has three possible scores. Lower total score indicate more severe nutritional problems (*i.e.*, 0-7 (undernourishment), 8-11 (risk of undernourishment), 12-14 (normal nutrition)):

- Has the senior lost weight during the last three months?: more than 3 kg (0), do not know (1), between 1 kg and 3 kg (2), no weight loss (3)
- What is the IMC indicator?: less than 19 (0), between 19 and 21 (1), between 21 and 23 (2), more than 23 (3)
- How many daily meals does the senior take?: one (0), two (1), three (2)

2.3.8 Behavioral Pathology in Alzheimer's Disease (BeAd)

Behavioral Pathology in Alzheimer's Disease (BeAd) scale detects behavioral impairments, such as presence of hallucinations, aggressiveness and anxiety [34]. Trained caregivers depict possible behavioral anomalies based on question replies. BeAd considers behavioral indicators, such as hallucinations, aggressiveness, affection, anxiety and phobia. Each abnormal behavior has four possible scores. Total score is the sum of partial scores. Higher total scores indicate more severe behavioral impairments:

- One's house is not one's house delusion: not present (0), complaints while at home to take him home (1), attempt to leave home (2), violent attempt to leave home (3)
- Visual Hallucinations: not present (0), not clearly defined (1), clearly defined hallucinations of objects and persons (2), verbal or physical actions and emotional responses to hallucinations (3)
- Wandering: not present (0), some (1), sufficient to require restraint (2), verbal or physical actions and emotional responses to attempts to prevent wandering (3)

2.3.9 Neuropsychiatric Inventory (NPI)

Neuropsychiatric Inventory (NPI) addresses behavioral impairments of elderly people [35]. Trained caregivers collect information from informal caregivers having contact with elderly people at least four hours per day and four days per week. NPI focuses on behavioral indicators, such as delusions, agitation, depression, euphoria, indifference, abnormal motor behavior, nighttime behaviors and appetite. Frequency and severity of each indicator have four and three scores respectively. An additional distress factor reflects emotional and psychological distress experienced by informal caregivers. Partial scores are equal to frequency multiplied by severity. Higher total scores indicate more severe behavioral impairments:

- Frequency: rarely (1), sometimes (2), often (3), very often (4)
- Severity: mild (1), moderate (2), severe (3)
- Distress: not at all (0), minimally(1), mildly (2), moderately(3), severely(4), very severely (5)

2.3.10 Quality of Life Scales (QoL)

Alzheimer's Disease Related Quality of Life (ADRQL) and Quality of Life Instrument for Persons with Dementia (QUALIDEM) evaluate quality of life of elderly people [57, 56]. Both tests study indicators that are related to one's quality of life:

- ADRQL: social interaction, awareness of self, feelings and moods, enjoyment of activities and response to surroundings
- QUALIDEM: relationship with caregivers, positive feelings, negative feelings, agitation, positive self-awareness, social relationships, isolation, spacial orientation and activities

2.3.11 Pain Assessment Scales

DOLOPLUS and ALGOPLUS scales evaluate pain level of elderly people [59, 58]. Trained caregivers rate pain level based on diverse indicators, such as speech, movement, cry, tears, body position, communication and social life. Each variable has four levels. Total score higher than 5 out of 30 reveals pain:

- Complaints: none (0), only after asking him (1), occasional and spontaneous (2), continuous and spontaneous (3)
- Mimicking: normal (0), painful (1), without expression (2), very abnormal (3)
- Sleep: usual (0), sleep difficulties (1), frequent sleep interruptions (2), insomnia (3)

2.3.12 Agitation Assessment Scales

Cohen-Mansfield Agitation Inventory (CMAI) and Pittsburgh Agitation Scale (PAS) evaluate agitation level of elderly people [60, 61]. Considered agitation indicators include abnormal vocalization, motor agitation, aggressiveness and resisting care. Each indicator has five outcomes and corresponding scores. Higher total score reflects more severe agitation:

- Abnormal vocalization: not present (0), low volume (1), louder (2), disruptive (3), extremely loud (4)
- Motor agitation: not present (0), moving about in chair at normal rate (1), increased rate of movements (2), rapid movements (3), intense movements (4)
- Aggressiveness: not present (0), verbal threats (1), threatening gestures (2), physical toward property (3), physical toward self or others (4)

2.3.13 Psycho-Geriatric Assessment Limitations

Geriatricians use psycho-geriatric scales to analyze elderly people behavior and identify possible cognitive impairments, autonomy problems, rapid mood changes, nutritional and behavioral anomalies (Table 2.4). Certain inconveniences limit the efficiency of psycho-geriatric scales. It is inconvenient for elderly people to recall past events with full details at assessment time [9]. It is also often not convenient for elderly people to move to assessment place [10]. Besides, requesting that individuals reply to given questions and perform determined tasks has potential negative impact on their future behaviors after assessment. For example, anxiety of seniors increases if they do not reply to orientation questions or perform mobility tasks.

Psycho-geriatric scales are insufficient to follow-up health status on a daily basis [9]. Subjective information and missing details might influence assessment results [12]. Therefore, proposed approach employs Internet of Things (IoT) technologies to collect objective observations of daily living that complete classical psycho-geriatric assessments.

2.4 Technological Health Change Detection Approaches

Psycho-geriatric scales and questionnaires have limitations in terms of monitoring elderly people behavior on a daily basis [9]. Thus, geriatricians need technological services to acquire new objective observations that complete their medical observations [11]. Monitoring technologies follow-up elderly people at home and in city, in order to early detect possible health changes [15]. Next sub-sections distinguish five categories of technological health change detection approaches.

2.4.1 Short-term Health Change Detection

This category target short-term changes occurring in specific time periods, such as falls and wandering during sleep. Bourke et al. use tri-axial accelerometer to measure acceleration,

and tri-axial gyroscope attached to fifth lumbar spine to measure angular velocity [62]. Machine-learning and decision-tree-based algorithm distinguish between real falls and normal walking patterns. Classification combines kinematic and temporal features (*e.g.*, horizontal velocity and vertical displacement). Machine learning techniques recognize classes of normal activities and falls using real training data (89 real falls and 368 normal activities).

Aloulou et al. deploy movement, pressure, proximity and vibration sensors in nursing-home rooms to detect wandering at night, showering for too long, leaving the wash-room tap on and toilet falls [63, 64]. Semantic reasoning (first order logic rules) recognizes activities of daily living in real time, in order to notify formal caregivers about detected anomalies. Caregivers observe increases in notification number after detecting health problems; *e.g.*, notification number increases from 6 to 12 per day after observing negative health changes.

Existing commercial products use movement and door sensors in combination with emergency button, in order to detect falls and wandering during sleep [65, 66]. Family members receive alerts, if abnormal inactivity is detected. Elderly people use emergency buttons to call caregivers.

Proposed approach analyzes overall behavior over long periods, in order to detect long-term changes in health status. These long-term changes require weeks and months to emerge, and are difficult to detect due to normal continuous variation in human behavior [67].

2.4.2 Retrospective Health Change Detection

Another category retrospectively investigates possible changes after change occurrence. Lee et al. use sensor-enhanced pillbox, land-line phone and coffeemaker to monitor medication taking, phone use and coffee making [68]. After six months of monitoring, they invite participants in a reflection session to improve their behavior performance. Reflection session allows to either confirm participant's own-confidence in managing monitored tasks of daily living or re-assessing over-confidence if monitoring data do not match with personal observations. 2SD-band technique detects changes in behavior after reflection session. It computes a band for the pre-reflection phase with bounds equal to two standard deviations above and below the mean. Abnormal behavior performance exists outside the defined band in the post-reflection phase.

Rantz et al. use motion and bed sensors to monitor motion, pulse, breathing, and bed restlessness [16]. After occurrence of significant health events, geriatricians review monitoring data to investigate possible correlations. Sensor observations help geriatricians focus care into areas that require more attention, confirm their medical assessment and detect a pattern of decline not normally detected in regular office visit. Geriatricians have access to a web-based interface with line graphs, histograms and pie charts. They also receive

real-time notifications, if significant health events occur (*e.g.*, monitoring system notifies a low pulse event if detected pulse is less than 30 beats per minute, and generates a high pulse event if greater than 100 beats per minute). Reviewing sensor data of 96-year-old participant having serious cardiac event allows to observe changes in pulse rate. Another 79-year-old participant shows high bed restlessness after a coronary bypass surgery. Bed restlessness returns to normal after rehabilitation program.

Sprint et al. use wearable fitness devices to collect physical activity data, such as step number, frequency, duration and intensity [69]. They compare monitoring data before and after 10-week rehabilitation session of elderly people having mobility impairments. Data mining techniques (*e.g.*, RuLSIF, texture-based dissimilarity, sw-PCAR and virtual classifier) measure change scores between pre-intervention and post-intervention windows. This retrospective comparison evaluates physical exercise impact; *e.g.*, change scores indicate decrease in daily step number for over-confident participants evaluating themselves as completely meeting their physical exercise goals.

Proposed approach continuously analyzes monitoring data on a daily basis, in order to early detect possible changes. This proactive change detection provides opportunity for daily assessment and subsequent intervention.

2.4.3 Population-scale Health Change Detection

Further category compares elderly people populations with or without a target disease, in order to investigate disease-related indicators at population scale. Existing studies investigate indicators of mild cognitive impairments (MCI), by employing bed sensors, personal computers, sensor-enhanced pillbox, motion sensors and sensor-enhanced phones. Monitoring data analyze sleep habits [70], computer use [71], medication taking [72], walking patterns [73], go out routine [74], phone use [75] and speech abilities [76]. Computer use involves cognitive domains such as attention and working memory. Medication adherence relies on cognitive skills such as prospective memory and executive functioning. Time out of home requires navigation, way-finding and physical capability. Phone use reflects size of friend, family and acquaintance network. Changes in these variables are related to mild cognitive impairments.

It was reported that MCI patients have less disturbed sleep (based on sleep time inferred from inactivity periods and bed movements), less computer use (based on mouse events and keyboard typing), more risk of medication non-adherence (based on daily specified times of medicine taking), more variable walking patterns (based on walking speed and frequency), shorter time out of home, less phone calls (based on number dialed and ring rate) and more spoken words than intact elderly people.

Proposed approach analyzes elderly people behavior at temporal scale, in order to detect person-centered changes compared to past habits. This allows to provide individual assessment and personalized intervention after detecting possible changes.

2.4.4 Intrusive Health Change Detection

This category uses intrusive technologies to capture video sequences, collect daily questionnaire-based information and record physical data using body sensors. Hodges et al. invite elderly people to wear bracelet with RFID reader for coffee-making monitoring [77]. They investigate possible correlation between coffee making performance and neuro-psychological assessment of 16 traumatic brain injury (TBI) subjects. Bracelet with RFID reader in association with 12 RFID tags in coffee maker components allows to measure coffee making duration (*i.e.*, how long it takes the participant to make coffee), action gaps (*i.e.*, periods of inactivity during coffee making), object misuse (*i.e.*, number of incorrect interactions with coffee maker components) and edit distance (*i.e.*, Levenshtein distance between monitored coffee making order and correct order). Edit distance shows most significant correlation with neuro-psychological integrity (*i.e.*, intellectual functioning, verbal and nonverbal reasoning, memory, and complex attention).

Allin et al. compute video and audio statistics using cameras and microphones for anomaly detection in interpersonal interactions, such as changes in activity, wandering, physically and verbally aggressive actions indicating Alzheimer [78]. They use Hidden Markov Models to build typical movement patterns for anomaly detection, kinematic and probabilistic models for fall detection, and emotion models based on face image and voice analysis.

Avvenuti et al. develop rule-based system to detect wandering and falls from bed during sleep using modern neuro-sensors (*e.g.* 10 electrodes placed on the scalp) to record brain activity (*i.e.*, electroencephalograph (EEG) and rapid eye movement (REM) signals), body accelerometers to record body movement and electro muscle strength (EMG) [79]. They monitor patient's behavior to understand the correlation between brain activity and body movement. Correlation enables to derive threshold values for anomaly detection.

Magill et al. investigate depression indicators for bipolar disorder (BD) patients using online-form-reported data [80, 81]. They target detection of mental state changes toward depression. Patient becomes aware of these changes and take appropriate actions. Phone application uses rules to allow each questionnaire to be personalized for individuals regarding content and timing.

Further studies monitor eating habits (*i.e.*, time when monitored person is eating or drinking while sitting at table) using accelerometer attached to person's wrist [82], mental

confusion based on analyzing video sequences of walking patterns [83], food intake based on analyzing mobile-phone photos [84], and vital signs using smart watch [85] and wearable pulse sensor [86].

Proposed approach selects unobtrusive monitoring technologies that are embedded in our real environment or in objects of daily living, do not interfere with natural behavior of elderly people and do not change their daily habits.

2.4.5 Simulation-based Health Change Detection

Another category simulates monitoring data by generating realistic life scenarios with artificial changes in health status [87]. Mshali et al. use Markovian models to generate activities of daily living that require mobility, communication and mental functions. Markovian models simulate realistic activity duration and frequencies, and generate changes in dependency levels (*i.e.*, activity duration and frequencies change accordingly to selected dependency level after each simulated change point). Grey Theory (single variable first order model GM(1,1)) learns initially simulated activity duration and frequencies, and regularly predicts future values. Change occurs, if predicted values do not match newly simulated activity duration and frequencies.

Lee et al. develop 3D simulators of human activities, in order to avoid lab experiments and real-life deployments [88]. Real deployments require manual installation and long-term maintenance. Simulators enable flexible management of sensor networks, and generate monitoring data for long period. They create variable activity trends, and test uncommon scenarios that require weeks and months to emerge in real-life deployments.

Proposed approach relies on real deployments, and analyzes real behavior over long period. Personal, context and medical information validate medical relevance of detected changes.

2.5 Conclusion and Discussion

Early detection of **health decline** is essential to improve assessment and intervention services for elderly people. **Geriatricians** chiefly rely on psycho-geriatric scales and questionnaires to analyze elderly people behavior and detect possible changes. These classical geriatric methods are insufficient to detect health changes on a daily basis. Geriatricians need **technological services** to complete their medical observations with new objective observations of daily living. Technological services continuously support geriatricians and elderly people by

integrating Internet of Things (IoT) technologies at home and in city, in order to early detect possible health changes (Table 2.5).

Table 2.5 Comparison of Health Change Detection Approaches

Reference	Focus	Technology	Technique	Limitation
Psycho-Geriatric Scales [27–35]	Activities of daily living, social life, nutritional status, mood, cognition, mobility	Questionnaires, scales	Manual evaluation	Incomplete, subjective assessment
Bourke [62]	Falls	Accelerometer, gyroscope	Machine learning, decision tree	Short-term change detection
Aloulou [63]	Wandering, showering for too long, leaving the wash-room tap on, falls	Movement, pressure, proximity, vibration sensors	Semantic reasoning	
Singtel [65]	Abnormal inactivity periods	Emergency button, door, motion sensors	Unspecified	
Senior Home [66]	Falls, wandering during sleep, sleep impairments	Emergency button, door, motion sensors	Unspecified	Retrospective change detection
Lee [68]	Medication taking, phone use, coffee making	Sensor-enhanced pillbox, phone, coffeemaker	2SD band	
Rantz [16]	Pulse, breathing, bed restlessness	Bed sensor	Manual evaluation	
Sprint [69]	Step number, frequency, duration, intensity	Wearable fitness devices	RuLSIF, texture-based dissimilarity, sw-PCAR, virtual classifier	
Hayes [70]	Sleep habits	Bed sensor	Regression models	Population-scale change detection
Kaye [71]	Computer use	Personal computer		
Hayes [72]	Medication taking	Electronic pillbox		
Hayes [73]	Walking patterns	Motion sensors		

Thielke [74]	Go out routine	Motion, door sensors		
Peterson [75]	Phone use	Sensor-enhanced land-line phone		
Dodge [76]	Speech	Webcam	Language processing techniques	
Hodges [77]	Coffee making	Bracelet, RFID reader, RFID tags in coffee maker	Levenshtein distance	Intrusive change detection
Allin [78]	Interpersonal interactions	Cameras, microphones	Video and audio statistics, hidden markov models	
Avvenuti [79]	Wandering, falls	Neuro-sensors	Data mining, rule-based reasoning	
Magill [80]	Depression	Phone application, motion, GPS, accelerometer	Phone-based form, sensor data analysis	
Tolstikov [82]	Eating	Accelerometer, RFID reader, tags	Dynamic bayesian network	
Zhang [83]	Mental confusion, walking patterns	Cameras	Video processing techniques	
Dalakeidi [84]	Food intake	Phone application	Image processing techniques	
Sashima [85]	Vital signs	Smart watch	Signal processing techniques	
Reddy [86]	Pulse	Wearable pulse sensor	Signal processing techniques	
Mshali [87]	Activities of daily living	Environmental sensors	Grey theory, hidden markov models	
Lee [88]	Activities of daily living	3D simulators	Event-driven simulation	

Existing technological approaches for health change detection have limitations in terms of (i) focusing on **short-term** health problems, (ii) **retrospectively** detecting health changes after their occurrence, (iii) detecting health changes at **population scale**, (iv) using **intrusive**

technologies to monitor elderly people behavior, and (v) analyzing elderly people behavior based on **simulations** and artificial change points.

In this thesis, **proposed technological approach** employs **unobtrusive** Internet of Things (IoT) technologies for **long-term** behavior monitoring and early detection of possible changes. **Proposed methodology** identifies **geriatric indicators** that can be monitored via unobtrusive IoT technologies, and are associated with physical and cognitive problems. This thesis develops **data processing algorithms** that convert raw sensor data into geriatric indicators. These geriatric indicators are analyzed on a daily basis, in order to early detect possible changes. This thesis **evaluates and adapts** further **statistical, probabilistic and machine-learning techniques** for long-term **change detection**. Adapting these techniques discards transient deviations, and retains permanent changes in monitored behavior. **Real 3-year deployments** in nursing home and individual houses validate proposed approach. **Medical clinic geriatrician** and **nursing home team** validate **medical relevance of detected changes**.

Chapter 3

Methodology: Translating Geriatric Needs via Internet of Things Technologies

Contents

3.1	Investigated Geriatric Needs	43
3.1.1	Geriatrician Needs	44
3.1.2	Nursing Home Needs	45
3.1.3	Caregiver and Family Member Needs	46
3.1.4	Elderly People Needs	46
3.1.5	Geriatric Need Comparison and Translation	47
3.2	Analyzed Health Change Indicators	48
3.2.1	Activity of Daily Living (ADL) Indicators	49
3.2.2	Mobility Indicators	50
3.2.3	Cognitive Indicators	50
3.2.4	Social Life Indicators	51
3.2.5	Nutritional Indicators	52
3.2.6	Emotional Indicators	52
3.3	Employed Unobtrusive Monitoring Technologies	53
3.3.1	Environmental Sensors	53
3.3.2	Sensor-Enhanced Devices	55

3.3.3	In-Phone-Embedded Sensors	56
3.4	Selected Health Change Metrics	57
3.5	Validation Approach	58
3.6	Conclusion and Discussion	59

Aging-related health problems have increasing economical burden on healthcare services. **Early detection** of physical and cognitive changes is essential to better adapt existing services for elderly people. Based on validated geriatric references and stakeholder feedbacks, this thesis identifies **geriatric needs** of elderly people, geriatricians, family members, caregivers and nursing home. They need to receive reliable information about **possible health changes** in early stages of their evolution **without intrusive monitoring**. In order to translate these geriatric needs, proposed technological approach employs unobtrusive Internet of Things (IoT) technologies for long-term behavior monitoring. This enables early detection of possible changes in physical and cognitive abilities. This chapter introduces **proposed methodology** for translating geriatric needs via unobtrusive monitoring technologies [20–24].

3.1 Investigated Geriatric Needs

Proposed methodology investigates real geriatric requirements based on validated geriatric references and personal interviews with geriatricians, nursing homes, caregivers, family members and elderly people (Fig. 3.1).



Fig. 3.1 Stakeholders and Geriatric Needs

Proposed approach stakeholders need to receive reliable information about possible health changes in early stages of their evolution without intrusive monitoring. They require to complete their personal and medical observations with new objective observations of daily

living, take care of their relatives living alone, feel safe at home without intrusive supervision, and create link between nursing homes and isolated elderly people.

Translating these geriatric needs is essential to justify usefulness of proposed approach, and improve its impact [25]. Bridging the gap between geriatric needs and proposed approach develops stakeholder-centered services [26]. This enhances stakeholder acceptability, motivation, confidence and self-direction while adopting proposed approach.

3.1.1 Geriatrician Needs

Geriatricians complete their medical assessments with objective observations via monitoring technologies. They need to early detect possible health changes toward more effective treatment. Geriatricians accept unobtrusive monitoring technologies that do not interfere with natural behavior of elderly people:

- Internet of Things (IoT) technologies provide **objective information** about activities of daily living occurring outside geriatrician office. This enhances medical assessments (e.g., follow-up sleep, toilet entries, activity periods, time out of home and visits for Parkinson patients) [11]. Geriatric scales and questionnaires are insufficient to follow-up health status on a daily basis. This leads to missing 75% of possible health changes among elderly people [12].
- Technological observations allow to **early detect possible health decline**, evaluate impact of medical treatments and interventions, and efficiently adapt them. Early detection of aging-related health problems enables proactive intervention by efficiently treating them and reducing their influence [13]. Proactive intervention prevents, slows down or restores detected health decline. This helps elderly people overcome autonomy loss if it's inevitable [14]. Elderly people have more chance to treat diseases in early stages of their evolution, regain affected functions and reduce disease impact.
- Technological services **improve efficiency of geriatrician's visit** by discussing more information in shorter time, and investigating past events that can be hardly recalled by patients [12]. Investigating health changes with medical scales and questionnaires relies on subjective and incomplete patient feedbacks [9]. Elderly people can not recall all past events at assessment time. Geriatrician visits are once or twice per year. Accessibility to healthcare services is often inconvenient for elderly people [10].
- **Unobtrusive monitoring technologies** do not interfere with natural behavior of elderly people [89]. These technologies continuously monitor real elderly people behav-

ior in the environment of their choice. This reduces misleading influence of integrating technologies in their life.

3.1.2 Nursing Home Needs

Nursing homes need to establish effective link between them and elderly people living alone at home. They need to remotely receive reliable information on health status, in order to offer personalized healthcare services for elderly people. Nursing homes require to maintain independent living at home, and identify elderly people at risk who really require entry to nursing home:

- Nursing homes are interested in receiving continuous information about **long-term behavior changes** that can not be observed by their medical team or by elderly people (*e.g.*, sleep impairments and activity periods) [9]. Long-term behavior changes require weeks and months to emerge, and are more difficult to detect [67]. Medical nursing home team can not observe all possible changes over long period, and assumes that human behavior is linear. Technological observations reveal undetectable change points in human behavior, that can be hidden by elderly people being afraid from entry to nursing home.
- Nursing homes need to receive **accurate and reliable information** about health status of elderly people. Detecting false change points in physical and cognitive abilities reduces usefulness and acceptability of proposed technological services. Receiving false alerts is no longer alarming, and represents no added value for using proposed technological services.
- Monitoring technologies enable **adapted intervention services**, such as conducting advanced medical assessments based on technological observations, adapting living environment if mobility impairments are detected, adjust nutritional programs if nutritional difficulties are observed, comply treatments based on detected health changes, and initialize home aid before required entry to nursing home [16].
- Early health change detection **delays entry to nursing home**, and maintains independent living at home [90]. Elderly people target to remain independent and active at home as long as possible [17]. Technological services continuously monitor their behavior in the environment of their choice, and enhance healthy aging in place.

- **Unobtrusive monitoring technologies** discretely operate in the environment, and do not require additional manual operating efforts [19]. Nursing home team does not require advanced technical skills for regular configuration and maintenance.

3.1.3 Caregiver and Family Member Needs

Caregivers and family members take care of their relatives living alone. They need to share continuous information on health status, and early detect possible changes:

- Family members require **continuous information** about activities of daily living and possible changes in health status [91]. Irregular caregiver and family visits are insufficient to assist their relatives living alone. Technological services complete their personal observations by acquiring objective observations on possible health changes. This improves their remote health assistance by taking subsequent actions. They intervene when intervention is the most effective.
- Caregivers and family members agree with **unobtrusive monitoring technologies** that do not affect individual privacy [18]. Unobtrusive monitoring technologies collect minimal information about monitored behavior, and extract relevant information on health status.

3.1.4 Elderly People Needs

Elderly people need to feel safe at home without intrusive supervision. They accept technologies that discretely operate in the environment and do not require manual operating efforts:

- Elderly people **refuse video and audio monitoring** (*e.g.*, cameras and microphones) that captures private information about their activities of daily living [18]. These technologies affect their individual privacy, increase their anxiety and reduce their engagement.
- Nowadays, it is inconvenient for elderly people to wear body sensors, charge their batteries and operate them [19]. Forgetting to wear body sensors is frequent among elderly people. This leads to monitoring interruptions. Elderly people reject online-based questionnaires including diverse questions and tasks [80]. Elderly people accept **unobtrusive technologies** becoming part of their own habitat without changing their daily habits [89].

- Elderly people **accept sharing health information** with family members and doctors to better understand their health status. Sharing health information provides opportunity for advanced assessment and early intervention [91]. Elderly people perceive benefits of early health change detection, and approve continuous evaluation of their health status.

3.1.5 Geriatric Need Comparison and Translation

Stakeholders share essential needs for early and unobtrusive health change detection (Table 3.1). Geriatricians and nursing homes are mainly interested in receiving reliable information on possible health changes, in order to enrich medical observations and improve medical assessments. Family members remotely assist their relatives living alone at home. Elderly people delay possible entry to nursing home by remaining as independent as possible.

Table 3.1 Comparison of Geriatric Stakeholder Needs

	Geriatricians	Nursing Homes	Family Members	Elderly People
Objective Monitoring	✓			
Early Change Detection	✓	✓	✓	✓
Early Intervention	✓	✓	✓	✓
Reliable Assessment	✓	✓		
Remote Monitoring		✓	✓	
Healthy Aging at Home		✓		✓
Unobtrusive Monitoring	✓	✓	✓	✓
Continuous Monitoring			✓	

In order to translate these geriatric needs, proposed approach employs unobtrusive monitoring technologies for long-term behavior monitoring. Online behavior analysis early detects possible changes that are related to physical and cognitive problems. Employed technologies provide objective observations of daily living, and remotely monitor elderly people in the environment of their choice. These technologies support continuous data collection. Developed data processing algorithms convert monitoring data into geriatric indicators and metrics that correlate with possible health changes. Change detection techniques analyze computed indicators on a daily basis, in order to distinguish between short-term and long-term changes. Detecting possible health changes enables effective and proactive intervention.

3.2 Analyzed Health Change Indicators

Effective translation of geriatric needs related to early and reliable health change detection requires definition of health change indicators. Health change indicators are complex tasks of daily living that are associated with physical and cognitive health (Fig. 3.2). These indicators involve physical and cognitive functions, such as spatio-temporal orientation, construction, calculation and attention. Unobtrusive monitoring technologies (*e.g.*, environmental sensors, sensor-enhanced devices and in-phone-embedded sensors) follow-up these geriatric indicators at home and in city without interfering with natural behavior of elderly people. Detecting changes in way and manner of executing geriatric indicators indicates physical and cognitive problems, such as autonomy loss, dementia, urinary infection, Parkinson, bipolar disorder and Alzheimer disease [14].

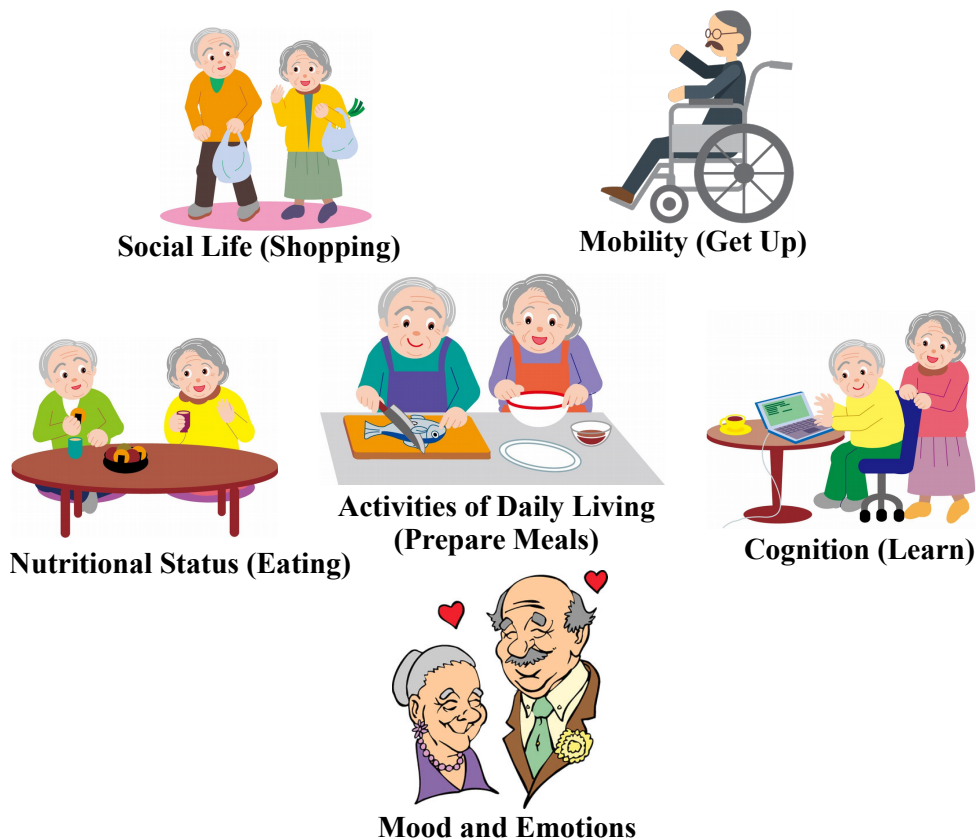


Fig. 3.2 Health Change Indicator Categories

Based on internationally-validated geriatric references (*e.g.*, SEGA [27], MMSE [28], GDS [29], IADL [30], AGGIR [31], GUGO [32], MNA [33], BeAd [34] and NPI [35]),

proposed methodology determines relevant health change indicators. It distinguishes 6 categories: activities of daily living, mobility, cognition, social life, nutrition and emotions.

SEGA considers frailty-related indicators, such as falls, nutrition, memory, vision, audition, social support and financial situation [27]. **MMSE** targets cognitive indicators, such as orientation, learning, attention, calculation, recall and construction [28]. **GDS** investigates emotional indicators, such as rapid mood changes and depression [29]. **IADL** identifies changes in activities of daily living that are associated with autonomy loss, such as using telephone, using means of transport, taking medicines and managing personal finances [30].

AGGIR investigates autonomy changes based on changes in position, movement indoors, hygiene, dressing, cooking, nutrition, medicines, household, technologies, movement outdoors, means of transport, free time and shopping [31]. **GUGO** targets motor behavior changes related to getting up, walking, turning around and sitting down [32]. **MNA** investigates nutritional indicators, such as eating difficulties, weight loss and protein intake insufficiency [33]. **BeAd** and **NPI** target behavioral indicators, such as presence of hallucinations, aggressiveness and anxiety [34, 35].

3.2.1 Activity of Daily Living (ADL) Indicators

Activities of daily living indicate significant changes in health status [27, 30, 31]. They represent complex tasks of daily living requiring advanced physical and cognitive abilities, such as attention, working memory, episodic memory, prospective memory and executive functioning. Activities of daily living include household, dressing, hygiene, elimination and phone use (Table 3.2). Integrating unobtrusive monitoring technologies at home follows-up these activities without changing regular habits, such as door, movement, proximity, bed, vibration, light, temperature and in-phone-embedded sensors. Physical or cognitive problems are detected, if elderly people do not spontaneously, totally, correctly or frequently execute these tasks.

Table 3.2 Activity of Daily Living (ADL) Indicators

Indicator	Examples	Relevance	Technology
Household	Clean, tidy-up rooms, dress table, put laundry, wash dishes	Physical, cognitive impairments, autonomy loss	Door, movement, proximity, bed, vibration, light, temperature sensors, phone
Upper dressing	Get and fit one's clothes over one's head and arms		
Middle dressing	Close one's clothes and belt		

Inferior dressing	Pass one's clothes from the lower body, shoes, socks
Upper hygiene	Shave, dress one's hair
Inferior hygiene	Hygiene of intimate, inferior members, legs, feet, nails
Elimination	Urinary and fecal elimination
Phone use	Answer, make calls, send alerts

3.2.2 Mobility Indicators

Mobility indicators are associated with physical health [27, 30–32]. Moving indoors and outdoors requires spatio-temporal orientation and executive functioning. Walking and changing positions require physical efforts and overall body control. Using in-phone-embedded sensors and collecting movement sensor data evaluates walking patterns, and detects possible falls (Table 3.3). Moving with partial or total dependence indicates possible physical problems, such as freezing periods and trembling in fingers due to Parkinson disease..

Table 3.3 Mobility Indicators

Indicator	Examples	Relevance	Technology
Moving	Between the rooms, to mail-boxes, to local trash, to common entertainment area	Parkinson, freezing periods, physical problems	In-phone-embedded sensors, beacons, movement, door, proximity sensors
Position changes	Walk, get up, turn around, sit		
Falls	During last six months		

3.2.3 Cognitive Indicators

Changes in cognitive functions have impact on quality of life [27, 28, 31, 34, 35]. Cognition controls all health change indicators, such as mobility, social life, nutrition, mood and emotions. Temporal and spatial orientation is essential to execute activities of daily living (Table 3.4). Learning, attention, calculation, language and construction are fundamental human functions. Employing sensor-enhanced objects of daily living (*e.g.*, smart television, car and computer), and embedding cognitive games (*e.g.*, integrating serious games in one's

phone or watch to evaluate cognitive skills) identify possible long-term changes in cognitive functions. Alzheimer disease is most common form of cognitive impairments among elderly people. It has seven stages from light, to mild and severe memory troubles, orientation difficulties and autonomy loss.

Table 3.4 Cognitive Indicators

Indicator	Examples	Relevance	Technology
Temporal orientation	Recognize season, day time, current year, current month	Alzheimer, frailty,	Sensor-enhanced objects of daily living, serious games
Spatial orientation	Recognize common places, one's house, neighborhood	cognitive impairments	
Executive functioning	Learning, attention, calculation, language, construction		
Decision making	Manage financial situation, perform administrative procedures, complete complex forms		

3.2.4 Social Life Indicators

Social activities involve diverse physical and cognitive functions [30, 31]. Social life includes communicating with others, respecting common social standards, using means of transport, shopping and attending cultural events (Table 3.5). City beacons in association with Bluetooth-enabled smart phones identify presence in outdoor points of interest, such as cinema, supermarket, shops and restaurants. Abnormal decreases in going out frequency indicate possible social isolation among elderly people.

Table 3.5 Social Life Indicators

Indicator	Examples	Relevance	Technology
Communication	Verbal and non-verbal communication with others	Social isolation,	In-phone-embedded sensors in association with city beacons
Relationships	Respect common social standards, not harm others, not behave aggressively	psychological troubles	
Social support	Carried burden by relatives		

Go out	Use means of transport, shopping, free time activities
--------	--

3.2.5 Nutritional Indicators

Nutrition indicates significant changes in health status [27, 31, 33]. Serving oneself and eating is essential to acquire sufficient protein, fruit, vegetable and water intake. Smart scales measure weight and body mass index. Integrating vibration, temperature and proximity sensors in one's oven or fridge follows-up preparing meals. Abnormal changes in weight and eating indicate possible Diabetes and digestive problems.

Table 3.6 Nutritional Indicators

Indicator	Examples	Relevance	Technology
Serve oneself	Cut meat, open a pot, peel fruit	Diabetes, digestive problems	Smart scale, oven, fridge, spoon, glass
Eat	Protein, fruit, vegetable, fluid, weight, body mass index		

3.2.6 Emotional Indicators

Rapid mood changes and emotional problems are related to aging process [29, 34, 35]. Shouting angrily, slamming doors and throwing things indicate agitation periods. Feeling sad, discouraged and useless reveals possible depression. Avoiding caregivers and showing worries about planned events is related to anxiety and fear. Analyzing content and type of watched TV programs, phone call frequency and emotional games evaluates emotional status. Changes in sleep patterns and activity level indicate possible mood changes due to Bipolar disorder.

Table 3.7 Emotional Indicators

Indicator	Examples	Relevance	Technology
Agitation	Upset with caregivers, hard to handle, shouting angrily, slam door, kick, throw things	Bipolar disorder, physical, cognitive diseases	Smart television, phone, serious games
Depression	Tears, feel sad, bad person, discouraged, no future, failure		

Anxiety	Worries about planned events, trembling, phobic avoidance
Euphoria	Feel too happy, inappropriate laughs, childish jokes

3.3 Employed Unobtrusive Monitoring Technologies

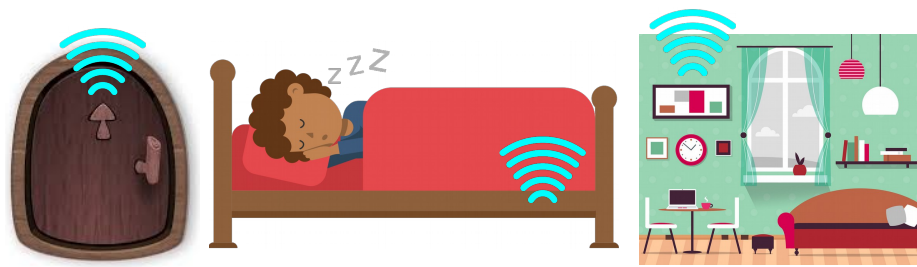
Internet of Things (IoT) technologies provide objective, continuous and unobtrusive monitoring of health change indicators. Integrating these technologies in environment and objects of daily living follows-up elderly people behavior and enables change analysis. Unobtrusive monitoring technologies do not change daily habits, do not interfere with natural behavior, and do not affect individual privacy. Technological observations collect minimal information about monitored behavior, and provide significant information on health change indicators. Environmental technologies like movement, door and bed sensors discretely monitor activity patterns, sleep habits and go out frequency. Sensor-enhanced oven detects preparing meals, and sensor-enhanced medicine box checks taking medicines. In-phone-embedded sensors like GPS, accelerometer and step detector in association with city beacons notify about outdoor activities (*e.g.*, social, commercial, entertainment, cultural and healthcare activities). Following, proposed methodology distinguishes 3 categories of unobtrusive monitoring technologies.

3.3.1 Environmental Sensors

Environmental sensors discretely operate at home and in city without interfering with natural behavior of elderly people (Fig. 3.3). **Movement sensors** detect presence and absence of movements in space and time. This allows to measure activity level, received visits, sleep interruptions and toilet entries (Table 3.8).

Contact sensors detect openings and closing of corresponding objects (*e.g.*, main door, fridge, medicine box and closet). These sensors follow-up house entries, nutritional habits and taking medicines. **Bed sensor** measures bed movements, pulse and respiration rate. These measurements determine sleep patterns, cardiac events and respiration anomalies.

Vibration, pressure and proximity sensors detect presence of nearby objects with or without physical contact. These sensors follow-up object usage (*e.g.*, glass, spoon and water tap), and identify possible changes (*e.g.*, drinking less water, watching television during expected sleep periods and phone use difficulties related to frailty).



Environmental Sensors Installed in Main Door, Bed and Living Room

Fig. 3.3 Examples of Environmental Sensors

Temperature, humidity and light sensors measure ambient temperature, humidity and light. These sensors provide information about weather conditions, and detect possible changes in monitored behavior (*e.g.*, go out less frequently during heavy snow periods, suffer from respiration problems due to relative humidity in air, and spend more time isolated at home in total darkness after depression).

Table 3.8 Raw and Inferred Data of Environmental Sensors

Technology	Raw Data	Inferred Data
Movement sensor	Presence and absence of movements in space and time	Walking patterns, received visits, sleep interruptions, toilet entries
Contact sensor	Openings and closings of house doors and daily objects	Come home, go out, prepare meal, take medicines, read books
Bed sensor	Bed movements, heart beats, respiration rate, rhythm, depth	Sleep time, wake-up time, sleep duration, bed restlessness, cardiac events, respiration anomalies
Vibration Sensor	Possible vibration of corresponding object	Drink water, open tap, use land-line phone, move furniture
Pressure sensor	Force per unit area of corresponding object	Sit down on chair, sofa, detect presence of multiple persons
Proximity sensor	Presence of nearby objects without any physical contact	Watch television, manage financial situation, use personal computer
Temperature sensor	Ambient temperature in space and time	Prepare meals, take shower, suffer from cold or heat
Humidity sensor	Ambient humidity in space and time	Urinary and fecal elimination, take shower, respiration problems

Light sensor	Ambient light in space and time	Sleep times, wake-up times, social isolation, possible depression
--------------	---------------------------------	---

3.3.2 Sensor-Enhanced Devices

Smart devices consist of diverse sensors, such as proximity, light, temperature, pressure and vibration sensors (Fig. 3.4). **Smart television** provides detailed information on watched programs, watching hours and duration. This indicates possible emotional problems for elderly people watching television during expected sleep periods (Table 3.9).

Smart boxes containing medicines, personal documents and jewellery provide evaluate medication adherence, managing administrative issues and autonomy impairments. Embedding sensors in **house furniture** identifies usage and content of oven, fridge, glass and spoon. Employing these smart devices determines nutritional habits, eating difficulties and water intake insufficiency. **Smart means of transport** include one's car, motorcycle and bike. Analyzing outdoor activities detects possible changes in cultural and social engagement.



Sensor-Enhanced Television, Fridge and Car

Fig. 3.4 Examples of Sensor-Enhanced Devices

Table 3.9 Raw and Inferred Data of Sensor-Enhanced Devices

Technology	Raw Data	Inferred Data
Smart Television	Switch on, off television	Watch television hours, duration, social, cultural, emotional isolation
Smart scale	Weight, pulse, burned calories, body mass index, fat rate	Nutritional changes, heart, respiration problems, treatment impact
Smart box	Usage of medicine, personal document, jewelry box	Take medicines, manage administrative issues, hygiene, dressing

Smart furniture	Usage and content of oven, fridge, glass, spoon	Prepare meals, eat, drink, serve oneself, autonomy impairments
Smart means of transport	Usage, location and direction of one's car, motorcycle, bike	Use means of transport, city points of interests, shopping, entertainment

3.3.3 In-Phone-Embedded Sensors

Smart phones consist of GPS, accelerometer, gyroscope, screen proximity, compass, bluetooth and near field communication (NFC) (Fig. 3.5). **Phone GPS** recognizes person location in city. This technology follows-up supermarket, restaurant, cinema, theater, hospital and house visits.

Phone accelerometer and **gyroscope** measure linear movement acceleration and angular rotational velocity. These sensors quantify walking patterns based on step number, frequency and duration, and detect possible falls. **Screen proximity** and **compass** detect making and receiving phone calls, using mobile applications and having physical impairments based on finger touch.

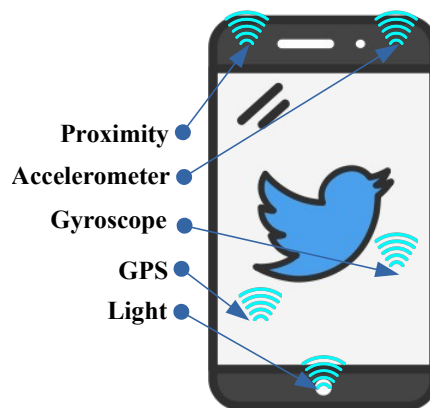


Fig. 3.5 Examples of In-Phone-Embedded Sensors

Bluetooth and **NFC** technologies enable communication with city beacons for precise person localization, and authorize communication with mobile payment systems. These technologies monitor elderly people visits and payments in shops, restaurants and entertainment places (Table 3.10).

Table 3.10 Raw and Inferred Data of In-Phone-Embedded Sensors

Technology	Raw Data	Inferred Data
GPS	Global position, time information, latitude, longitude	Supermarket, restaurant, cinema, theater, hospital, house visits
Accelerometer, gyroscope	Linear movement acceleration, angular rotational velocity	Step number, intensity, frequency, walking patterns, falls
Proximity, compass	Screen proximity, phone, person direction	Phone calls, mobile application usage, finger trembling
Bluetooth, NFC	Communication with other Bluetooth-enabled, NFC-enabled devices	City points of interests in association with beacons, payments

3.4 Selected Health Change Metrics

Proposed methodology analyzes health change indicators regarding time, place, number and duration (Table 3.11). These analysis metrics quantify way and manner of executing health change indicators. Change detection algorithms analyze quantified indicators for possible change detection; e.g., sleep interruption number increases during anxiety periods, go shopping frequency decreases because of mobility impairments, toilet entries increase due to urinary infection, and preparing meal duration increases because of cognitive problems.

Time refers to start and end times of executing monitored activities; e.g., eating hours change due to nutritional problems, watching TV hours change because of increased interest in new television programs, sleep hours are irregular due to sleep troubles, going out hours are changing thanks to raised interest in social activities, and taking medicine hours are adhered thanks to cognitive status improvement.

Table 3.11 Examples of Health Change Metrics

Metric	Examples
Time	Times of sleep, wake-up, watch tv, take medicine, go out, work
Place	Places of shopping, entertainment, physical, cultural activities
Number	Number of sleep interruptions, toilet entries, meals, phone calls
Duration	Household, shower, sleep, visit, get up, move, go out duration

Place describes where monitored activities are executed; e.g., toilet entries become more frequent due to physical diseases, going to local market becomes less frequent due to mobility impairments, detected falls outdoors become more frequent due to fear of going outside, visiting senior activity center becomes less usual due to social isolation, and visiting city park becomes more frequent thanks to raised interest in physical exercise.

Number refers to quantity and amount of human activity execution; e.g., number of senior activity center visits decreases due to social isolation, step count increases thanks to an improvement in mobility status, number of friend visits decreases due to social isolation, number of movements decreases due to walk impairments, number of sport center visits increases thanks to raised interest in physical exercise, and number of hospitalizations decreases thanks to health status improvement.

Duration is related to length of executing monitored activities; e.g., duration of preparing meals increases due to cognitive impairments, duration of sleep impairments decreases thanks to an improvement in emotional status, duration of stair climbing increases due to walk impairments, time spent out of home increases thanks to raised interest in social interactions, and time spent in free time activities increases thanks to raised interest in active aging.

3.5 Validation Approach

Evaluating relevance of detected changes requires collection of personal, context and medical observations (Table 3.12). These observations provide better understanding of detected changes and investigate their origin.

Personal observations are provided by elderly people, family members and informal caregivers. Personal interviews discuss technological observations; e.g., detected increase in sleep impairments is correlated with observed anxiety periods due to Alzheimer disease, detected decrease in activity level is correlated with pain in leg, detected changes in activity level correlate with personal feelings of slowness in physical movements and trembling in fingers related to Parkinson, and detected changes in preparing meal duration correlate with forgetting recent events related to cognitive impairments.

Context information provide global understanding of detected changes; e.g., detected change in phone use is correlated with family conflicts, detected change in going out routine is correlated with weather conditions, moving across rooms decreases after moving television to bedroom, recent hospitalization of husband raises wife's anxiety, and recent friend visits improve emotional state.

Medical information validate relevance of detected changes; e.g., geriatric scale results confirm detected changes in activity level and nutritional intake, audition and vision test

scores confirm detected changes in social engagement, cognition test confirms detected changes in dependence level, and health records report physical and mental diseases explaining detected changes in activities of daily living.

Table 3.12 Examples of Personal, Context and Medical Observations

	Examples
Personal Observations	Personal interviews, feedbacks, feelings, change interpretations, change correlations
Context Observations	Weather conditions, social, cultural events, family visits, changes in daily habits, living environment
Medical Observations	Psycho-geriatric scale results, audition, vision test scores, geriatrician feedback, change explication

3.6 Conclusion and Discussion

Proposed methodology in this thesis identifies **real needs** of elderly people, family members and family doctors. They need to **early** detect possible changes in health status **without intrusive monitoring**. Geriatricians are interested in integrating new technological observations, in order to complete their medical observations. Family members and nursing home team need to establish new link between them and elderly people living alone at home. Compared to existing methodologies, this thesis targets detection of long-term changes in monitored behavior via unobtrusive technologies on a daily basis and at temporal scale.

Effective translation of geriatric needs requires identification of **health change indicators**. Proposed methodology in this thesis uses validated geriatric references to define activities of daily living that are associated with physical and health problems, and can be monitored via unobtrusive technologies. Physical, cognitive, social, nutritional and emotional activities of daily living highly correlate with aging-related health problems.

Employed technologies in this thesis discretely operate in the environment, in order to measure real behavior evolution. Environmental sensors, sensor-enhanced devices and in-phone-embedded sensors **unobtrusively** monitor elderly people behavior without changing their daily habits. Analyzing monitored indicators on a daily basis enables early change detection in health status. Correlating technological observations with medical and personal observations is essential to validate **medical relevance** of detected changes.

Chapter 4

Implementation: ChangeTracker Service for Online Behavior Analysis and Continuous Change Detection

Contents

4.1	Developed Data Processing Algorithms	62
4.1.1	Time At Home Algorithm	63
4.1.2	Visit Detection Algorithm	65
4.1.3	Wake-up and Sleep Time Detection Algorithm	66
4.1.4	Weighted Toilet Entry Algorithm	67
4.1.5	Weighted Sleep Interruption Algorithm	68
4.1.6	Weighted Movement Number Algorithm	69
4.2	Evaluated and Adapted Change Detection Techniques	70
4.2.1	Z-Score Change Detection Technique	72
4.2.2	Bootstrap Change Detection Technique	73
4.2.3	CUSUM Change Detection Technique	74
4.2.4	SD-Band Change Detection Technique	76
4.2.5	PELT Change Detection Technique	77
4.2.6	Naive Bayes Classifier Change Detection Technique	77
4.2.7	Bayesian Change Detection Technique	78
4.2.8	ULSIF Change Detection Technique	79

4.2.9	One-Class SVM Change Detection Technique	80
4.2.10	Affinity Propagation, K-Means and Mean Shift Change Detection Techniques	81
4.3	ChangeTracker Service Implementation Architecture	82
4.3.1	Model Layer for Data Acquisition and Storage	83
4.3.2	Controller Layer for Data Processing and Change Detection . . .	85
4.3.3	View Layer for Data Visualization and Change Notification . . .	87
4.4	Ambient Assisted Living Platform UbiSMART	90
4.4.1	HomeDesc Service for Sensor Network Modeling and Configura- tion	92
4.4.2	SensLog Service for Raw Data Visualization	93
4.4.3	Life Service for Real-Time Activity Recognition	94
4.5	Conclusion and Discussion	95

Developed web-based service **ChangeTracker** in this thesis is integrated in ambient assisted living platform **UbiSMART** [20–24]. UbiSMART platform uses environmental sensor data to infer activities of daily living in real time using semantic reasoning [63, 64]. UbiSMART does not detect long-term changes in inferred activities. ChangeTracker service computes geriatric indicators, and detects long-term changes in health status.

ChangeTracker acquires sensor data in real time, and processes them on a daily basis. Its implementation architecture consists of model, view and controller layers (Fig. 4.1). **Model layer** collects sensor data via Raspberry-Pi gateway at home. SensorML standard defines distributed sensor network [92]. O&M standard defines data format [93]. MQTT protocol controls data transfer via Internet to central server.

Controller layer implements **data processing algorithms** that convert raw data into inferred data, such as extracting activity level from movement sensor data. **Change detection techniques** receive inferred data as input, and provide detected changes as output. Daily change analysis discards transient deviations and retains only continuous deviations.

View layer provides easy-to-use graphical interface for showing inferred data and their daily evolution. Users receive notifications per SMS and email from 2 to 10 days after change occurrence to confirm that detected changes really persist, investigate possible causes and take actions.

This chapter presents **implementation approach** of proposed methodology. This thesis develops data processing algorithms, evaluates and adapts further change detection techniques. In addition, this chapter presents employed unobtrusive technological solutions, programming languages and data communication protocols.

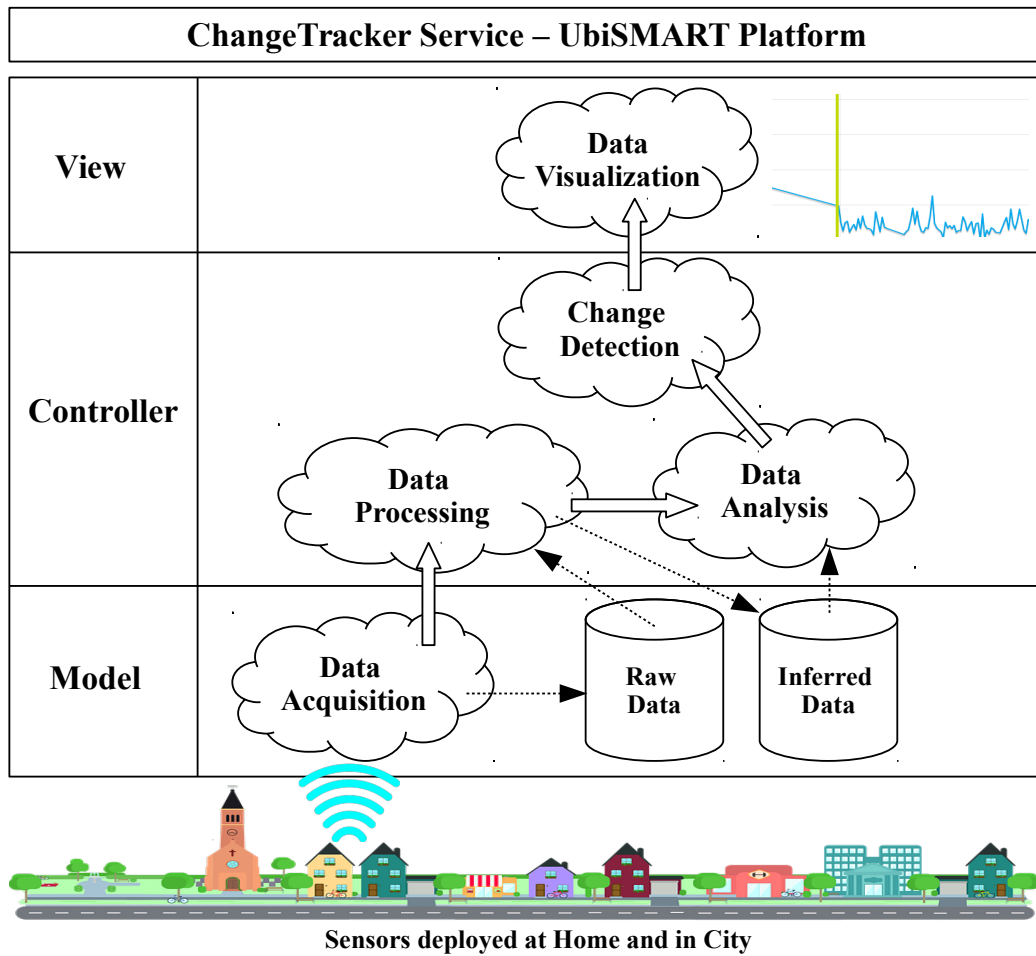


Fig. 4.1 Implementation Architecture of ChangeTracker Service in UbiSMART Platform

4.1 Developed Data Processing Algorithms

In this thesis, data processing algorithms extract health change indicators from collected sensor data. Movement sensors detect presence and absence of movements in each room (*e.g.*, living room, bedroom, kitchen, toilet and bathroom). Door sensors notify about main house entries, by detecting door openings and closings. Despite the basic information delivered by these movement and door sensors, developed data processing algorithms compute inferred data that are related to possible health changes (Table 4.1).

Toilet movement sensor follows-up toilet entry times, duration and number that are related to possible urinary infection [27]. Sleep habits (*e.g.*, wake-up time, sleep time, duration and interruptions) indicate possible cognitive impairments and Parkinson freezing periods [28]. Analyzing go-out routine considers inactivity periods and main door events,

and investigates possible social isolation [29]. Activity level is associated with mobility and cognitive impairments [32]. Decreases in visits indicate possible social isolation [31].

Data processing algorithms discard days with no sensor events (*e.g.*, during hospitalization and system-downtime periods). These algorithms weight health change indicators regarding time alone at home (*i.e.*, discard go out and visit periods) to avoid detecting irrelevant changes. Discarding go out periods avoids detecting irrelevant decreases in toilet entries. Discarding visit periods avoids detecting irrelevant increases in activity level.

Table 4.1 Case Study Raw and Inferred Data

Technologies	Raw Data	Inferred Data	Medical Relevance	Analysis Metrics
Movement Sensors	Presence and absence of movements	Toilet Entries	Urinary infection	Times, duration, number at sleep period, number at wake-up period
		Sleep Habits	Cognitive impairments, Parkinson	Wake-up time, sleep time, duration, interruptions
Door Sensors	Door openings and closings	Go Out	Social isolation	Times, duration
		Activity Level	Mobility and cognitive impairments	Number, duration
		Visits	Social isolation	Number, duration

4.1.1 Time At Home Algorithm

Time at home algorithm computes presence time at home in hours (Algorithm 1). Initialization phase divides day into 24 time blocks, and computes detected movement number and main door event number for each time block; *e.g.*, time block starts at 7h, ends at 8h, has 23 movements and 2 door events. Identifying inactivity periods (*i.e.*, consecutive time blocks with no movements) is essential to determine go out blocks. If consecutive time blocks have no movements, are preceded and followed by door events, then go out is detected. Going out before midnight generates door events only before inactivity block. Coming back after midnight generates door events only after inactivity block.

Time out home is equal to total duration of go out blocks. Fig. 4.2 shows real participant data. Participant makes few movements in first time blocks (between 0h and 7h) corresponding to sleep period. Six consecutive time blocks with no movements occur between 10h and 15h. This inactivity period is preceded and followed by main door openings (at 9h and 16h).

Total duration of going out home is consequently 6 hours. Time at home algorithm does not detect going out home without opening or closing main door. It is difficult to distinguish between sleep periods and going out periods without correlating inactivity periods with main door events.

```

Data: Movement and main door sensor events
Result: Time at home (hours)
divide day into 24 time blocks;
foreach timeBlock do
    | timeBlock.movementNumber = detected movement number;
    | timeBlock.doorEventNumber = main door event number;
end
investigate inactivity periods;
forall timeBlocks do
    | if consecutive time blocks have no movements then
    | | define new inactivityBlock;
    | end
end
foreach inactivityBlock do
    | if preceded and followed by door openings then
    | | detect going out period;
    | else if begins at midnight and followed by door openings then
    | | detect coming back home after midnight;
    | else if ends at midnight and preceded by door openings then
    | | detect going out before midnight;
end
time out home = total duration of go out blocks;
time at home = 24 - time out home;

```

Algorithm 1: Time at Home Algorithm

Time Blocks	0h	1h	...	10h	...	15h	...	23h				
Movement Number	5	0	...	40	0	0	0	0	0	34	...	3
Door Opening				x						x		
Time At Home	x	x	x	x						x	x	x

Fig. 4.2 Application of Time At Home Algorithm Based on Movements and Door Openings

4.1.2 Visit Detection Algorithm

Visit detection algorithm identifies received visits based on parallel activity periods (Algorithm 2). Activity periods are sequences of movements with time difference less than 30s. Longer time difference (e.g., 1 min) does not distinguish between normal room changes and parallel activity periods in different rooms; e.g., person moves in room 1, goes to room 2 and comes back to room 1 in less than 1 min. Shorter time difference (e.g., 10 s) builds single-movement activity periods considering that movement sensors are fired each 10s. Investigating parallel activity periods in different rooms enables visit detection. Elderly people living alone at home are never present in different rooms at same time, unless they are receiving visits.

```

Data: Movement sensor events
Result: Received visit duration (hours)
compute activity periods for each room;
foreach room do
    | order room sensor events ascending by time;
    | if movements build sequences with time difference less than 30s then
    | | define new activity period;
    | end
end
investigate parallel activity periods;
order all activity periods ascending by time;
forall activityPeriods do
    | if parallel activity periods in different rooms then
    | | define new visit blocks;
    | end
end
visit duration = total duration of visit blocks;

```

Algorithm 2: Visit Detection Algorithm

Visit duration is equal to total duration of visit blocks. Fig. 4.3 shows detected movements in rooms 1 and 2. First three movements in room 1 build an activity period. Fourth detected movement does not belong to any activity period, since its time difference is higher than 30s. Third detected activity period in room 1 occurs in parallel with another activity period in room 2 (i.e., second activity period starts before first activity period end). Participant consequently receives visit at 11h (i.e., activity period time). Visit detection algorithm does not identify visits occurring without parallel activity periods. It is difficult to distinguish

between normal increase in activity level and multiple person presence; e.g., activity level increases during intensive execution of activities of daily living.

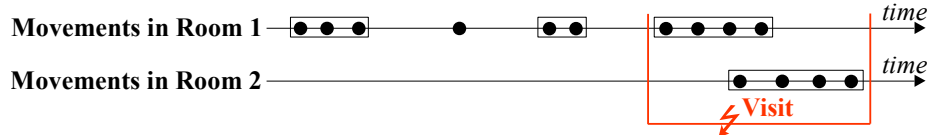


Fig. 4.3 Application of Visit Detection Algorithm Based on Parallel Activity Periods

4.1.3 Wake-up and Sleep Time Detection Algorithm

Wake-up and sleep time detection algorithm investigates changes in activity level (Algorithm 3). First increase in activity level when person is at home corresponds to wake-up time. Last decrease in activity level when person is at home corresponds to sleep time. First increase and last increase in activity level are significant even if they do not always match with real wake-up and sleep times; e.g., person is lying on bed without sleeping. Following-up changes in activity level identifies possible cognitive impairments, such as sleeping later at night due to Parkinson trembling periods. Change detection technique (e.g., bootstrap [94]) differentiates between transient and continuous increases and decreases in activity level.

Sleep duration is equal to time difference between wake-up time and sleep time. Fig. 4.4 shows hourly evolution of detected movement number. Person does not move or perform few movements until 6h. Change detection technique identifies first increase in activity level at 7h. This corresponds to wake-up time. Despite normal variation in activity level during day, change detection technique identifies last decrease at 20h. This corresponds to sleep time. Wake-up and sleep time detection algorithm does not detect if person sleeps few hours or does not sleep at all; e.g., Parkinson patients sleep at most 2 consecutive hours at night. Non-identification of sleep times indicates consequently abnormal sleep habits.

Time Blocks	0h	...	7h	...	20h	21h	22h	23h
Movement Number	5	...	0 0	10 39	...	47	21	17 1 3
Wake-Up Time			x					
Sleep Time					x			

Fig. 4.4 Application of Wake-Up and Sleep Time Detection Algorithm Based on Activity Level Changes

```

Data: Movement sensor events
Result: Wake-up and sleep times
divide day into 24 time blocks;
foreach timeBlock do
  | timeBlock.movementNumber = detected movement number;
end
investigate changes in activity level;
forall timeBlocks.movementNumber do
  | apply change detection technique;
end
detect wake-up and sleep times;
if firstIncrease.time is earlier than lastDecrease.time then
  | if person is at home before firstIncrease.time then
  | | wakeUpTime = firstIncrease.time;
  | end
  | if person is at home after lastDecrease.time then
  | | sleepTime = lastDecrease.time;
  | end
end

```

Algorithm 3: Wake-up and Sleep Time Detection Algorithm

4.1.4 Weighted Toilet Entry Algorithm

Weighted toilet entry algorithm weights toilet events regarding time alone at home (Algorithm 4). Discarding go out and visit periods is essential to avoid detecting irrelevant changes in toilet entries, such as irrelevant decreases in toilet entries after going out and irrelevant increases in toilet entries during visits. Dividing day into 24 time blocks allows to compute toilet event number when person is alone at home (*i.e.*, consider time blocks when person is at home without receiving visits).

Fig. 4.5 shows real participant data. Toilet sensor detects 16 events on 2017-06-29. Participant is present at home during 22 hours. Weighted toilet event number is equal to toilet event number divided by time alone at home (*i.e.*, $16 / 22 = 0.73$). Participant enters more frequently to toilet on 2017-09-12 with an average of 1.22 toilet event per hour. Family doctor confirms urinary infection a couple of weeks after.


```

Data: Toilet sensor events
Result: Weighted toilet events
divide day into 24 time blocks;
foreach timeBlock do
  | if person is alone at home then
  | | toiletEventNumber += timeBlock.toiletEventNumber;
  | | timeAloneAtHome += 1;
  | end
end
if timeAloneAtHome > 0 then
  | weightedToiletEvents = toiletEventNumber / timeAloneAtHome;
end

```

Algorithm 4: Weighted Toilet Entry Algorithm

Date	Toilet Event Number	Time Alone At Home (hours)	Weighted Toilet Events
2017-06-29	16	22	0.73
2017-06-30	8	20	0.4
...			
2017-09-12	28	23	1.22

Fig. 4.5 Application of Weighted Toilet Entry Algorithm

4.1.5 Weighted Sleep Interruption Algorithm

Weighted sleep interruption algorithm measures night activity periods that are associated with sleep interruptions (Algorithm 5). Sleep interruptions indicate possible cognitive and emotional problems, such as feeling depressed after husband's death and not being able to sleep during Parkinson trembling periods. Wake-up and sleep time detection algorithm defines sleep period. If these times are undetectable (*e.g.*, person does not sleep or sleeps few hours), sleep period starts at midnight and ends at 6h. Computing movement number during sleep periods when person is alone at home quantifies sleep interruptions.

Fig. 4.6 shows real participant data. This participant sleeps at most 2 consecutive hours at night. Defining sleep period between 0h and 6h enables detection of 12 movements on 2018-03-09. Weighting sleep interruptions to time alone at home between 0h and 6h provides an average of 2 movements per hour. This average increases on 2018-05-16 reaching 21 movements per hour. Parkinson trembling periods generate frequent sleep interruptions and explain detected increase.

```

Data: Night movement sensor events
Result: Weighted sleep interruptions
consider night time blocks;
foreach timeBlock do
  | if person is alone at home then
  | | sleepInterruptionNumber += timeBlock.movementNumber;
  | | timeAloneAtHome += 1;
  | end
end
if timeAloneAtHome > 0 then
  | weightedSleepInterruptions = sleepInterruptionNumber / timeAloneAtHome;
end

```

Algorithm 5: Weighted Sleep Interruption Algorithm

Date	Night Movement Number	Time Alone At Night (hours)	Weighted Sleep Interruptions
2018-03-09	12	6	2
2018-03-10	8	6	1.34
...			
2018-05-16	127	6	21.34

Fig. 4.6 Application of Weighted Sleep Interruption Algorithm

4.1.6 Weighted Movement Number Algorithm

Weighted movement number algorithm measures activity level (Algorithm 6). Movements are related to physical impairments, such as moving less at home due to mobility impairments and moving more at home after rehabilitation program. This algorithm considers all detected movements at home. Discarding visit and go out periods avoids detecting irrelevant changes, such as activity level increases during visits and activity level decreases after going out. Weighted movement number refers to dividing detected movement number by time alone at home.

Fig. 4.7 presents real participant data. Time alone at home is 11 hours on 2018-02-09 with 178 detected movements. Weighted average consequently corresponds to 16 movements per hour. Computed average increases on 2019-02-25 reaching 51 movements per hour. Participant experiences high activity periods due to Parkinson treatment change.

```

Data: Movement sensor events
Result: Weighted movement number
divide day into 24 time blocks;
foreach timeBlock do
  | if person is alone at home then
  | | movementNumber += timeBlock.movementNumber;
  | | timeAloneAtHome += 1;
  | end
end
if timeAloneAtHome > 0 then
  | weightedMovementNumber = movementNumber / timeAloneAtHome;
end

```

Algorithm 6: Weighted Movement Number Algorithm

Date	Detected Movement Number	Time Alone At Home (hours)	Weighted Movement Number
2018-02-09	178	11	16.18
2018-02-10	156	16	9.75
...			
2018-02-25	563	11	51.18

Fig. 4.7 Application of Weighted Movement Number Algorithm

4.2 Evaluated and Adapted Change Detection Techniques

Change detection refers to identifying **continuous** changes in time. Changes are instances in time where statistical properties are considerably different before and after this time. Evaluated and adapted change detection techniques in this thesis discard transient deviations, and target long-term changes that require weeks or months to emerge. These techniques analyze data **online** and require few or no training data (Table 4.2).

Behavior change refers to any continuous change in way and manner of executing activities of daily living [41]. Change detection techniques distinguish between normal variation in human behavior and **long-term changes**, such as significant increases in toilet entries associated with urinary infection and significant decreases in activity level associated with mobility impairments.

Z-Score, CUSUM, Naive Bayes Classifier, ULSIF and One-Class SVM techniques target **single change point detection** (*i.e.*, detect first change point after reference phase). **Proposed adaptation** in this thesis defines **moving reference phase** for multiple change

point detection (*i.e.*, define new reference phase after change occurrence for future change detection).

SD-Band technique detects outliers (*i.e.*, transient deviations). **Proposed adaptation** in this thesis sets **moving window** for consecutive deviation detection (*i.e.*, if consecutive deviations are detected, change occurs). Affinity Propagation, K-Means and Mean Shift techniques separate data into clusters. **Proposed adaptation** in this thesis computes **class ratio** including current data point, in order to detect changes between current and past clusters.

Table 4.2 Evaluated and Adapted Change Detection Techniques

Technique	Key Idea	Adapted
Z-Score [95]	Computes difference between window and population means in units of the standard error. Change occurs, if absolute value is higher than a threshold.	yes
Bootstrap [94]	Calculates magnitude of change based on differences between data values and data mean. Change occurs, if at least 90% of generated bootstraps have lower magnitude of change. It splits data into new segments separated by detected change, and investigates new change points.	no
CUSUM [96]	Determines reference parameters (<i>e.g.</i> , mean and standard deviation) in an initial phase, and recursively computes cumulative sums of positive and negative deviations to identify change points.	yes
SD-Band [97]	Calculates a band with bounds equal to 1 standard deviation above and below global mean. Change occurs, if consecutive data values are outside the bounds.	yes
PELT [98]	Uses penalized Likelihood Ratio Test to identify candidate change points. It minimizes this test to infer optimal change point number and positions.	no
Naive Bayes Classifier [99]	Uses Bayes theorem to classify normal and changing data. Normal probability density defines change probability.	yes
Bayesian [100]	Computes probability of change points with recursive application of Bayesian inference. Probability threshold allows to identify change points.	no

ULSIF [101]	Estimates direct density ratio of moving window and population probability distributions. Change occurs, if estimated ratio is lower than selected threshold.	yes
One-Class SVM [102]	Detects soft boundary of reference data to classify new data points as belonging to reference class or not. Change occurs, if current data point does not belong to reference class.	yes
Affinity Propagation, K-Means, Mean Shift [103–105]	Separate past data into clusters. K-Means requires number of clusters. Affinity propagation and mean shift automatically infer cluster number. Change occurs, if cluster including current data point contains less than 10% of all past data.	yes

4.2.1 Z-Score Change Detection Technique

Z-Score technique investigates change points by comparing moving window data to all past data [95]. Computing mean and standard deviation of all past data evaluates global characteristics (Algorithm 7). Defining window length and computing corresponding mean and standard deviation evaluates recent characteristics. Z-Score refers to window mean and global mean difference in terms of standard error ($standardError = globalStandardDeviation / \sqrt{windowLength}$). If absolute value of Z-Score is higher than selected threshold, change occurs.

```

Data: Data, z-score threshold, window length
Result: Detected change points
analyze data until first change point detection;
while no change point detection do
    globalMean = mean of all past data;
    windowMean = mean of moving window;
    globalStandardDeviation = standard deviation of all past data;
    windowStandardDeviation = window standard deviation;
    standardError = globalStandardDeviation / square root of windowLength;
    zscore = (windowMean - globalMean) / standardError;
    if absolute value of zscore > zscoreThreshold then
        define data point as new change point;
        restart zscore algorithm from current data point;
    end
end

```

Algorithm 7: Z-Score Change Detection Technique

Z-Score is robust to outliers and detects change points in seasonal signals. Its performance depends on hyper-parameters, such as Z-Score threshold and window length. Detection occurs with delay as effect of having local window; e.g, Z-Score detects increase in toilet entries 7 days after change occurrence if window length is 7.

- **Proposed Adaptation**

Comparing window mean to global mean enables **single change point detection**. Z-Score identifies first change point compared to past reference data. Proposed adaptation sets **moving analysis phase**. Adapted Z-Score technique restarts change point investigation from current data point, if change occurs. This enables **multiple change point detection**.

4.2.2 Bootstrap Change Detection Technique

Bootstrap technique compares randomly re-ordered data points and original data points for change detection [94]. It computes cumulative sums of differences between data values and data mean ($S[i] = S[i - 1] + (data[i] - dataMean)$). This determines magnitude of change by subtracting highest from lowest cumulative sum ($S_{diff} = S_{max} - S_{min}$). Generating 1000 bootstraps by randomly re-ordering original data confirms whether change occurs or not. If 90% of generated bootstraps have lower magnitude of change, change occurs (Algorithm 8).

Defining change location requires Mean Square Error (MSE) estimation. MSE estimator splits N data in two segments 1 to m and m+1 to N, calculates averages M_1 and M_2 , and studies how well data fit in both averages by computing sum of squares of differences between data values and data mean for each segment ($MSE(m) = \sum_{i=1}^m (data[i] - M_1)^2 + \sum_{i=m+1}^N (data[i] - M_2)^2$). Data point minimizing MSE estimator corresponds to first point after change.

Splitting data into two new segments and restarting analysis phase enables multiple change point detection. Bootstrap technique reduces false positives by computing change confidence level. Confidence level corresponds to bootstrap percentage having lower magnitude of change than original data. MSE estimator provides accurate definition of change location. Bootstrap technique reduces false negatives by splitting data before and after change point, and restarting change investigation. This enables detection of significant change points that are missed by other techniques.

```

Data: Data
Result: Detected change points
compute cumulative sums of differences between data values and data mean;
foreach data point do
  | currentCumulativeSum = previousCumulativeSum + (dataPoint.value - dataMean);
end
determine magnitude of change;
magnitudeOfChange = highest cumulativeSum - lowest cumulativeSum;
compute confidence level;
generate 1000 bootstraps by randomly re-ordering original data;
foreach bootstrap do
  | compute magnitude of change;
end
if 90% of bootstraps have lower magnitude of change then
  change occurs;
  investigate change location;
  use Mean Square Error (MSE) estimator to define change location;
  foreach data point do
    | split data into two segments;
    | compute segment means;
    | compute sum of squares of differences between data values and data mean for
      | each segment;
    | add both sums;
    if data point minimizes Mean Square Error (MSE) estimator then
      | define data point as change point;
    end
  end
  split data into two new segments;
  restart bootstrap technique for each segment;
end

```

Algorithm 8: Bootstrap Change Detection Technique

4.2.3 CUSUM Change Detection Technique

Cumulative Sum Control Chart (CUSUM) technique computes cumulative sums of positive and negative deviations for change detection [96]. Reference phase defines important parameters that control change detection in analysis phase (Algorithm 9):

- **M** refers to mean of reference data
- **SD** defines standard deviation of reference data

- **SHIFT** determines shift of interest related to smallest detectable deviation ($\text{SHIFT} = 1 * \text{SD}$ [106])
- **K** is allowance parameter related to shift of interest ($K = 0.5 * \text{SHIFT}$ [96])
- **H** is decision parameter that determines whether change occurs or not. Decision parameter definition uses published tables, specific software or standard deviation value ($H = 5 * \text{SD}$ [96, 107]).

```

Data: Data, reference period length
Result: Detected change points
compute reference parameters;
m = mean of reference data;
sd = standard deviation of reference data;
shift = 1 * sd;
k = 0.5 * shift;
h = 5 * sd;
while no change point detection do
    standardize data point;
    z = (dataPoint.value - mean) / sd;
    compute cumulative sums;
    shigh[i] = max(0, shigh[i-1] +z -k);
    slow[i] = min(0, slow[i-1] +z +k);
    if shigh[i] > h or slow[i] < -h then
        define data point as new change point;
        define new reference phase from change point;
        restart cusum algorithm;
    end
end

```

Algorithm 9: CUSUM Change Detection Technique

Analysis phase standardizes each data point based on reference mean and standard deviation ($data[i] = (data[i] - M)/SD$). Cumulative sums recursively accumulate positive ($S_{HIGH}[i] = \max(0, S_{HIGH}[i-1] + data[i] - K)$) and negative deviations ($S_{LOW}[i] = \min(0, S_{LOW}[i-1] + data[i] + K)$). In case S_{HIGH} is higher than $+H$ or S_{LOW} is lower than $-H$, positive or negative change occurs.

CUSUM technique analyzes data online and detects possible changes compared to reference phase. This technique is dependent on reference phase data, length and decision parameter H . Reference phase requires stable data variation with no predictable change points. Decision parameter value has influence on true positive rate.

- **Proposed Adaptation**

Comparing current data points to **static reference phase** enables single change point detection. CUSUM detects first change after reference phase, based on reference parameters (*e.g.*, mean and standard deviation). Proposed adaptation sets **moving reference phase**. Defining new reference phase starting from detected change point enables **multiple change point detection**.

4.2.4 SD-Band Change Detection Technique

SD-Band technique computes mean and standard deviation of past data for change detection [97]. It defines a band with 1 standard deviation above and below past data mean (Algorithm 10). Deviating data points are higher or lower than band borders (*i.e.*, deviations are higher than $mean + standardDeviation$ or lower than $mean - standardDeviation$).

```

Data: Data, reference phase length, window length
Result: Detected change points
skip reference phase;
while no change point detection do
    mean = mean of all past data;
    standardDeviation = standard deviation of all past data;
    superiorLimit = mean + standardDeviation;
    inferiorLimit = mean - standardDeviation;
    if windowLength data points are higher than superiorLimit or windowLength data points are lower than inferiorLimit then
        change occurs;
        define first deviating data point as new change point;
        continue change investigation;
    end
end

```

Algorithm 10: SD-Band Change Detection Technique

- **Proposed Adaptation**

SD-Band technique targets **short-term change detection**. Deviating data points do not necessarily persist. Proposed adaptation defines **moving window**, in order to detect **long-term changes**. If consecutive deviations are detected (*i.e.*, N deviations are detected corresponding to window length N), change occurs. Change type depends on deviation direction; *e.g.*, if N consecutive deviations are higher than superior band limit or lower than inferior band limit, positive or negative change occurs.

4.2.5 PELT Change Detection Technique

Pruned Exact Linear Time (PELT) method minimizes a cost function (*e.g.*, penalized likelihood) over possible numbers and locations of change points [98]. PELT combines optimal partitioning and pruning (Fig. 4.8). Pruning step removes values never minimizing cost function at each iteration. Combining optimal partitioning and pruning reduces computational costs. This does not affect resulting change points.

Optimal Partitioning

Input: A set of data of the form, (y_1, y_2, \dots, y_n) where $y_i \in \mathbb{R}$.
 A measure of fit $\mathcal{C}(\cdot)$ dependent on the data.
 A penalty constant β which does not depend on the number or location of changepoints.

Initialise: Let n = length of data and set $F(0) = -\beta$, $cp(0) = NULL$.

Iterate for $\tau^* = 1, \dots, n$

1. Calculate $F(\tau^*) = \min_{0 \leq \tau < \tau^*} [F(\tau) + \mathcal{C}(y_{(\tau+1):\tau^*}) + \beta]$.
2. Let $\tau' = \arg \{ \min_{0 \leq \tau < \tau^*} [F(\tau) + \mathcal{C}(y_{(\tau+1):\tau^*}) + \beta] \}$.
3. Set $cp(\tau^*) = (cp(\tau'), \tau')$.

Output the change points recorded in $cp(n)$.

Fig. 4.8 PELT Change Detection Technique

4.2.6 Naive Bayes Classifier Change Detection Technique

Naive Bayes Classifier (NBC) applies Bayes' theorem with independence assumptions between features [99]. Defining classes, common features and training instances enables association of new instances to pre-defined classes. Bayes' theorem computes probability of class C given feature x ($p(C | x) = (p(C) * p(x | C)) / p(x)$).

• Proposed Adaptation

Naive Bayes Classifier targets **association of instances to classes**. Proposed adaptation defines **one class with one feature** (Algorithm 11). This moving normal class contains all past data. Computing normal probability density of current data point (considering mean and standard deviation of normal class) defines change probability (*i.e.*, probability that current data point belongs to normal class). If normal probability density is lower than selected threshold, change occurs. Restarting analysis phase from detected change point enables future change point detection.

```

Data: Data, reference phase length, probability threshold
Result: Detected change points
skip reference phase;
analyze data until first change point detection;
while no change point detection do
    mean = mean of all past data;
    standardDeviation = standard deviation of all past data;
    npd = normal probability density of data point regarding mean and
        standardDeviation;
    if npd < probabilityThreshold then
        define data point as new change point;
        restart naive bayes classifier algorithm from current data point;
    end
end

```

Algorithm 11: Naive Bayes Classifier Change Detection Technique

4.2.7 Bayesian Change Detection Technique

Bayesian change detection technique recursively computes probability of change points using Bayesian inference and Forward-Backward algorithm [100]. Probability threshold identifies number and position of change points.

$$\begin{aligned}
 P(t, s) &= \Pr(y_{t:s} | t, s \text{ in the same segment}) \\
 &= \int \prod_{i=t}^s f(y_i | \theta) \pi(\theta) d\theta.
 \end{aligned}$$

Fig. 4.9 Bayesian Log-Likelihood of Data sequence [t, s]

$$Q(t) = \Pr(y_{t:n} | \text{change point at } t - 1)$$

Fig. 4.10 Bayesian Log-Likelihood of Data [t, n]

Computing probability of change points requires prior probability of having two successive change points with distance t , and likelihood model of data in sequence $[s, t]$ without change point. Bayesian technique assumes uniform prior over sequence length and piece-wise Gaussian model.

Bayesian technique computes $P(t, s)$ log-likelihood of data sequence $[t, s]$ without change point between t and s (Fig. 4.9). It defines $Q(t)$ log-likelihood of data $[t, n]$ (Fig. 4.10) and

$Pcp(i, t)$ log-likelihood of change point i being at location t . Probability change point is sum of these probabilities.

4.2.8 ULSIF Change Detection Technique

Unconstrained Least Squares Importance Fitting (ULSIF) method estimates direct density ratio of moving window and population probability distributions [101]. Change occurs, if estimated ratio is lower than selected threshold. ULSIF technique compares recent data probability distribution $p(x)$ and global data probability distribution $q(x)$ by computing their density ratio ($w(x) = p(x)/q(x)$) (Fig. 4.11).

Input: $\{\mathbf{x}_i^{te}\}_{i=1}^{n_{te}}$ and $\{\mathbf{x}_j^{tr}\}_{j=1}^{n_{tr}}$

Output: $\hat{w}(\mathbf{x})$

$b \leftarrow \min(100, n_{tr}); \quad \bar{n} = \min(n_{te}, n_{tr});$

Randomly choose b centers $\{\mathbf{c}_\ell\}_{\ell=1}^b$ from $\{\mathbf{x}_j^{tr}\}_{j=1}^{n_{tr}}$;

For each candidate of Gaussian width σ

$$\hat{H}_{\ell, \ell'} = \frac{1}{n_{te}} \sum_{i=1}^{n_{te}} \exp\left(-\frac{\|\mathbf{x}_i^{te} - \mathbf{c}_\ell\|^2 + \|\mathbf{x}_i^{te} - \mathbf{c}_{\ell'}\|^2}{2\sigma^2}\right) \text{ for } \ell, \ell' = 1, \dots, b;$$

$$\hat{h}_\ell = \frac{1}{n_{tr}} \sum_{j=1}^{n_{tr}} \exp\left(-\frac{\|\mathbf{x}_j^{tr} - \mathbf{c}_\ell\|^2}{2\sigma^2}\right) \text{ for } \ell = 1, \dots, b;$$

$$X_{\ell, i} \leftarrow \exp\left(-\frac{\|\mathbf{x}_i^{te} - \mathbf{c}_\ell\|^2}{2\sigma^2}\right) \text{ for } i = 1, \dots, \bar{n} \text{ and } \ell = 1, \dots, b;$$

$$X'_{\ell, i} \leftarrow \exp\left(-\frac{\|\mathbf{x}_i^{tr} - \mathbf{c}_\ell\|^2}{2\sigma^2}\right) \text{ for } i = 1, \dots, \bar{n} \text{ and } \ell = 1, \dots, b;$$

For each candidate of regularization parameter λ

$$\hat{\mathbf{B}} \leftarrow \hat{\mathbf{H}} + \frac{\lambda(n_{te} - 1)}{n_{te}} \mathbf{I}_b;$$

$$\mathbf{B}_0 \leftarrow \hat{\mathbf{B}}^{-1} \hat{\mathbf{h}} \mathbf{1}_{\bar{n}}^\top + \hat{\mathbf{B}}^{-1} \mathbf{X} \text{diag}\left(\frac{\hat{\mathbf{h}}^\top \hat{\mathbf{B}}^{-1} \mathbf{X}}{n_{te} \mathbf{1}_{\bar{n}}^\top - \mathbf{1}_b^\top (\mathbf{X} * \hat{\mathbf{B}}^{-1} \mathbf{X})}\right);$$

$$\mathbf{B}_1 \leftarrow \hat{\mathbf{B}}^{-1} \mathbf{X}' + \hat{\mathbf{B}}^{-1} \mathbf{X} \text{diag}\left(\frac{\mathbf{1}_b^\top (\mathbf{X}' * \hat{\mathbf{B}}^{-1} \mathbf{X})}{n_{te} \mathbf{1}_{\bar{n}}^\top - \mathbf{1}_b^\top (\mathbf{X} * \hat{\mathbf{B}}^{-1} \mathbf{X})}\right);$$

$$\mathbf{B}_2 \leftarrow \max\left(\mathbf{O}_{b \times \bar{n}}, \frac{n_{te} - 1}{n_{te}(n_{tr} - 1)} (n_{tr} \mathbf{B}_0 - \mathbf{B}_1)\right);$$

$$\mathbf{r} \leftarrow (\mathbf{1}_b^\top (\mathbf{X} * \mathbf{B}_2))^\top; \quad \mathbf{r}' \leftarrow (\mathbf{1}_b^\top (\mathbf{X}' * \mathbf{B}_2))^\top;$$

$$\text{LOOCV}(\sigma, \lambda) \leftarrow \frac{\mathbf{r}^\top \mathbf{r}}{2\bar{n}} - \frac{\mathbf{1}_{\bar{n}}^\top \mathbf{r}_{tr}}{\bar{n}};$$

Fig. 4.11 ULSIF Change Detection Technique

Comparing probability distributions of data samples evaluates their dissimilarity (*e.g.*, between window and global data samples). Higher difference increase probability change point between both samples. ULSIF does not compute both probability distributions, but

their ratio. Computing density ratio is simpler than computing both probability distributions. ULSIF estimates this ratio using Pearson divergence dissimilarity measure.

- **Proposed Adaptation**

ULSIF targets detection of **first change** compared to past reference data. Proposed adaptation defines **moving reference phase** for **multiple change detection**. Analysis phase considers detected change point as new starting point, and investigates possible changes. This iterative process enables online change detection (*i.e.*, detect changes while data are collected).

4.2.9 One-Class SVM Change Detection Technique

One-Class Support Vector Machine (SVM) technique detects soft boundary of reference data to classify new data points as belonging to reference class or not [102]. SVM technique defines multiple classes and corresponding features. It uses training data to build reference models. These reference models enable association of new instances to reference classes. One-Class SVM defines one class including all training data. This reference class recognizes new instances as normal (*i.e.*, belonging to reference class) or abnormal (*i.e.*, not belonging to reference class).

```

Data: Data, reference period length
Result: Detected change points
use reference data to train classifier;
model = classifier.fit(trainingData);
while no change point detection do
    predict change probability of current data point;
    prediction = model.predict(dataPoint);
    if data point does not belong to reference class then
        define data point as new change point;
        restart one-class svm algorithm from current data point;
    end
end

```

Algorithm 12: One-Class SVM Change Detection Technique

- **Proposed Adaptation**

One-Class SVM classifies data using **static training phase**. Proposed adaptation sets **moving training phase** (Algorithm 12). Initial training phase defines initial reference class.

If current data point does not belong to initial reference class, first change occurs. Re-starting training phase from detected change point enables future change investigation.

4.2.10 Affinity Propagation, K-Means and Mean Shift Change Detection Techniques

Affinity Propagation, K-Means and Mean Shift are clustering techniques [103–105]. They recognize clusters among training data. These clusters enable association of new instances. K-Means requires number of clusters N . It separates training data into N clusters having corresponding centroids (*i.e.*, cluster means). K-Means centroids minimize inertia, or within-cluster sum of squared criterion.

```

Data: Data
Result: Detected change points
analyze data until first change point detection;
while no change point detection do
    | classify all past data into clusters;
    | clusters = applyClusteringTechnique(pastData);
    | compute current cluster ratio (including current data point);
    | if currentClusterRatio < 10% then
    | | define data point as new change point;
    | | restart clustering from current data point;
    | end
end

```

Algorithm 13: Clustering Change Detection Technique

Affinity Propagation and Mean Shift automatically infer cluster number. Affinity Propagation exchanges messages between sample pairs until convergence. Final matching samples build cluster representatives. Messages define similarity criterion between samples in response to their values. Iterative message transfer reaches convergence for cluster definition. Mean Shift investigates density blobs of data samples. Updating candidates for centroids defines cluster means. Further filtering of centroid candidates eliminates duplicates and forms final clusters.

- **Proposed Adaptation**

Affinity Propagation, K-Means and Mean Shift **separate data into clusters**. Proposed adaptation targets **change detection between clusters** (Algorithm 13). Computing **current cluster ratio** (*i.e.*, cluster including current data point) among past clusters defines change

probability. If current class ratio is lower than 10%, change occurs. Re-applying clustering technique starting from detected change point investigates new change points.

4.3 ChangeTracker Service Implementation Architecture

Web-based service ChangeTracker implements proposed methodology for early and unobtrusive detection of possible health changes [20–24]. Developed service takes advantage of ambient assisted living platform UbiSMART, that provides sensor network configuration, raw data collection and real-time activity recognition services. Whereas UbiSMART collects sensor data for short-term anomaly detection (*e.g.*, fall and wandering at night), ChangeTracker targets long-term changes that take weeks or months to emerge.

Developed service extracts health change indicators on a daily basis. It analyses toilet entries, sleep habits, time out home, activity level and visits using movement and door sensors. Computing these health change indicators enables investigation of possible changes in health status. Implemented change detection techniques differentiate between transient and continuous changes. ChangeTracker service provides users with reliable information about health status and possible changes.

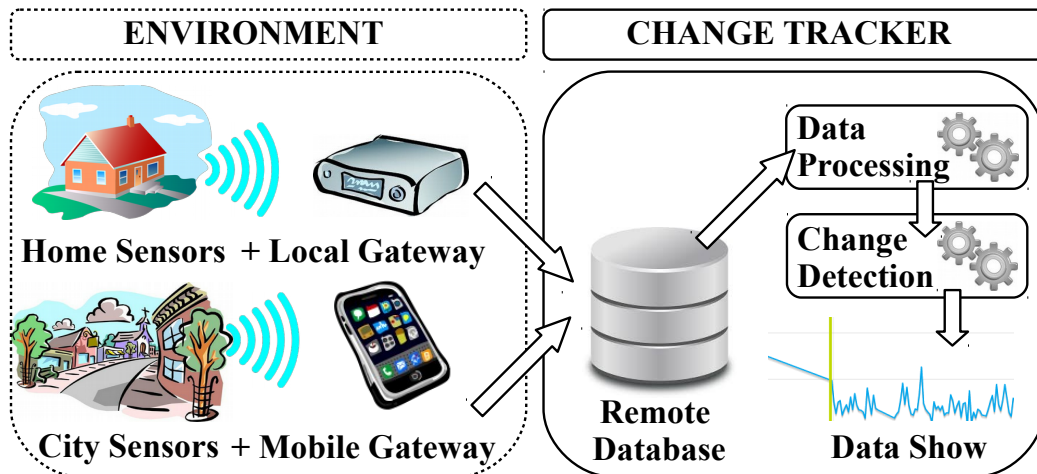


Fig. 4.12 Client-Server Implementation Architecture of ChangeTracker Service

Implementation architecture consists of model, controller and view layers (Fig. 4.12). Model layer manages acquisition and storage of raw sensor data. Locally deployed Raspberry-Pi gateways send sensor data via Internet to central server. Controller layer implements data processing algorithms that compute inferred data; *e.g.*, activity periods based on movement sensor data. It also implements change detection techniques. These techniques analyze data

online and differentiate between transient and continuous deviations. View layer provides users with graphical interface for data visualization and change notifications; e.g., caregivers examine daily evolution of health change indicators and receive notifications about recently-detected change points.

4.3.1 Model Layer for Data Acquisition and Storage

Model layer links ChangeTracker to monitoring environment. It manages acquisition of sensor observations. Sensor Modeling Language (SensorML) describes sensor network in XML format [92]. It identifies sensor types and locations; e.g., movement sensor is deployed in bedroom (Listing 4.1). Sensor network description automates association of sensor events to their points of interest.

```
<sml: classifier>
<sml:Term definition="http://sensorml.com/ont/swe/property/
  SensorType">
<sml:label>Sensor Type</sml:label>
</sml:Term>
</sml: classifier>
<sml: position>
<gml:Point gml:id="stationLocation">
<gml:coordinates>Location ID</gml:coordinates>
</gml:Point>
</sml: position>
```

Listing 4.1 SensorML Template for Modeling Sensor Network

Locally-deployed gateways at home receive sensor events, and adapt their format. Observation And Measurement (O&M) format defines standard attributes for all sensor types [93]. This resolves interoperability issues in large-scale deployments. Sensor ID and type identify received event; e.g., sensor type is "Motion" and sensor ID is "A1" (Listing 4.2). Declaring gateway ID and location ID associates received event to its feature of interest; e.g., gateway "RaspberryPI-b8:27:eb:80:c1:a6" collects movement sensor event coming from room "LivingRoom1". Further attributes are observation type, value and time; e.g., movement sensor sends "On" event of type "Boolean" at "2018-07-27T18:38:10+02:00". O&M defines a reference to SensorML description in "ObservedProperty" attribute.


```
{
  "id": "<Gateway-Type>/<MAC-Address>/<SensorID>/<Time-UTC-format>",
  "type": "TruthObservation",
  "phenomenonTime": {
    "instant": "<Time-UTC-format>"
  },
  "observedProperty": {
    "href": "<Sensor-Description-Link>"
  },
  "procedure": "<Sensor-Description>",
  "featureOfInterest": {
    "href": "<Location-ID>"
  },
  "resultTime": "<Time-UTC-format>",
  "result": {
    "uom": "<Observation-Type>",
    "value": "<Observation-Value>"
  }
}
```

Listing 4.2 O&M Data Format Template

Machine-to-machine Internet of Things (MQTT) protocol controls data transfer [108]. Gateways publish sensor events on pre-defined topics; e.g., topic "house/47/marmitek/sensor/A1" is associated with motion sensor "A1" in house 47 (Fig. 4.13). ChangeTracker subscribes to these topics, in order to remotely receive sensor events. MQTT broker manages gateway publications and server subscriptions. Anonymous topics enhance system security and data privacy.

Open source relational database PostgreSQL manages data storage [109]; e.g., "Event" table contains sensor event dates, values and corresponding location IDs (Fig. 4.14). Further tables contain sensor network configurations (e.g., sensor number, types, IDs and locations), and user credentials (e.g., login and password). Database administrator uses private keys for secure database access. PostgreSQL enables table indexing for quick read operations. Write operations generate new IDs, creation and update times. ChangeTracker service uses application programming interface (API) to access database.

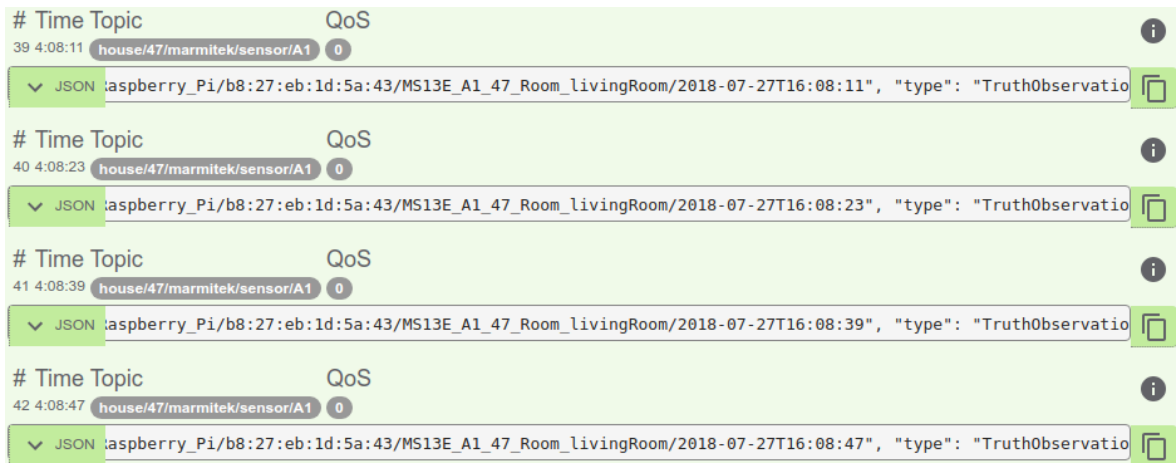


Fig. 4.13 MQTT-Communicated Sensor Event Example

```

ubidb=# select * from event order by date desc limit 5;

```

id	createdAt	updatedAt	date	house	sensor	value
2902035	2018-07-27 14:12:11+00	2018-07-27 14:12:11+00	2018-07-27 14:12:11+00	47	A2	on
2902034	2018-07-27 14:11:52+00	2018-07-27 14:11:52+00	2018-07-27 14:11:52+00	42	A5	off
2902033	2018-07-27 14:11:45+00	2018-07-27 14:11:45+00	2018-07-27 14:11:45+00	47	A2	on
2902032	2018-07-27 14:11:23+00	2018-07-27 14:11:23+00	2018-07-27 14:11:23+00	47	A2	off
2902031	2018-07-27 14:10:48+00	2018-07-27 14:10:48+00	2018-07-27 14:10:48+00	42	A5	on

(5 rows)

Fig. 4.14 Sensor Event Table in PostgreSQL Database

4.3.2 Controller Layer for Data Processing and Change Detection

Controller layer is implemented in JavaScript (Listing 4.3). It defines service name, logging interface for debugging options and linking interface to view layer. Each view has corresponding function for data retrieval, computation and upload; e.g., "indexPage" view has function "service.indexPage" to retrieve required information.

```

var servicePrototype = require ('../service');
var ubi = require('ubiutils');
var log = ubi.log('changetracker_ubiservice');
var service = servicePrototype.create("ChangeTracker");

service.indexPage = function(params, res) {
  service.getIndexPageInformation(params, {}, function(
    result) {
    result.title = sails.config.appName + ": " + res.
      locals.tr('ChangeTracker');
    res.view('servicesRepository/' + service.name + '/
      indexPage', result);
  });
};

```

```

    });
};

```

Listing 4.3 JavaScript Service Prototype

Dedicated application programming interface (API) enables access to database (Listing 4.4). Read and write operations specify search conditions and created objects; e.g., view "indexPath" retrieves house description by specifying its ID and performing asynchronous access to database. Call-back functions initiate data queries and wait until response. Errors occur if database access is not allowed or data query is not correct.

```

service.getIndexPathInformation = function(params, res,
    opt_cb) {
    var houseId = parseInt(params.house);
    var result = {};
    var conditions = {};

    conditions.id = houseId;
    sails.models.house.findOne().where(conditions).exec(
        function(errorHouse, house) {
            if (errorHouse) return log.error(errorHouse);
            if (!house) return log.error('No house is found with
                ID #' + houseId);

            result.houseId = houseId;
            result.houseDescription = house.description;
            if (opt_cb) opt_cb(result); else res.json(result);
        });
};

```

Listing 4.4 Database Access Example

Implemented data processing algorithms analyze data on a daily basis. These algorithms convert raw sensor data into health change indicators; e.g., converting movement sensor data into weighted toilet entries (Listing 4.5). Data processing algorithms compute visits based on parallel activity periods, go out habits based on inactivity periods and sleep interruptions based on activity periods at night.

```

service.getToiletInformation = function(params, res) {
    var houseId = parseInt(params.house);

```

```

var conditions = {};
var dayToiletEntries = [];
var eventDays = [];

sails.models.event.find().where(conditions).sort("date
ASC").exec(function(errorEvents, events) {
  if (errorEvents) return log.error(errorEvents);
  if (!events) return log.error('No sensor events');

  //Analyze sensor events day by day
  eventDays = getEventDays(events);
  for (i in eventDays) {
    //Analyze events of current day
    dayToiletEntries.push(getDayToiletEntries(
      eventDays[i]));
  }
});
};

```

Listing 4.5 Toilet Entry Computation Example

Change detection techniques receive computed indicators as input, and provide possible changes as output. They analyze data online, in order to detect changes as early as possible (Listing 4.6). Implemented change detection techniques differentiate between transient and continuous changes in monitored indicators, such as statistical, probabilistic and machine-learning techniques.

```

//Get change points
for (i in dayToiletEntries) data.push(dayToiletEntries[i].
  value);
changePoints = applyChangeDetectionTechnique(data);

```

Listing 4.6 Toilet Entry Change Detection Example

4.3.3 View Layer for Data Visualization and Change Notification

View layer links ChangeTracker service to end users. Friendly user interface targets elderly people, family members and family doctor. Access is available via secure HTTPS connection,

and requires configuration of user accounts; e.g., elderly citizen has anonymous ID "42" and has exclusive access to corresponding monitoring data.

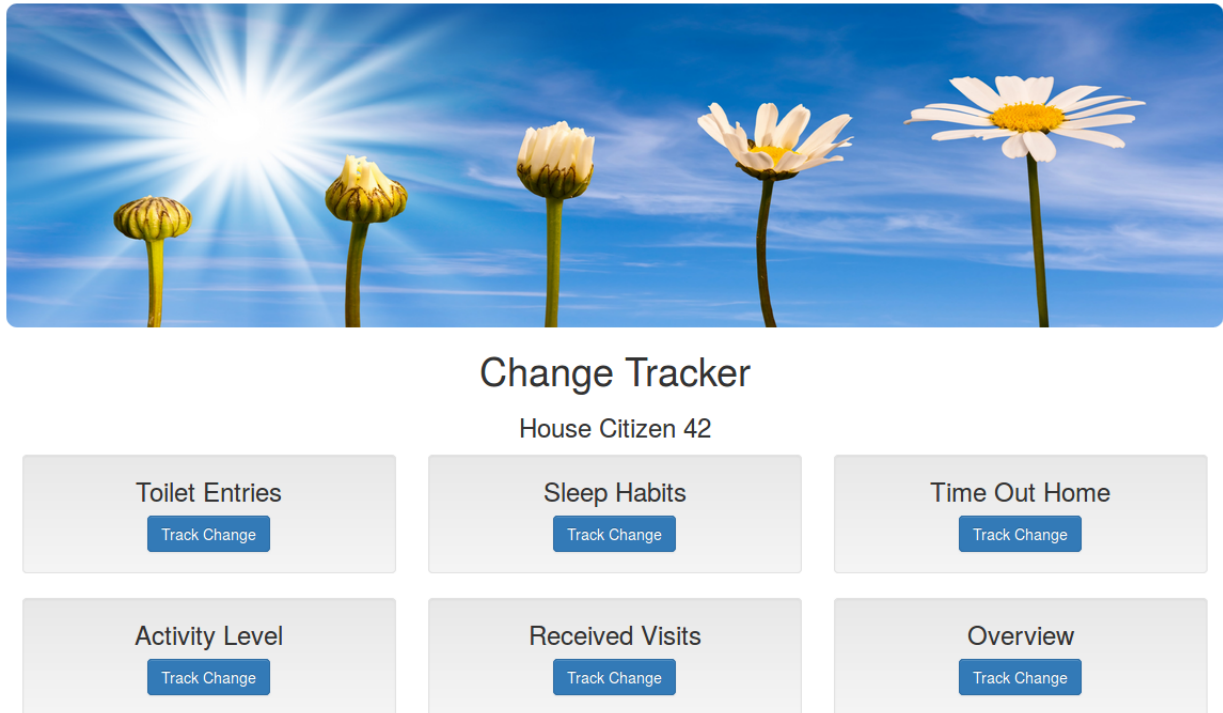


Fig. 4.15 Index Page View of ChangeTracker Service

"IndexPage" view presents main features, such as toilet entries based on toilet events, sleep habits based on activity periods at night, time out of home based on inactivity periods, activity level based on movement sensor events and received visits based on parallel activity periods (Fig. 4.15). "Track Change" button provides access to corresponding health change indicator view. "Overview" feature provides multi-dimensional correlation of all health change indicators.

Each health change indicator has dedicated view; e.g., "Toilet Entries" view shows daily evolution of weighted toilet entries and detected change points (Fig. 4.16). Blue curve describes daily evolution by specifying dates on x axis and values on y axis. Vertical green lines indicate detected change points; e.g., two consecutive increases in toilet entries are detected on 2017-09-12 and 2017-11-06. Further tables provide more information about change points (*e.g.*, change date, mean before and mean after), and numerical values.

"Daily Information" view shows hourly evolution of activity level and activity periods on selected day (Fig. 4.17). Blue bars measure detected movement number per hour by specifying time on x axis and value on y axis. Further table presents activity periods that are sequences of movements separated by less than 30s. Users follow-up activity period

start time, end time, location and whether visit occurs or not. Analyzing activity periods provides global understating of daily habits, wake-up time, sleep time, sleep interruptions, and received visits.

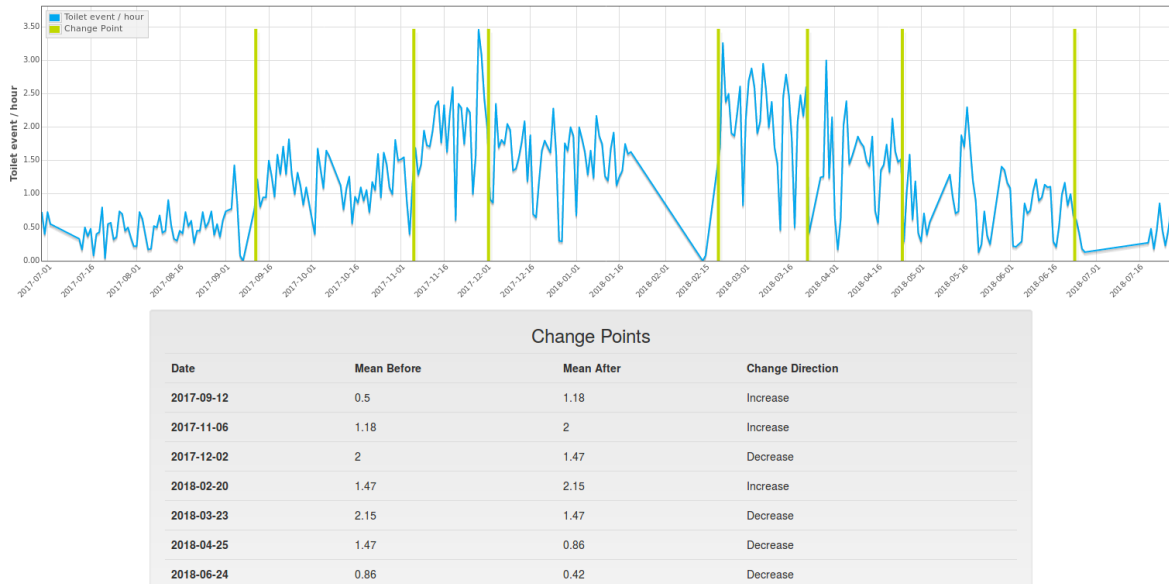


Fig. 4.16 Toilet Entry View of ChangeTracker Service

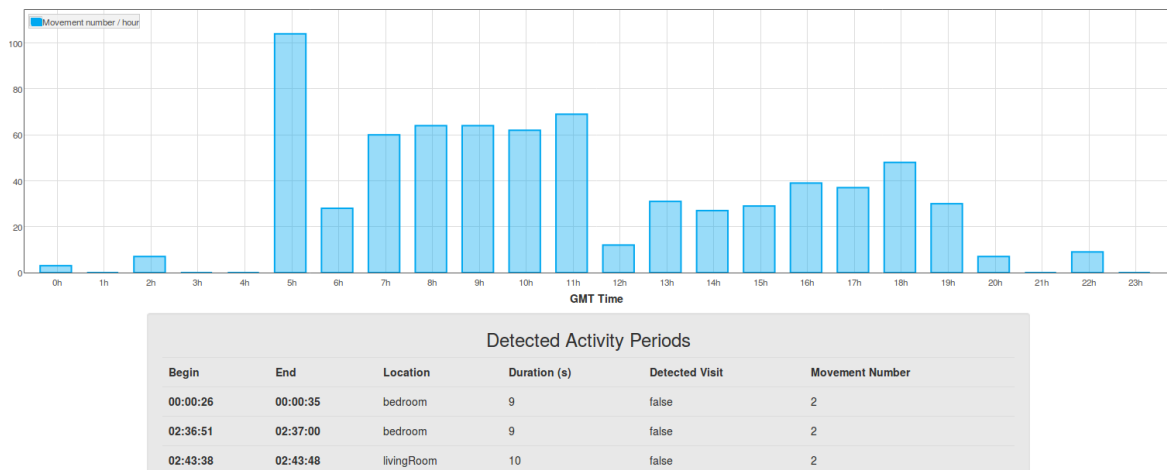


Fig. 4.17 Daily Information View of ChangeTracker Service

Users receive change notifications per Email and SMS under request (Listing 4.7). Configuration file defines mails and phone numbers. Notification are sent from 2 to 10 days after change occurrence, in order to confirm that detected change is really permanent and provide opportunity for early change explication. Simple Mail Transfer Protocol (SMTP) controls Email transfer by specifying receiver Email address, subject and text via Google

API [110]. Twilio library controls SMS transfer by declaring receiver, sender phone numbers and message content [111].

```

function send_change_notification (changePointText , emails ,
  phoneNumbers) {
  var subject = "[Change Tracker] Alert";
  var headerText += "Recent change points are detected. <
    br><br>";
  var i = 0;

  for (i=0; i < emails.length; i++) {
    mail(emails[i], subject , headerText +
      changePointText);
  }

  for (i=0; i < phoneNumbers.length; i++) {
    sms(phoneNumbers[i], headerText + changePointText);
  }
}

```

Listing 4.7 Mail and SMS Change Notification Example

4.4 Ambient Assisted Living Platform UbiSMART

UbiSMART targets assistance of elderly people with increased risk of dependence in managing activities of daily living [112, 113, 63, 64]. It uses environmental sensor data to infer activities of daily living, such as employing movement and door sensors to follow-up taking shower in bathroom, preparing meal in kitchen, watching television in living room and sleeping in bedroom. Semantic model describes living environment and reasoning engine infers possible activities in real time. UbiSMART identifies short-term changes in monitored activities, such as wandering at night, showering for too long, leaving the wash-room tap on, toilet falls and running away from home.

UbiSMART develops web-based services [112]. These services target non-expert users in large-scale deployments. Implementation architecture consists of 3 components: UbiGate, UbiBrain and UbiServices (Fig. 4.18).

UbiGate links UbiSMART to its deployment environment. This component manages sensor data collections and transfer to central server. UbiGate consists of adapters (developed

in Python from client side and JavaScript from server side) converting sensor signals into sensor events that can be transferred via Internet. Abstract adapter interface is instantiated correspondingly to sensor type and data communication protocol; e.g., adaptable generic functions manage movement or door sensors using X10 or Z-Wave communication protocol.

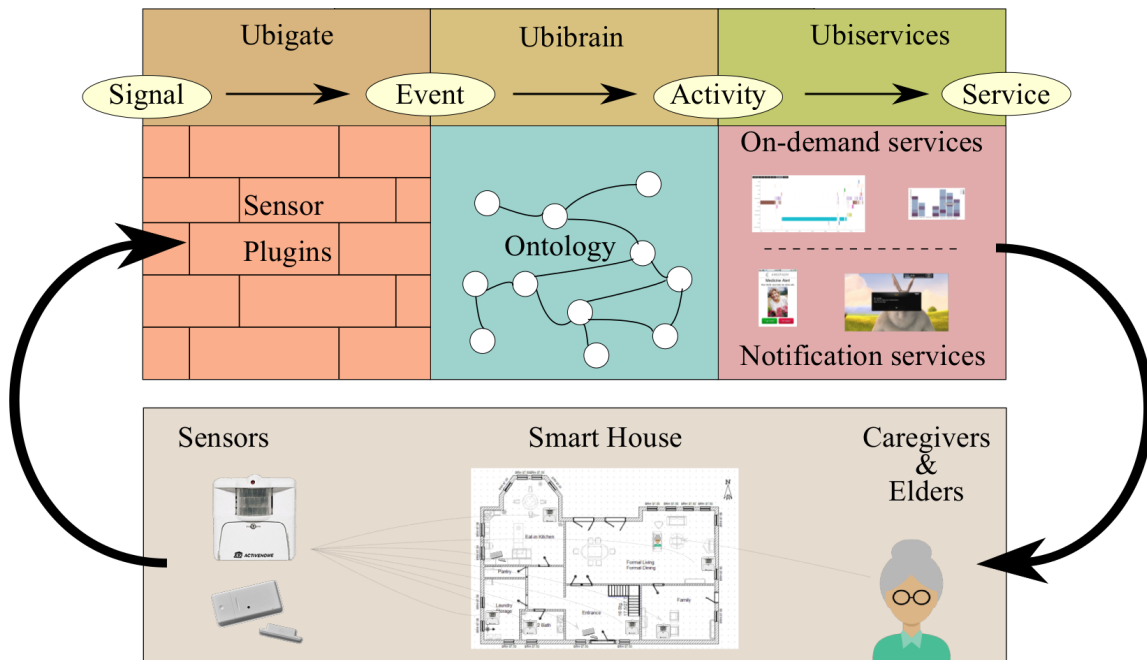


Fig. 4.18 Implementation Architecture of UbiSMART Platform

UbiBrain builds knowledge about deployment environment. Semantic model describes monitoring environment, sensor types, locations, events, user roles and activities. Specific model instantiates generic model to describe specific environment; e.g., specific ontology instantiates sensor type "Movement Sensor", location type "Living Room" and defines specific relationship "Movement Sensor is deployed in Living Room". Reasoning engine defines rules to infer activities of daily living in real time, such as watching television in living room, going to toilet, taking shower in bathroom, preparing meal in kitchen and sleeping in bedroom. These rules identify anomalies, such as falling, wandering at night, showering for too long, leaving wash-room tap on and running away; e.g., IF-Then rule detects leaving home for too long "If last movement is detected since a long time and main door is opened, then possible running away is detected".

UbiServices develops interactive user interface. Developed services target system administrators, elderly people, family members and family doctors. Generic service template defines service name, log access points, function prototypes and user interface. Instantiating this generic template is essential to integrate services in UbiSMART. HomeDesc service

models deployed sensor network. SensLog service shows sensor observations. Life service presents inferred activities.

4.4.1 HomeDesc Service for Sensor Network Modeling and Configuration

HomeDesc targets non-expert users like formal and informal caregivers. It configures sensor locations in a couple of minutes, such as living room, bedroom, kitchen and bathroom (Fig. 4.19). Sensor locations include house doors and furniture, such as main house entries, fridge, oven and microwave. These locations represent points of interest at home.

The screenshot displays the HomeDesc service configuration interface, divided into three main sections: Rooms, Objects, and Sensors.

Rooms Section: Features an "Add room" button and a table with columns "Type" and "Name".

Type	Name	
Living room	livingRoom	×
Bedroom	bedroom	×
Kitchen	kitchen	×
Toilet	toilet	×
Bathroom	bathroom	×
Living room	escalier	×

Objects Section: Features an "Add object" button and a table with columns "Type" and "Name".

Type	Name
Door	mainDoor
Fridge	fridge
Door	garageDoor

Sensors Section: Features an "Add sensor" button and a table with columns "ID", "SensApp", and "Binding".

ID	SensApp	Binding	
A1	Motion Sensor	livingRoom	×
A2	Motion Sensor	kitchen	×
A5	Motion Sensor	toilet	×
A3	Motion Sensor	bedroom	×
A4	Motion Sensor	bathroom	×
A6	Motion Sensor	escalier	×
C6F280	Contact Sensor	mainDoor	×
69EF80	Contact Sensor	fridge	×
2D0C00	Contact Sensor	garageDoor	×

Fig. 4.19 Graphical User Interface of HomeDesc Service

Users configure sensor IDs and locations. Embedded web-services receive new sensor events and propose corresponding IDs for possible inclusion. Drop-down list associates

sensors to locations, such as movement sensor "A1" in living room and contact sensor "AB45Z5" on main door.

HomeDesc generates specific ontology modeling sensor network. This specific ontology instantiates generic ontology by defining sensors and their locations. HomeDesc sends sensor configuration locally-deployed gateway. Local gateways use this configuration to convert sensor signals into sensor events and send them via Internet. Sensor configuration consists in basic description of sensor IDs, types and locations in JSON format.

4.4.2 SensLog Service for Raw Data Visualization



Fig. 4.20 Graphical User Interface of SensLog Service

SensLog shows received sensor events in real time. Formal and informal caregivers follow-up elderly people location and activities; e.g., monitored person sleeps in bedroom, then wakes-up at 8h and goes to toilet. SensLog service enables visualization of past sensor events over a couple of days. This provides global understanding about daily habits and possible abnormal activities, such as sleeping regularly between 22h and 8h based on inactivity periods, and wandering during sleep based on abnormal activity periods at night.

User interface shows time on x axis and sensor events on y axis (Fig. 4.20). Sensor events depend on sensor types; e.g., movement sensors send "On" and "Off" events indicating presence and absence of movements (each 10 seconds for "On" events, and after 1 minute for "Off" events). Door sensors send "Normal" and "Alert" events indicating door openings and closings.

SensLog has access to database containing received sensor events. Embedded web-services enable real-time visualization of sensor observations. Dot colors differentiate between sensor types. Horizontal lines show timely evolution of sensor firings. Users select sensor firings to determine exact time-stamp.

4.4.3 Life Service for Real-Time Activity Recognition

Life service recognizes activities of daily living in real time and identifies possible anomalies for subsequent intervention. Whereas SensLog service shows raw sensor data, Life service uses raw sensor data to infer possible activities using semantic reasoning, such as watching television in living room, sleeping in bedroom, taking shower in bathroom and preparing meal in kitchen.

Semantic reasoning receives sensor events, prior knowledge of specific ontology and inference rules to determine posterior knowledge. Specific ontology updates its state based on inferred activities; e.g., monitored person has relationship "Is Located In" associated with "Living Room" based on detected sensor events in living room. This relationship changes to "Is Located In" associated with "Kitchen" based on sensor events in kitchen. IF-Then rules infer complex activities of daily living, such as taking shower "If sensor events are detected in bathroom and temperature sensor indicates increase, then person takes shower in bathroom". Defined thresholds determine possible anomalies, such as falling "If person is in toilet and no movements are detected for long time, then possible fall is detected", and running away "If long inactivity period is detected after opening main door, then possible running away is detected".

Formal and informal caregivers use Life service to monitor time, place, duration and frequency of executing activities (Fig. 4.21). Different colors distinguish between activity types. On x axis, users follow-up activity execution start time, end time and duration. On y axis, users observe inferred activities. Life service sends anomaly notifications to caregivers, if abnormal activities are detected. Further notifications inform caregivers about normal activities after anomaly detection, such as going to kitchen after possible fall in toilet and coming back home after possible running away.

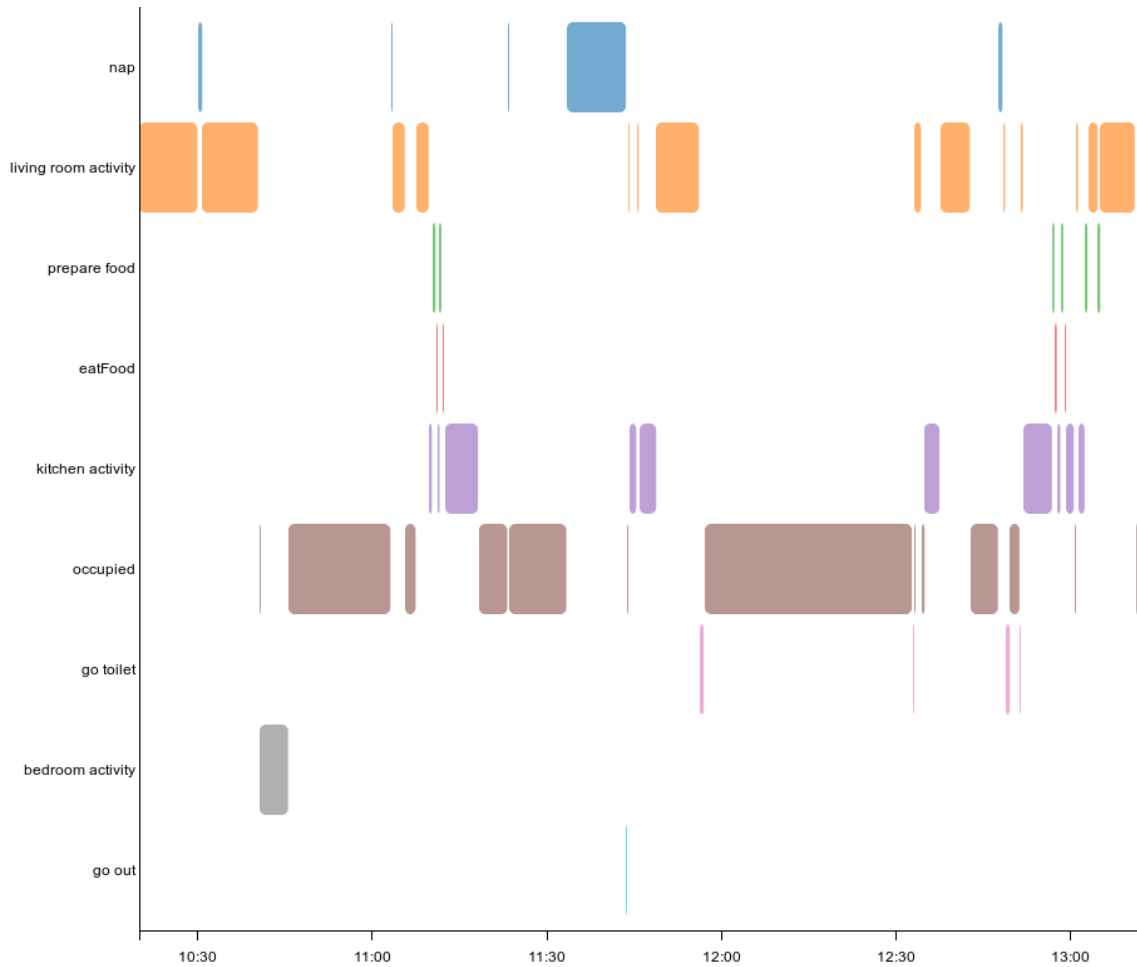


Fig. 4.21 Graphical User Interface of Life Service

4.5 Conclusion and Discussion

Developed application **ChangeTracker** in this thesis provides elderly people, family members and family doctor with **online behavior analysis** and **continuous change detection**. This application is integrated in ambient assisted living platform UbiSMART. UbiSMART acquires sensor observations and infers activities of daily living in real time. This platform does not detect changes in inferred activities. ChangeTracker implements new change detection service, by converting sensor observations into geriatric indicators and analyzing them online for long-term change identification.

Implemented **data processing algorithms** in this thesis compute health change indicators, such as **activity level** based on activity periods, **sleep interruptions** based on activity periods at night, **toilet entries** based on toilet sensor observations, **received visits** based on parallel activity periods and **time out of home** based on inactivity periods. All computed

indicators are weighted to presence time alone at home. Discarding go out periods and visit periods is essential to avoid detecting irrelevant changes, such as toilet entry decreases after going out more frequently and activity level increases during presence of multiple persons.

Evaluated and adapted **change detection techniques** in this thesis investigate possible changes in monitored indicators. Statistical, probabilistic and machine-learning techniques apply different filters on detected deviations and identify changes with different granularity. Z-Score, Naive Bayes Classifier, ULSIF and One-Class SVM detect changes based on static or single reference phase. SD-Band technique identifies short-term changes. Affinity propagation, K-Means and Mean Shift classify data into clusters. **Adapting** these techniques enables **multiple long-term change detection**. This thesis adapts Z-Score, Naive Bayes Classifier, ULSIF and One-Class SVM by defining **moving reference phase**. This allows to re-initialize reference phase after change detection, in order to detect future changes. Proposed adaptation to SD-Band defines **moving window** of consecutive deviations for long-term change detection. Proposed adaptation to clustering techniques computes **rate** of cluster including current data point to identify possible change point.

Chapter 5

Validation: Real Deployments and Experimental Results

Contents

5.1	Recruitment Process and Data Collection	99
5.1.1	Local Medical Partners and Experimental House	99
5.1.2	Validation Environment and Technological Solutions	102
5.1.3	Medical Participant Profiles and Analysis Indicators	105
5.2	Early Health Change Detection Examples	113
5.2.1	Detected Health Changes for Participant A	113
5.2.2	Detected Health Changes for Participant B	115
5.2.3	Detected Health Changes for Participant C	117
5.2.4	Detected Health Changes for Participant D	119
5.2.5	Detected Health Changes for Participant E	120
5.2.6	Detected Health Changes for Participants F and G	122
5.2.7	Detected Health Changes for Participants H and I	124
5.2.8	Detected Health Changes for Participants J and K	126
5.2.9	Detected Health Changes for Participants L and M	127
5.2.10	Detected Health Changes for Participants N and O	129
5.2.11	Detected Health Changes for Participants T and U	130
5.2.12	Detected Health Changes for Participants V, X and Y	132
5.3	Health Change Cause Investigation and Medical Relevance Validation . .	134

5.3.1	Personal, Context and Medical Information Collection	135
5.3.2	Possible Health Change Cause Categories and Rates	137
5.3.3	Health Change Detection Ontology	139
5.3.4	Change Detection Technique Performance Evaluation	141
5.4	Conclusion and Discussion	146

Real deployments in 3 French cities Montpellier, Lattes and Occagnes validate proposed technological approach in this thesis. **Medical clinic "Beau Soleil"** [36] (Montpellier), **metropolis council** [114] (Montpellier), **public health autonomy center "ETAPE"** [115] (Lattes) and **nursing home "Saint Vincent de Paul"** [37] (Occagnes) provide help with recruitment process. In total, **25 elderly people** living alone at home or nursing home participate in experimentation. Movement sensors in each room and door sensors at main entries collect monitoring data during 3 years. Analysis algorithms extract geriatric indicators and detect long-term changes in health status.

Medical clinic geriatrician Dr. Émilie Guettard [36] and **nursing home team** [37] validate **medical relevance** of technological observations in this thesis. Medical clinic "Beau Soleil" does not only help with recruitment process, but also provides medical interpretations of detected changes. After obtaining ethical approval, Dr. Émilie Guettard conducts initial **interviews** with participants. These interviews enable **health status diagnosis** at experimentation begin. Patients consult medical clinic geriatrician each 2 months, and earlier under request. Further interviews occur 6 months and 12 months after monitoring begin, in order to review health status and investigate possible **change causes**. Participants V, X and Y are actually Parkinson patients of Dr. Émilie Guettard (see sub-section 5.2.12 for more information). She identifies changes in toilet entries, time out of home and activity level, that are associated with mobility impairments and treatment side effects.

Nursing home team consists of **nurses, geriatricians** and **psychotherapists**. They continuously **record medical observations** using tablets. These electronic health records include hospitalizations, mobility problems, memory troubles, anxiety periods, prescribed treatments, social habits and nutritional programs. **Correlating medical observations** with **technological observations** is essential to validate medical relevance of detected changes in this thesis. Participants A-I and L are nursing home residents (see section 5.2 for more information). Nursing home team identifies increases in sleep interruptions during anxiety periods, decreases in activity level due to mobility impairments, and increases in toilet entries because of urinary infection.

5.1 Recruitment Process and Data Collection

Three-year deployment in nursing home and individual houses validate proposed technological approach. Local medical partners provide help with recruitment process. Promoting experimentation through newspaper articles, presentation sessions and exhibition stands in local medical events are key steps for recruitment process (Figure 5.1).



Fig. 5.1 Cooperating Partners in Recruitment Process

In total, 25 elderly people living alone at home or nursing home participate in experimentation having an average age 86 years. Movement sensors deployed in each room and door sensors installed at main entries collect basic information about elderly people behavior. Wireless Marmitek MS13E movement sensors [116] and DS90 contact sensors [117] collect monitoring data. Movement sensors send events each 10 seconds while detecting movements. Contact sensors send events after opening or closing corresponding door. Local Raspberry-Pi gateway receives sensor events using X10 communication protocol and transfer them in real time via Internet to dedicated server. Despite the basic information collected by these sensors (*i.e.*, presence and absence of movements, and door openings and closings), developed data processing algorithms extract health change indicators on a daily basis, such as toilet entries, sleep interruptions, visits, activity level and time out of home.

5.1.1 Local Medical Partners and Experimental House

Deployments take place in 3 French cities Montpellier, Lattes and Occagnes. Cooperating partners help with recruitment process (Figure 5.1). Medical clinic "Beau Soleil" (Montpellier) [36], nursing home "Saint Vincent de Paul" (Occagnes) [37], metropolis council

(Montpellier) [114] and health autonomy center "ETAPE" (Lattes) [115] are interested in health change detection services. They involve their elderly citizens, members, patients and residents in adopting technological solutions. Local medical events and presentation sessions promote health change detection services for dozens of elderly people aged 65 years old and over (Fig 5.2). Potential participants visit experimental house in Lattes (provided by health autonomy center "ETAPE") for more information about sensing technologies in real-life conditions.



Fig. 5.2 Local Medical Events Promoting Recruitment Process

Medical clinic "Beau Soleil" [36] needs to monitor activities of daily living occurring outside geriatrician's office. Cooperating geriatrician Dr. Émilie Guettard is interested in enriching classical medical assessments (*e.g.*, geriatric scales and tests) with new objective observations of daily living, such as sleep habits, toilet entries, activity periods, time out of home and social habits for Parkinson patients. Proposed monitoring system employs unobtrusive technologies that do not interfere with natural behavior of elderly people and do not affect their privacy. Recruited participants via medical clinic "Beau Soleil" are Parkinson patients. They experience frequent trembling in fingers and legs, sudden freezing periods and regular sleep interruptions. Their main focus is efficient evaluation of medical treatment impact (*i.e.*, whether prescribed treatments are really useful or not) by detecting possible health changes in early stages of their evolution.

Nursing home "Saint Vincent de Paul" [37] needs to establish new link with elderly people living alone at home. This nursing home provides geriatric services for regular residents, and proposes further services for elderly people before entry to nursing home. Elderly people remain as long possible at home and do not prefer to leave their own habitat. Proposed monitoring system helps nursing home to follow-up activities of daily living at home, analyze them and early detect possible changes. Early health change detection provides opportunity for effective intervention, such as adapting own habitat, enhancing nutritive program, improving prescribed treatments and launching home aid. Recruited participants

via nursing home live alone at home and have diverse mobility and cognitive problems (*e.g.*, Alzheimer and Frailty). These participants are still able to manage their activities of daily living at home (partially or totally), and do not require immediate entry to nursing home. Main nursing home focus is how to select elderly people requiring urgent entry to nursing home and when to initialize remote services.



Experimental House Front View



Main Door Sensor



Fridge Sensor



Bathroom Sensor

Fig. 5.3 Experimental House in Lattes and Tested Technologies

Montpellier metropolis council [114] targets better adaptation of city services for elderly people needs. Aging rates are considerably increasing and representing huge burden on public health and economy. Proposed monitoring system does not only evaluate health status at temporal scale, but also provides global health statistics for all participants in large-scale deployments. Detected health changes and associated medical diagnosis provide significant information to take actions. Metropolis council and health organizations acquire global health statistics to better adapt intervention policies and usefully reduce health costs. Recruited participants are elderly citizens living alone at home and using public means of transport. Their main focus is how to early detect possible health changes based on indoor and outdoor behavior monitoring. Possible decreases in going out frequency and using public means of transport are key indicators for frailty, mobility and cognitive problems.

Public health autonomy organization "ETAPE" [115] is interested in optimizing intervention services for elderly people with independence difficulties. This organization proposes new technological solutions that better adapt living environment for elderly people needs, such as using smart glasses that reduce vision problems, smart spoons that simplify nutritive tasks, moving staircase that reduces mobility problems, and smart phones with simple screen functions and buttons specially adapted for elderly people with cognitive problems. "ETAPE" targets better understanding of physical and cognitive needs, and better adaptation of intervention services. Recruited participants via "ETAPE" live alone at home, and need continuous evaluation of proposed intervention services. Proposed health change detection service allows to make better decisions of when to initiate intervention services, and which services to select.

Local medical partners organize presentation sessions and exhibition stands to better promote experimentation objectives and initialize recruitment process (Figure 5.2). Dozens of elderly people participate in these events. Potential participants ask for more information about employed technological solutions, real benefits of adopting them at home and predictable risks. Elderly people show considerable interest in early health change detection and more acceptance for unobtrusive monitoring. Newspaper articles better explain long experimentation period and final objectives.

Interested participants have diverse medical and social profiles, such as living in couple with autonomy problems, living alone with partial independence and residing in nursing home with cognitive problems. Inclusion criteria exclusively select elderly people (i) living alone at home or nursing home, (ii) aged 65 years old and over, (iii) being partially or totally active by going out regularly, managing personal activities of daily living with no or partial help and optionally using public means of transport, and (iv) being healthy or affected by medical problems in early stages of their evolution.

An experimental house provided by "ETAPE" in Lattes represents testing environment (Figure 5.3). All employed technologies are tested before any real deployments, such as movement sensors, contact sensors, gateway, receiver and Internet access point. This house consists of bedroom, living room, kitchen and bathroom with toilet. Movement sensors detect presence and absence of movements in each room. Contact sensors follow-up main house entries and fridge openings. Potential participants attend live demonstration sessions and observe monitoring system deployed in real-life conditions.

5.1.2 Validation Environment and Technological Solutions

In total, 25 elderly people participate in proposed experimentation (Table 5.1). They live alone at home or nursing home, and integrate proposed sensing technologies at their own

habitat for several weeks and months (*e.g.*, monitoring period reaches 3 years for participants C, E, G and I starting from 2015 until 2018). Participants have an average age 86 years old, and are partially or totally active (*i.e.*, frequently go out, manage diverse activities of daily living and receive visits at home). All participants agree with long experimentation period, experimentation objectives and employed unobtrusive technological solutions.



Fig. 5.4 Nursing Home Deployments and Employed Technologies

Nursing home deployments take place in Occagnes, France (Figure 5.4). Deployments start from 2014-09-14 until 2018-11-30 (Table 5.1). Sensing technologies exclusively monitor nursing home residents inside their rooms; *i.e.*, no technologies are deployed in common places. Nursing home rooms consist of bedrooms, bathrooms and toilets. Contact sensors detect main door openings and closings. Movement sensors notify about presence and absence of movements. Monitored participants are affected by diverse physical and cognitive diseases, such as walking difficulties, social isolation, wandering and early Alzheimer symptoms. They stay in their individual rooms for daily hygiene, rest and sleep, and leave for lunch, dinner and common social activities (*e.g.*, participants A, B, C, D, E, F, G, H, I and L).

Individual house deployments take place in 3 French cities Occagnes, Montpellier and Lattes (Figure 5.5). Deployments start from 2016-10-11 until 2018-11-30 (*e.g.*, participants J, K, M, N, O, P, Q, R, S, T, U, V, W, X and Y). Participants live alone at home, frequently go out and receive visits. Contact and movement sensors are deployed on each main door

(*e.g.*, main entry and exit doors) and room (*e.g.*, bedroom, bathroom, toilet, living room and kitchen) for continuous behavior monitoring.



Fig. 5.5 Individual House Deployments and Employed Technologies

Developed web-based service ChangeTracker acquires raw data in real time and performs daily analysis for early change detection. Locally-deployed Raspberry-Pi gateways collect sensor data and send them via Internet using MQTT communication protocol [108]. Defining topics is essential to control communication between gateways and ChangeTracker service. This enhances system security and data privacy by defining anonymous topics and discarding sensor events coming from unknown topics.

O&M standard defines exchanged data format [93]. It resolves interoperability issues in large-scale deployments by specifying same attributes for all sensor types. SensorML standard additionally describes global sensor network [92]. It is important to identify sensor types and associated points of interest for consistent data acquisition. PostgreSQL manages data storage [109]. It enables table indexing for quick data retrieval operations. Stored and updated data have corresponding creation and update times. Dedicated application programming interface (API) enables ChangeTracker to access database and perform online data processing.

Table 5.1 Participant ID, Gender, Monitoring Start, End and Place at Nursing Home (NH) and Individual Houses (IH)

ID	Gender	Age	NH	IH	Start	End
A	M	90	x		2014-09-23	2015-02-13
B	M	90	x		2015-03-15	2015-08-03
C	M	84	x		2015-09-10	2018-11-30
D	F	85	x		2014-09-23	2015-08-06
E	F	98	x		2015-08-13	2018-11-30
F	F	87	x		2014-09-23	2017-01-18
G	F	90	x		2014-09-23	2018-11-30
H	F	95	x		2014-09-14	2015-06-03
I	F	95	x		2015-06-04	2018-11-30
J	F	93		x	2014-11-24	2015-10-12
K	M	87		x	2016-10-11	2017-01-30
L	F	90	x		2017-04-04	2018-11-30
M	M	94		x	2016-10-11	2018-11-30
N	F	94		x	2016-10-11	2018-11-30
O	F	92		x	2016-10-11	2018-11-30
P	F	91		x	2017-04-07	2017-06-30
Q	M	89		x	2017-04-06	2017-05-28
R	F	90		x	2017-04-06	2017-06-15
S	F	85		x	2017-04-06	2017-05-14
T	F	88		x	2017-04-06	2018-11-30
U	F	83		x	2017-06-29	2018-11-30
V	M	69		x	2017-10-20	2018-11-30
W	F	78		x	2018-01-25	2018-03-15
X	F	62		x	2018-02-02	2018-11-30
Y	M	59		x	2018-02-09	2018-11-30

5.1.3 Medical Participant Profiles and Analysis Indicators

Recruited participants have diverse daily and weekly habits, and medical profiles (Table 5.2). First interviews with elderly people, their family members and formal caregivers investigate health status at monitoring period begin. Initial health status diagnosis validates participant recruitment and provides primary explications for detected health changes. Reported regular habits on daily, weekly and monthly basis provide global understating of monitored behavior; e.g., reporting frequent engagement in outdoor activities and detecting future decrease in go out frequency indicate possible social isolation.

Nursing home residents have regular habits due to their restricted living environment (Table 5.2). Participants B, C, I and L often stay in their rooms. They do not prefer

going outside for medical reasons, such as walking impairments and depression periods. Participants A, D and H are engaged in common activities organized at nursing home, such as lunch, dinner and entertainment sessions. Participants E, F and G are still attached to their family members. They frequently receive family visits in nursing home and take part of family events outside nursing home.

Reported medical profiles for nursing home residents highlight diverse physical and cognitive problems. Mobility impairments (*e.g.*, walking impairments and falls) affect almost all participants, such as participants B and F not being able to walk without walking stick or medical walker. Quite advanced stages of Alzheimer disease affect participants E, F and G. They easily forget recent events due to memory impairments. Participants C and D experience serious anxiety and depression periods in first months after their entry to nursing home. Diabetes and respiratory problems influence health status of participants H and G respectively.

Table 5.2 Regular Participant Habits and Reported Health Information Related to Cognitive Impairments (CG), Physical Impairments (PH), Diabetes (DB), Frequent Visits (FV) and Go Out (FG)

ID	Regular Habits	Health Info	CG	PH	DB	FV	FG
A	Wakes up at 7h30-8h. Takes breakfast, then shower. Stays in room whole morning. Frequent daily daughter visits at 11h. Brought to canteen for lunch midday. Stays outside room in common living room (downstairs). Tea time in common living room (downstairs) at 16h30. Brought back to room at 17h-18h. Dinner in room.	Mobility problems. Frequent falls.		✓		✓	✓
B	Stays often in room. Receives some son visits in nursing home. Goes out sometimes with family members.	Uses walking stick. Pain in leg. Nutritional problems.		✓			

C	Stays most often in his room, sitting on his chair. Does not prefer to go out his room. Does not prefer to get involved in nursing home activities.	Inactive person. Anxiety and sleep impairments reported in first months after entry to nursing home.					
D	Wakes up at 7h-8h. Takes breakfast, then shower. Goes out to move around in corridors. Her children visit her sometimes in her room or outside. She stays most often in common living room (downstairs). Dinner in the canteen. Goes back to room at 20h and sleeps.	Alzheimer. Wandering. Anxiety periods. Depression. Falls. 4 hospitalizations.	✓			✓	✓
E	Frequent daughter visits. Frequent go out with family.	Quite active person. Some anxiety periods. Memory impairments. Pain in leg. Hearing problems.	✓			✓	✓
F	Wakes up at 8h. Takes breakfast, then shower. Sleeps again. Lunch in the canteen at 12h-12h30. Goes back to room for sleep. Dinner in the canteen at 19h. Goes back to room for sleep.	Always sick. Alzheimer. Sleeps for long periods. Walks with medical walker.	✓	✓		✓	✓

G	Wakes up at 8h. Takes breakfast, then shower. Stays in room whole morning. Frequent family visits. Frequent go out with family. Lunch in the canteen at 12h. Goes back to her room. Tea in her room. Dinner in the canteen at 19h. Brought back to her room for sleep.	Alzheimer. Walks with wheelchair outside her room. Oxygen supply. Respiratory problems. Weight loss. 4 hospitalizations.	✓	✓	✓	✓	
H	Wakes up at 7h-8h. Takes breakfast, then shower. Stays in room whole morning. Lunch in the canteen at 12h30. Stays in common living room whole afternoon. Dinner in the canteen. Goes back to her room for sleep at 20h.	Diabetes.			✓	✓	✓
I	Often stays in her room playing cross-world puzzles or phoning family members. Frequently receives family visits in nursing home.	Blood pressure problems. Pain in leg.				✓	
J	Sleeps for long periods. Often visit neighbors. Frequently receives family visits at home. Prefers reading books and watching television.	Nutritional problems. Mobility problems.		✓		✓	
K	Wakes up at 8h. Home aid 4 times per day. Stays most often at home. Sometimes goes out with daughter or caregiver.	Alzheimer. Diabetes. Vision and audition problems.	✓		✓	✓	
L	Does not prefer to go out her room. Often receive visits from her daughters.	Smokes a lot. Walking difficulties.		✓		✓	

M	Wakes up at 7h. Goes to toilet. Takes breakfast. Goes out for 1 hour to take care of animals. Goes out between 12h30 and 14h for lunch with his daughter. Reads newspapers. Frequently goes out during the day. Friend visit Sundays midday. Goes out shopping Wednesdays.	Very active person. No special diseases. Recent mobility impairments. Recent social isolation. Recent nutritional problems.	✓		✓
N	Wakes up at 8h. Takes breakfast. Goes to toilet. Takes lunch at 12h. Prefers watching television. Dinner 19h. Watches television again. Sleeps at 21h30-22h. Frequent family visits. Home aid 3 times per week. Goes out shopping Tuesdays at 10h. Goes out for lunch with son Sundays.	Active person. Type-2 Diabetes. No sleep drugs.		✓	✓
O	Wakes up at 6h-7h. Goes to toilet. Takes breakfast. Home aid for household at 9h. Lunch midday. Son visit at 18h30-19h for dinner and drugs. Takes sleep drugs and sleeps at 20h30. Several visits during the day, but alone at night. Goes out for lunch with son Sundays.	Always sick. Diabetes. Walks with medical walker. Heart problems. Vision problems. Many falls. Sleep drugs each night.	✓	✓	✓
P	Wakes up at 7h30-8h. Home aid visits 3 times per day (morning, midday and evening). Niece and neighbor visits during the day. Sleeps earlier than before (at 20h, and before at 22h).	Alzheimer. Some falls and hospitalizations.	✓		✓

Q	Possible late waking up. Goes to toilet. Takes breakfast. Home aid for household middays (except weekend). Sleeps afternoon. Dinner between 18h30 and 19h30. Sleeps at 20h. Goes to nursing home Thursdays. Visits his son weekends.	No special diseases.	✓	✓	
R	Home aid visits 3 times per day (morning, midday and evening). Sometimes goes out. Family visits on weekends.	Memory impairments. Walks with medical walker.	✓	✓	✓
S	Wakes up at 8h30. Goes to toilet. Takes breakfast. Reads newspapers. Lunch midday. Goes out for 1 hour. Comes back home. Watches television. Dinner in the evening. Sleeps at 22h30. Home aid Wednesdays afternoon. Goes out shopping once per week.	Heart problems. Many falls without damage.	✓	✓	
T	Wakes up at 8h. Goes to toilet. Takes breakfast. Goes out for shopping. Lunch midday. Watches television at 13h. Household afternoon. Dinner at 19h. Watches television again. Sleeps at 22h30. Often wakes-up during sleep. Frequent relative and home aid visits.	Active person. Possible falls at night and in cave stairs during day. Drugs for blood pressure.	✓		

U	Wakes up at 6h-7h. Home aid visits each day in the morning. Lives alone. Daughter house is nearby. Monthly visits to and from daughter.	Heart problems. Urinary infection.		✓
V	Lives alone. Takes public transport. Walks outside. Daily home aid visits. Goes to dancing and theater clubs twice per week.	Parkinson. Freezing periods.		✓
W	Lives alone. Has a car. Does not use public transport. Monthly receives daughter visits at home.	Very active. Independent. Pain in leg. Falls since a long time.		✓
X	Lives alone. Monthly receives visits from sons. Goes to dancing and theater clubs twice per week. Has a car. Uses public means of transport.	Active person. Independent. Parkinson. Trembling in fingers. Pain in leg.	✓	✓
Y	Lives alone. Rarely receives friend visits. Goes shopping several times per week. Exclusively uses public means of transport.	Active person. Independent. Parkinson. Hyperactivity periods.	✓	✓

Elderly people living alone at home are still independent and report regular activities indoors and outdoors (Table 5.2). Almost all participants early wake-up in the morning (*e.g.*, participants M, N, O, P, S, T and U). They go to toilet, then eat breakfast. Watching television is a preferred activity by participants N, S and T. Family members frequently visit and invite monitored participants (*e.g.*, participants J, N, O, R and U). Professional caregivers (*i.e.*, regular home aid) assist elderly people by their activities of daily living, such as household and taking medicines for participants K, N, Q and R. Participants V, X and Y are frequently engaged in dancing and theater clubs. They often use public means of transport.

Individual house participants have more stable health status than nursing home participants. Participants M, Q and T show positive healthy profile at monitoring period begin with no special diseases. They are active, and frequently go outside. Parkinson affects participants

V, X and Y since a couple of years. This causes frequent freezing periods and trembling in fingers. Falls and walking impairments are reported for participants S and W. Diabetes influence medical profile of participants N and O. Participants P and R experience early stages of Alzheimer disease.

Table 5.3 Analyzed Health Change Indicators

Technologies	Raw Data	Inferred Data	Medical Relevance	Analysis Metrics
Movement Sensors	Presence and absence of movements	Toilet Entries	Urinary infection	Times, duration, number at sleep period, number at wake-up period
		Sleep Habits	Cognitive impairments, Parkinson	Wake-up time, sleep time, duration, interruptions
Door Sensors	Door openings and closings	Go Out	Social isolation	Times, duration
		Activity Level	Mobility and cognitive impairments	Number, duration
		Visits	Social isolation	Number, duration

Initially reported medical profiles notify about diverse physical and cognitive problems. Developed analysis algorithms consider health change indicators that are related to reported physical and cognitive problems (Table 5.3). Employed movement sensors detect presence and absence of movements in each room (*e.g.*, living room, bedroom, kitchen, toilet and bathroom) for elderly people living alone at home. Door sensor notify about main house entries, by detecting door openings and closings. Despite the basic information delivered by these movement and door sensors, developed data processing algorithms compute inferred data, such as toilet entries, sleep habits, go out routine, activity level and visits.

Toilet movement sensor follows-up toilet entry times, duration and number that are related to possible urinary infection [27]. Weighting toilet entry number to presence time alone at home avoids detecting irrelevant decreases in toilet entries during frequent go-out periods. Sleep habits (*e.g.*, wake-up time, sleep time, duration and interruptions) indicate possible cognitive impairments and Parkinson hyperactivity periods [28]. Sleep interruptions refer to detected movement periods at night. Wake-up and sleep times are estimated based on activity level changes.

Analyzing go-out routine considers inactivity periods and main door events, and investigates possible social isolation [29]. Activity level is mainly associated with mobility and cognitive impairments [32]. Activity level refers to detected movement number divided by

presence time alone at home. Decreases in visits indicate possible social isolation [31]. Visits are detected based on parallel activity periods at home.

5.2 Early Health Change Detection Examples

Analyzing recruited elderly people behavior over weeks and months identifies relevant changes in their health conditions. Developed analysis algorithms collect sensor data in real-time, and compute health change indicators on a daily basis, such as activity level, time out of home, toilet entries and sleep interruptions. Change detection techniques investigate long-term changes in computed indicators. These techniques analyze data online, in order to early detect possible changes; i.e., change detection occurs even before personal observation of monitored elderly people and medical diagnosis of family doctor.

Following examples present detected changes for monitored participants. Reported health information by elderly people, family members and family doctors validate medical relevance of detected changes. Change notification service informs users from 2 to 10 days after change occurrence. These notifications provide opportunity to confirm that detected changes are really permanent, and investigate possible correlations with geriatric observations. Regular review meetings with elderly people, family members and family doctors (each 4 months with nursing home and each 2 months with individual houses) review detected changes for multi-dimensional correlations.

5.2.1 Detected Health Changes for Participant A

Fig. 5.6 shows daily evolution of activity level (movement/hour) for participant A. Analysis algorithms detect decrease in activity level on 2015-01-24. Nursing home team notices diverse medical problems, such as falls and mobility problems on 2015-01-23, and high body temperature on 2015-02-11. Urgent hospitalization occurs on 2015-02-04. Death occurs one day after. Analysis algorithms detect mobility impairments one month before hospitalization and death.

Fig. 5.7 presents daily evolution of time out of room (hours). Change detection techniques notify about decrease in go out frequency on 2014-10-10. Nursing home nurses confirm frequent falls and severe mobility impairments from 2014-10 until 2015-01. Death occurs on 2015-02-15. Developed monitoring system confirms observed changes in time out of room 4 months before death.

Fig 5.8 indicates detected changes in sleep interruptions at night (between 0h and 6h) for participant A. Developed monitoring system observes 3 consecutive changes in sleep

interruptions on 2014-10-15, 2015-01-09 and 2015-01-27. Medical nursing home team reports mobility impairments, falls and hyper-temperature from 2014-10 until 2015-01. Detected changes in sleep interruptions correlate with health decline of participant A. They occur 4 months before hospitalization and death.

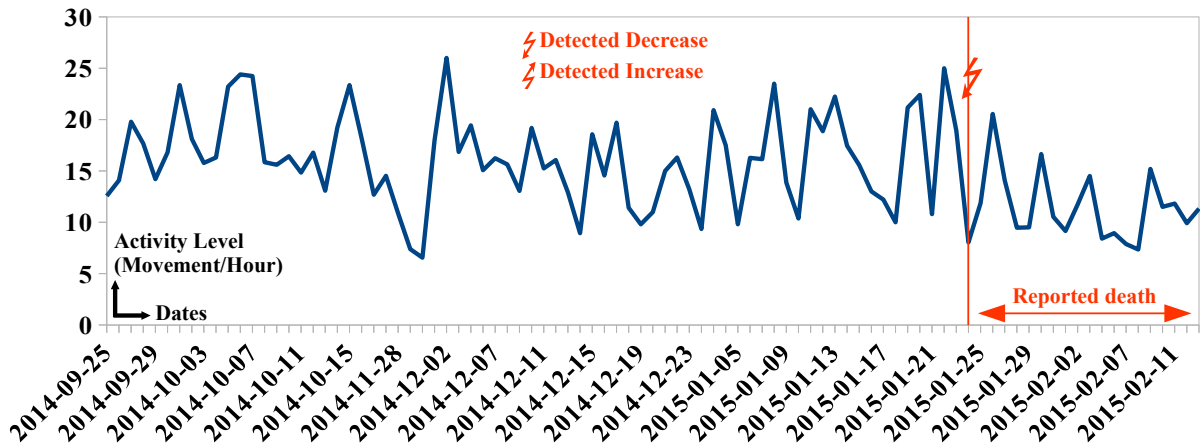


Fig. 5.6 Detected Changes in Activity Level of Participant A Due to Death

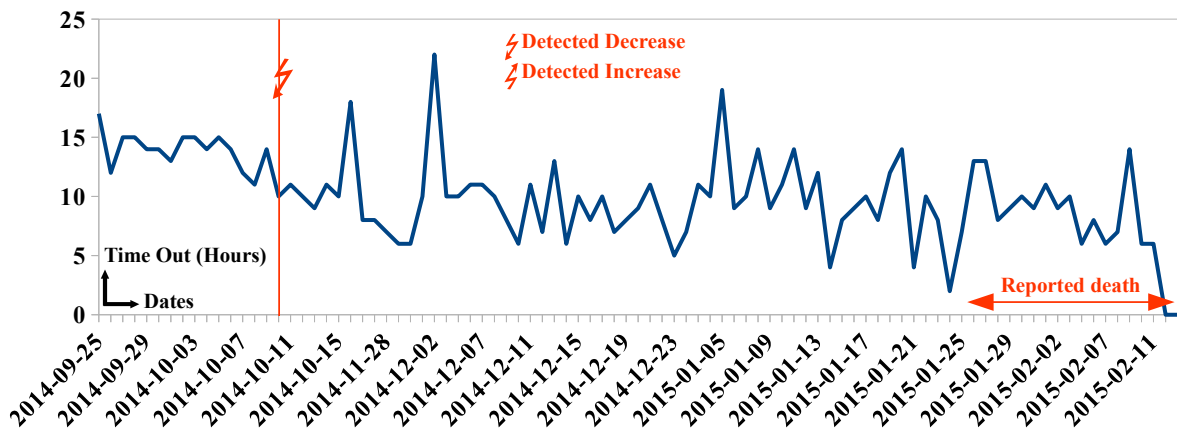


Fig. 5.7 Detected Changes in Time Out of Participant A Due to Death

Table 5.4 sums-up detected changes in sleep interruptions, activity level and time out of room. Developed analysis algorithms indicate long-term decreases from 2014-10 until 2015-01. Medical nursing home team explains detected changes by serious decline in physical abilities of participant A. They report diverse mobility problems, such as falls and high body temperature from 2014-10 until 2015-01. Participant A requires urgent hospitalization on 2015-02-14 and dies on 2015-02-15. Change detection techniques identify physical health decline of participant A 4 months before hospitalization and death.

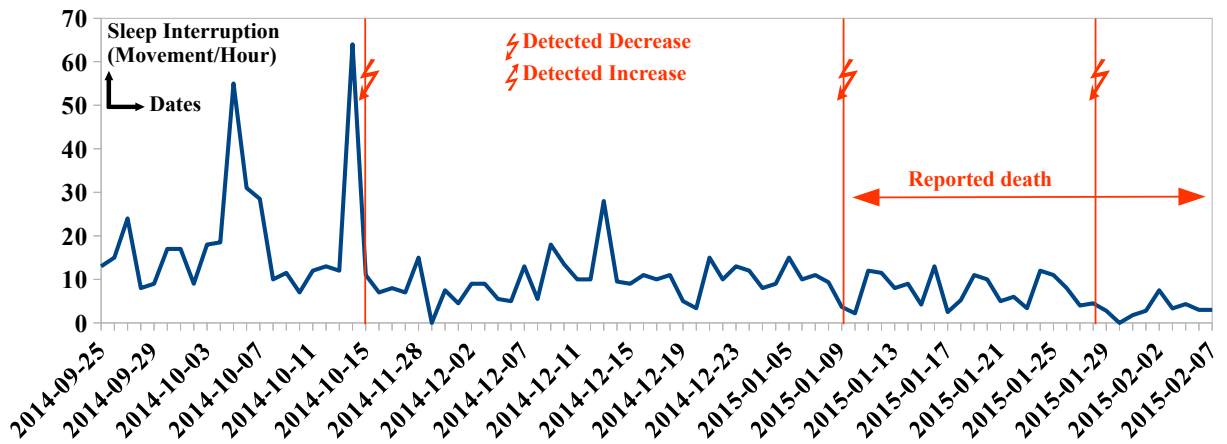


Fig. 5.8 Detected Changes in Sleep Interruptions of Participant A Due to Death

Table 5.4 Early Change Detection Examples for Participant A

Change Indicator	Change Date	Mean Before	Mean After	Direction
Sleep Interruptions	2014-10-15	19.63	9.94	Decrease
Sleep Interruptions	2015-01-09	9.94	7.65	Decrease
Sleep Interruptions	2015-01-27	7.65	3.37	Decrease
Time Out	2014-10-10	14.0	9.22	Decrease
Activity Level	2015-01-24	16.26	11.42	Decrease

5.2.2 Detected Health Changes for Participant B

Daily evolution of time out of room (hours) changes over monitoring period for participant B (Fig. 5.9). Participant B experiences two increases in go out frequency on 2015-03-26 and 2015-06-04. Nurses report frequent family invitations between 2015-03 and 2015-06. Family members invite participant B for diverse family events and shopping activities outside nursing home. Detected increases in time out of room correlate with personal engagement in outdoor activities.

Fig. 5.10 shows daily evolution of activity level for participant B. Developed analysis algorithms detect decrease in activity level (inside nursing home room) on 2015-05-28. Nursing home team confirms pain in leg and mobility impairments affecting participant B in 2015-05 and 2015-06. These walking difficulties reduce indoor activity level. Detected changes in activity level correlate with mobility problems.

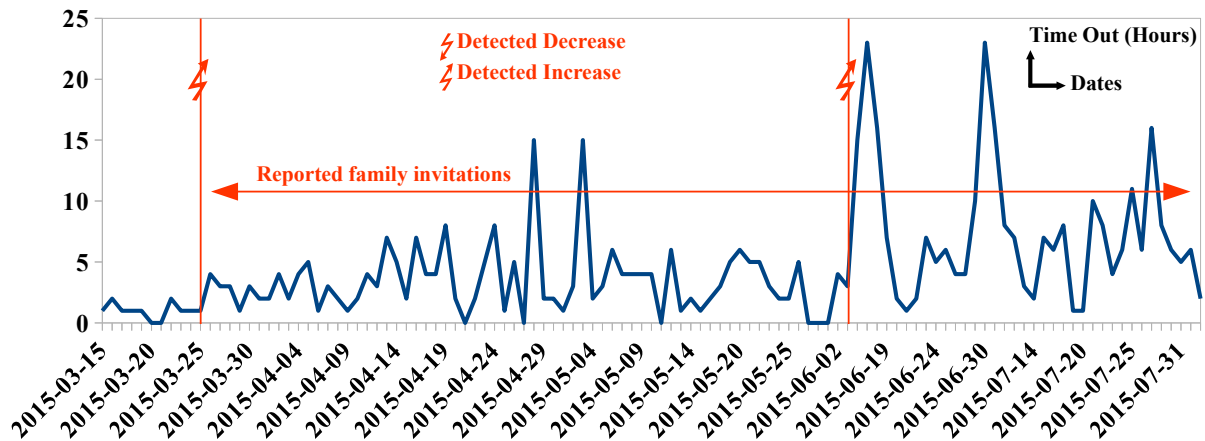


Fig. 5.9 Detected Changes in Time Out of Participant B Due to Frequent Family Invitations

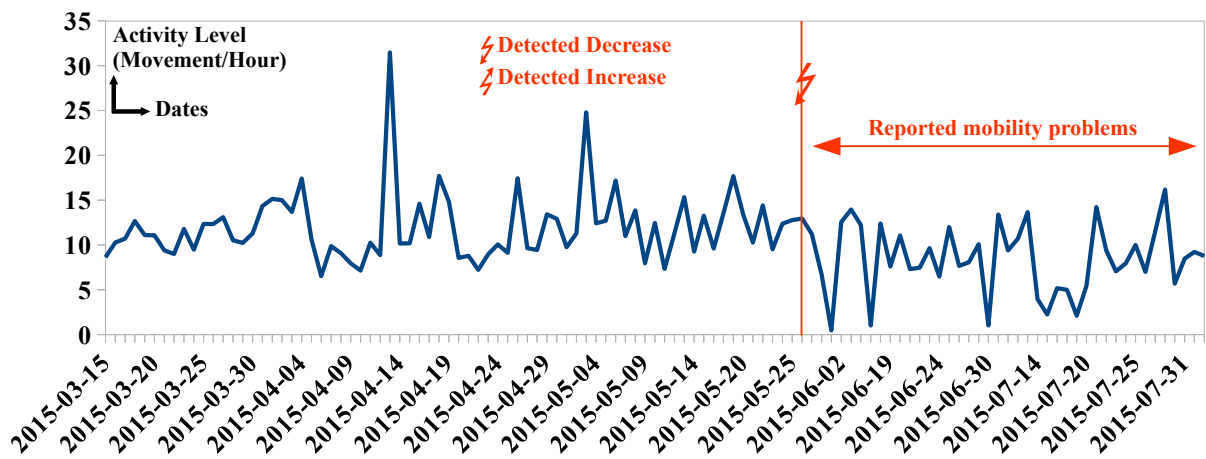


Fig. 5.10 Detected Changes in Activity Level of Participant B Due to Mobility Impairments

Participant B experiences long-term changes in time out of room and activity level (Table 5.5). Change detection techniques indicate increases in go out frequency and decrease in activity level between 2015-03 and 2015-06. While family invitations outside nursing home are increasing, activity level inside room is decreasing. Medical team observes positive engagement of participant B in going out with family, and negative mobility problems due to pain in leg. Analysis algorithms detect long-term changes in social engagement and physical health status that confirm formal observations of nurses and informal observations of family members.

Table 5.5 Early Change Detection Examples for Participant B

Change Indicator	Change Date	Mean Before	Mean After	Direction
Time Out	2015-03-26	1.0	3.47	Increase
Time Out	2015-06-04	3.47	7.56	Increase
Activity Level	2015-05-28	11.95	8.35	Decrease

5.2.3 Detected Health Changes for Participant C

Fig 5.11 shows daily evolution of activity level (movement/hour) for participant C. Developed analysis algorithms detect 3 consecutive decreases in activity level on 2015-09-18, 2016-02-29 and 2016-03-14. Participant C experiences anxiety and depression a couple of months after first entry to nursing home on 2015-09-09. He stays often in his room on his chair and sleeps for long hours. Nursing home team notices small improvement in his physical health status in 2016-04, that is correlated with detected increase in activity level on 2016-03-29. Indoor activity level remains low until monitoring period end, except between 2016-05-14 and 2016-05-28. Detected increase on 2016-05-14 is associated with room change on 2016-05-10. Participant C does not feel comfortable in his new room and shows hyperactivity periods. A couple of weeks later, detected decrease on 2016-05-28 indicates return to normal activity level. Technologically-detected changes in activity level confirm reported anxiety.

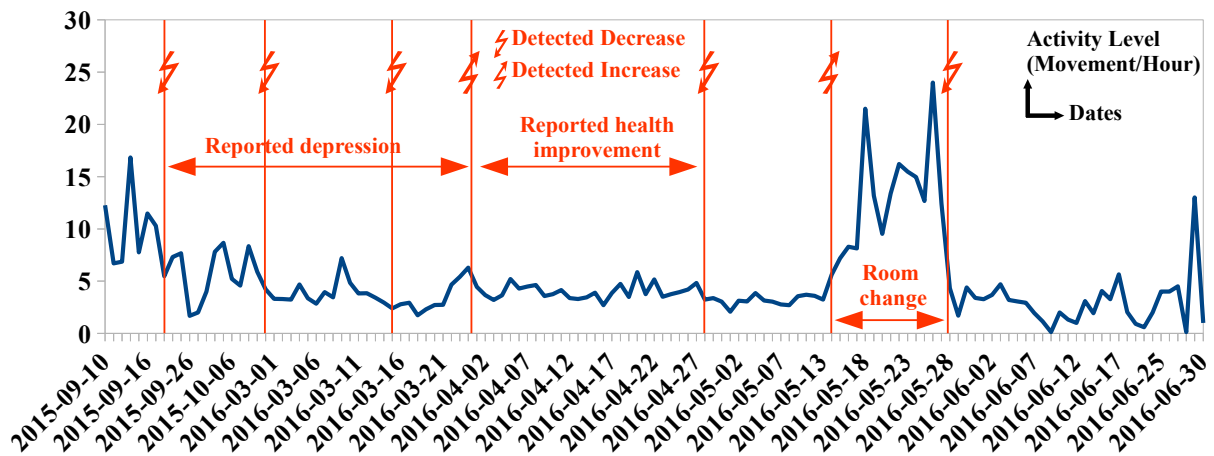


Fig. 5.11 Detected Changes in Activity Level of Participant C Due to Depression and Room Change

Fig 5.12 shows daily evolution of sleep interruptions at night (movement/hour). Detected decrease in sleep interruptions on 2015-10-13 is related to long sleep periods of participant C. He feels anxious and depressed in first months after entry to nursing home. Sleep interruption

level remains low until monitoring period end, except between 2016-05-17 and 2016-05-28. An increase in sleep interruptions occurs on 2016-05-17 a couple of days after room change. Participant C feels more anxious after being placed in a new environment. This hyperactivity period remains only for a couple of weeks. Developed analysis algorithms detect changes in sleep interruptions that are correlated with anxiety periods.

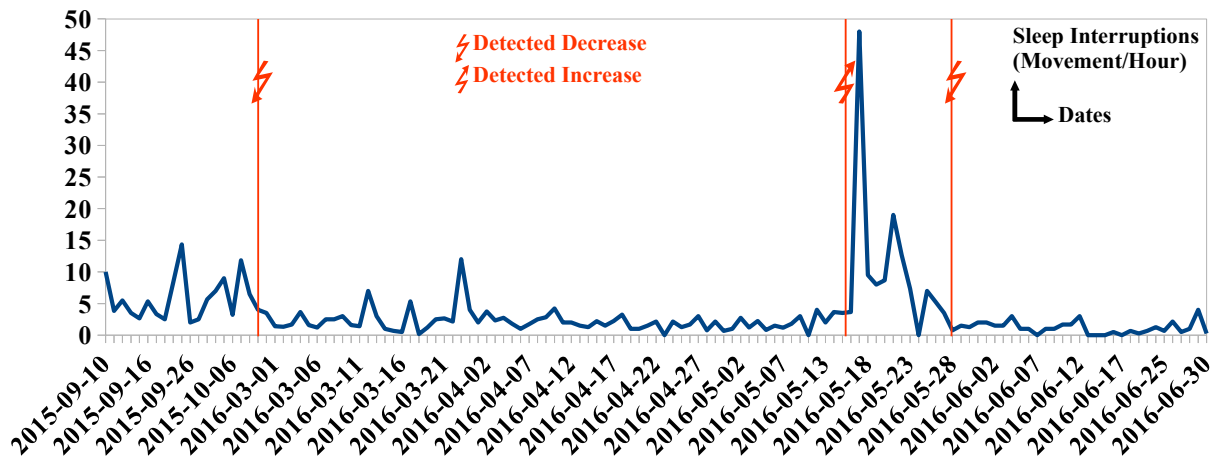


Fig. 5.12 Detected Changes in Sleep Interruptions of Participant C Due to Depression and Room Change

Table 5.6 presents detected changes in sleep interruptions and activity level of participant C. Detected decreases in both dimensions between 2015-09 and 2016-03 are associated with anxiety periods. Participant C has just entered to nursing home, feels depressed, does not move a lot and does not prefer to go outside his room. He sleeps for long periods. Significant increases in activity level and sleep interruptions occur a couple of days after room change on 2016-05-10. New living environment causes additional anxiety and hyperactivity periods for participant C. Adaptation to new room takes a couple of weeks before retrieving normal low activity level. Proposed monitoring system informs medical nursing home team about changes in activity level that confirm observed anxiety periods.

Table 5.6 Early Change Detection Examples for Participant C

Change Indicator	Change Date	Mean Before	Mean After	Direction
Sleep Interruptions	2015-10-13	5.95	2.28	Decrease
Sleep Interruptions	2016-05-17	2.28	11.72	Increase
Sleep Interruptions	2016-05-28	11.72	1.39	Decrease
Activity Level	2015-09-18	10.31	5.72	Decrease

Activity Level	2016-02-29	5.72	3.96	Decrease
Activity Level	2016-03-14	3.96	2.57	Decrease
Activity Level	2016-03-29	2.57	4.17	Increase
Activity Level	2016-04-28	4.17	3.17	Decrease
Activity Level	2016-05-14	3.17	13.04	Increase
Activity Level	2016-05-28	13.04	2.7	Decrease

5.2.4 Detected Health Changes for Participant D

Nursing home team observes early stages of Alzheimer disease for participant D in 2015-02, including anxiety periods and memory impairments. Measured sleep interruptions (between 0h and 6h) increase on 2015-02-15 (Fig 5.13). This increase is related to bed restlessness and more activity periods detected at night. Detected increase in sleep interruptions confirms observed cognitive problems related to Alzheimer disease.

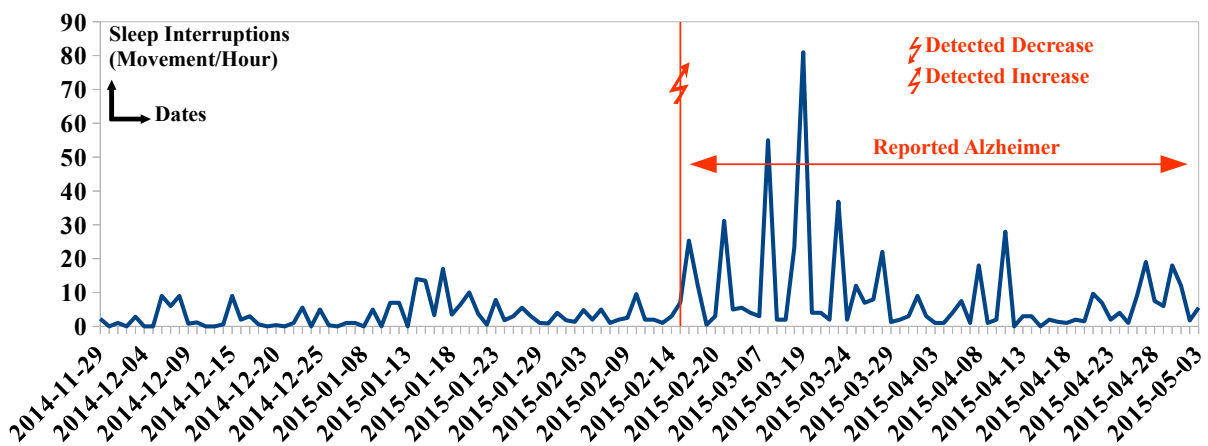


Fig. 5.13 Detected Changes in Sleep Interruptions of Participant D Due to Alzheimer

Nurses observe diverse agitation and hyperactivity periods starting from 2015-02. Movement sensors deployed inside resident room measure global activity level, and enable detection of diverse changes starting from 2015-02 (Fig 5.14). Three significant increases are detected on 2015-02-17, 2015-04-25 and 2015-07-12. Two additional decreases are detected on 2015-05-09 and 2015-07-31. These changes identify abnormal activity level changes. Nursing home team explains these changes by agitation periods.

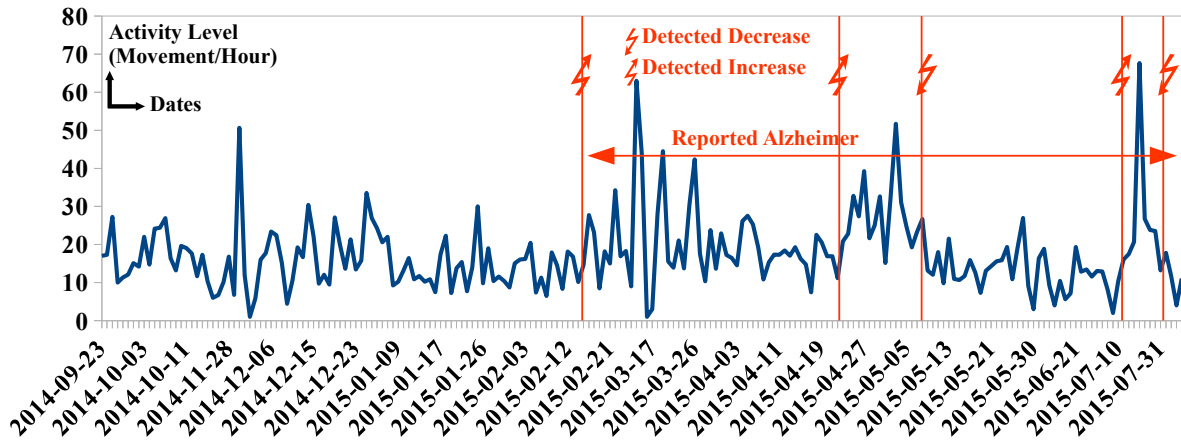


Fig. 5.14 Detected Changes in Activity Level of Participant D Due to Alzheimer

Detected changes in activity level and sleep interruptions indicate abnormal behavior of participant D (Table 5.7). Increases and decreases in both dimensions are detected starting from 2015-02. Nursing home team observes agitation and anxiety periods related to early stages of Alzheimer disease. Analyzed health change indicators confirm early symptoms of Alzheimer disease and provide opportunity for better treatment.

Table 5.7 Early Change Detection Examples for Participant D

Change Indicator	Change Date	Mean Before	Mean After	Direction
Sleep Interruptions	2015-02-15	3.43	9.26	Increase
Activity Level	2015-02-17	15.62	20.25	Increase
Activity Level	2015-04-25	20.25	28.79	Increase
Activity Level	2015-05-09	28.79	12.71	Decrease
Activity Level	2015-07-12	12.71	30.0	Increase
Activity Level	2015-07-31	30.0	11.55	Decrease

5.2.5 Detected Health Changes for Participant E

Fig 5.15 shows daily evolution of activity level (inside room) for participant E. Analysis algorithms identify diverse changes over one year (from 2016-10 until 2017-10). Three decreases in activity level are detected on 2016-10-26, 2017-01-12 and 2017-06-18. Three increases are detected on 2016-11-20, 2017-05-03 and 2017-07-11. Nursing home team reports severe agitation and hyperactivity periods for participant E. This abnormal variation

in activity level is related to advanced stages of Alzheimer disease. Participant E requires intensive care and treatment of cognitive impairments. Technologically-detected changes confirm medically-diagnosed problems of participant E.

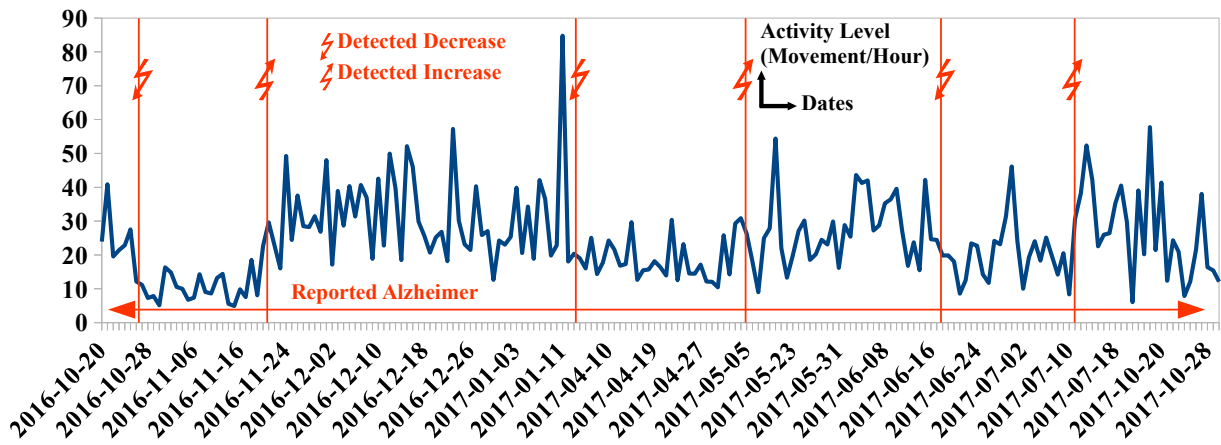


Fig. 5.15 Detected Changes in Activity Level of Participant E Due to Alzheimer

Toilet entries of participant E show continuous increases starting from 2015-08 (Fig 5.16). Applied change detection techniques identify four consecutive increases on 2015-09-02, 2016-03-04, 2016-04-15 and 2016-05-15. Participant E experiences continuous vomiting and diarrhea periods (reported between 2018-09 and 2016-05). Vomiting and diarrhea cause frequent toilet entries associated with headaches and anxiety. Sensor observations early detect significant changes in toilet entries that are associated with physical problems.

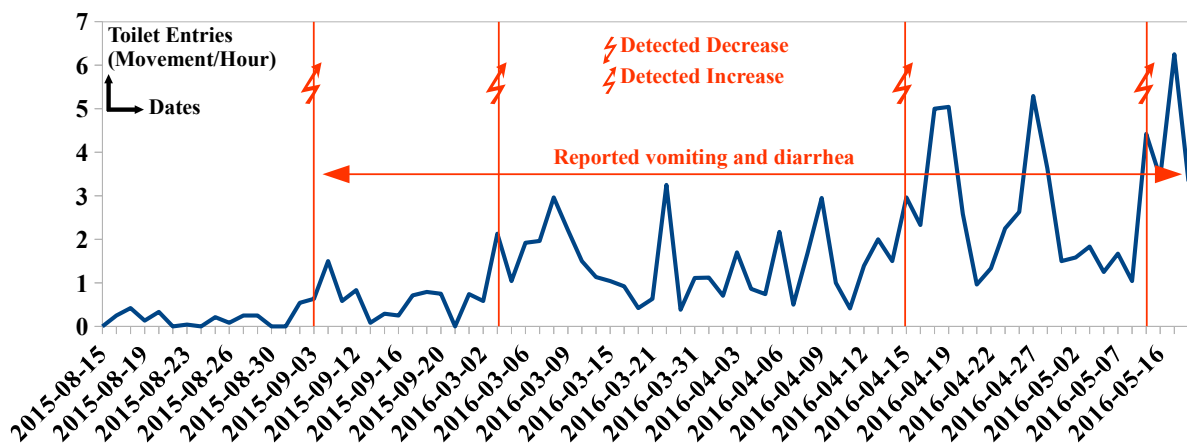


Fig. 5.16 Detected Changes in Toilet Entries of Participant E Due to Vomiting and Diarrhea

Participant E has diverse physical and cognitive problems generating high instability in toilet entries and activity level (Table 5.8). Four consecutive increases in toilet entries

between 2015-09 and 2016-05 indicate severe vomiting and diarrhea periods. Six increases and decreases in activity level between 2016-10 and 2017-07 indicate severe agitation periods related to Alzheimer disease. Nursing home team explains detected changes by serious health decline for participant E. She requires intensive care and treatment.

Table 5.8 Early Change Detection Examples for Participant E

Change Indicator	Change Date	Mean Before	Mean After	Direction
Toilet Entries	2015-09-02	0.14	0.59	Increase
Toilet Entries	2016-03-04	0.59	1.42	Increase
Toilet Entries	2016-04-15	1.42	2.52	Increase
Toilet Entries	2016-05-15	2.52	4.36	Increase
Activity Level	2016-10-26	27.04	10.16	Decrease
Activity Level	2016-11-20	10.16	31.44	Increase
Activity Level	2017-01-12	31.44	17.92	Decrease
Activity Level	2017-05-03	17.92	27.45	Increase
Activity Level	2017-06-18	27.45	19.98	Decrease
Activity Level	2017-07-11	19.98	33.1	Increase

5.2.6 Detected Health Changes for Participants F and G

Participant G shows abnormal variability in activity level inside nursing home room (Fig 5.17). Sensor observations enable detection of 3 decreases on 2014-10-16, 2015-04-14 and 2015-06-03. They also indicate 3 increases on 2015-02-04, 2015-05-22 and 2015-07-24. This abnormal variation in monitored health change indicator is associated with hyperactivity periods of participant G due to advanced stages of Alzheimer disease. Participant G shows serious decline in physical and cognitive abilities. Detected changes confirm abnormal behavior of participant G, as daily observed by nurses.

Participant F has similar health problems related to advanced stages of Alzheimer disease. Two consecutive increases affect sleep interruptions on 2015-05-25 and 2015-08-30 (Fig. 5.18). Nursing home team observes significant increase in anxiety periods starting from 2015-05, such as being agitated in the morning in 2015-06, not being able to sleep in 2015-07 and not being able to go to toilet in 2015-08. Significant increase in sleep interruptions occurs on 2016-04-22, a couple of days after informing participant F about her husband's

death. She was very upset and anxious. Detected changes in sleep interruptions correlate with observed anxiety periods.

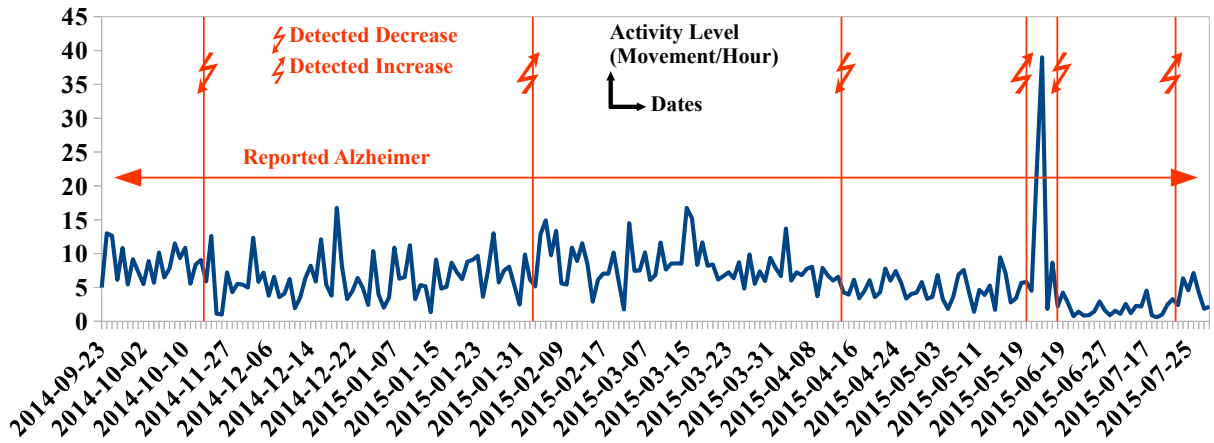


Fig. 5.17 Detected Changes in Activity Level of Participant G Due to Alzheimer

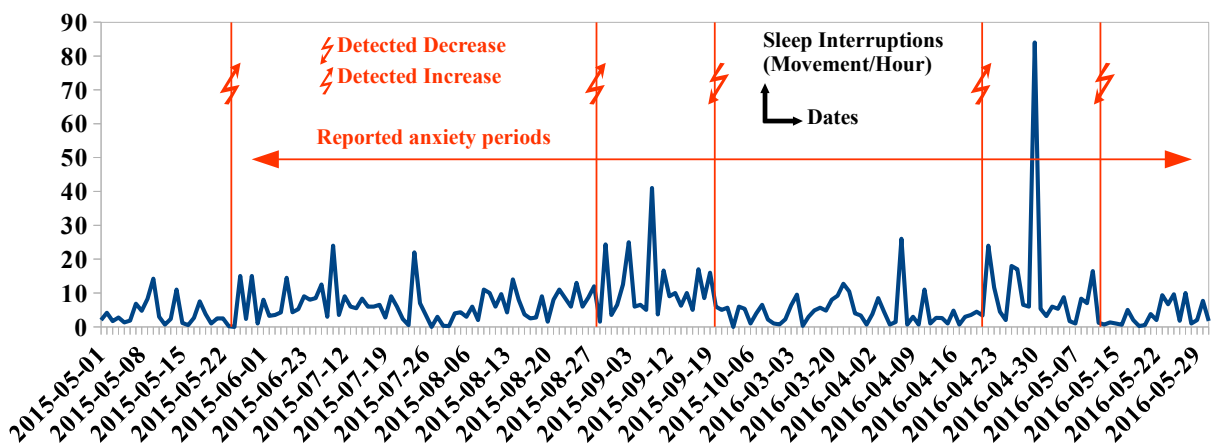


Fig. 5.18 Detected Changes in Sleep Interruptions of Participant F Due to Anxiety

Tables 5.9 and 5.10 sum-up detected changes in sleep interruptions and activity level for participants F and G respectively. Both participants are affected by serious memory impairments, anxiety periods and physical problems. Advanced stages of Alzheimer disease considerably influence their health status. Analyzed health change indicators detect abnormal variation in their activity level during the day and at night.

Table 5.9 Early Change Detection Examples for Participant F

Change Indicator	Change Date	Mean Before	Mean After	Direction
Sleep Interruptions	2015-05-25	3.48	6.75	Increase
Sleep Interruptions	2015-08-30	6.75	12.23	Increase
Sleep Interruptions	2015-09-20	12.23	4.59	Decrease
Sleep Interruptions	2016-04-22	4.59	12.46	Increase
Sleep Interruptions	2016-05-11	12.46	4.07	Decrease

Table 5.10 Early Change Detection Examples for Participant G

Change Indicator	Change Date	Mean Before	Mean After	Direction
Activity Level	2014-10-16	8.51	6.23	Decrease
Activity Level	2015-02-04	6.23	8.3	Increase
Activity Level	2015-04-14	8.3	4.8	Decrease
Activity Level	2015-05-22	4.8	30.75	Increase
Activity Level	2015-06-03	30.75	2.17	Decrease
Activity Level	2015-07-24	2.17	4.44	Increase

5.2.7 Detected Health Changes for Participants H and I

Three consecutive increases affect daily evolution of toilet entries for participant I (Fig. 5.19). Participant I enters more frequently to toilet on 2015-09-13, 2016-05-05 and 2016-05-17. Formal caregivers and nursing home geriatrician confirm urinary infection symptoms starting from 2015-10. They observe frequent toilet entries, vomiting and diarrhea periods until 2016-04. Detected increases in toilet entries identify urinary infection event a couple of weeks before caregiver observations.

One significant decrease affects daily evolution of toilet entries for participant H (Fig 5.20). This decrease occurs on 2015-01-16. Nursing home team observes increase in mobility impairments for participant H in 2015-01. Participant H is no longer able to go independently to toilet. Fecal elimination is observed on bed and all over the room. Detected decrease in toilet entries identifies serious autonomy problem in managing activities of daily living.

Participant H and I show changes in toilet entries (Tables 5.11 and 5.12). Whereas participant H enters less frequently to toilet from 2015-01, participant I enters more frequently to toilet from 2015-09. Mobility impairments reduce toilet entries of first participant. Urinary

infection explains detected increases for second participant. Developed analysis algorithms identify physical impairments of monitored participants, such as urinary infection and mobility problems.

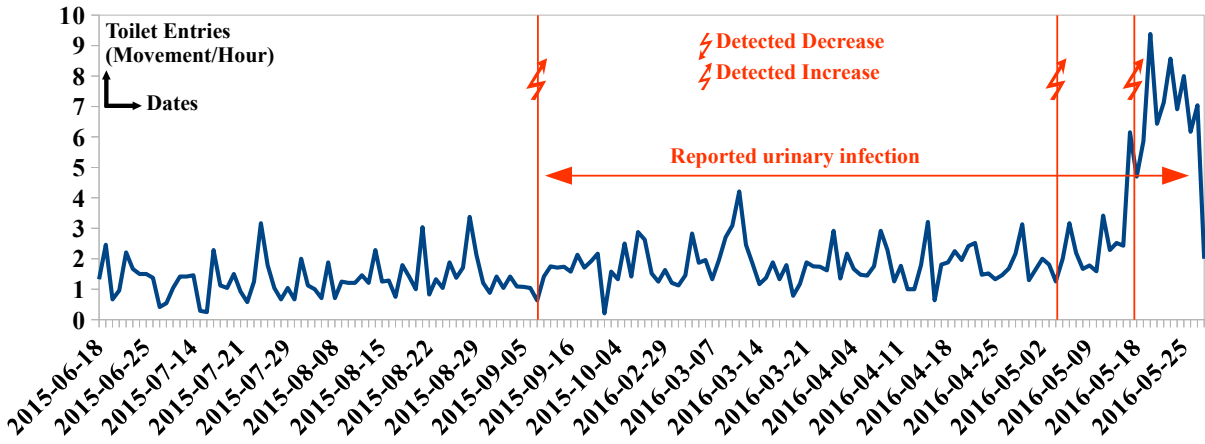


Fig. 5.19 Detected Changes in Toilet Entries of Participant I Due to Urinary Infection

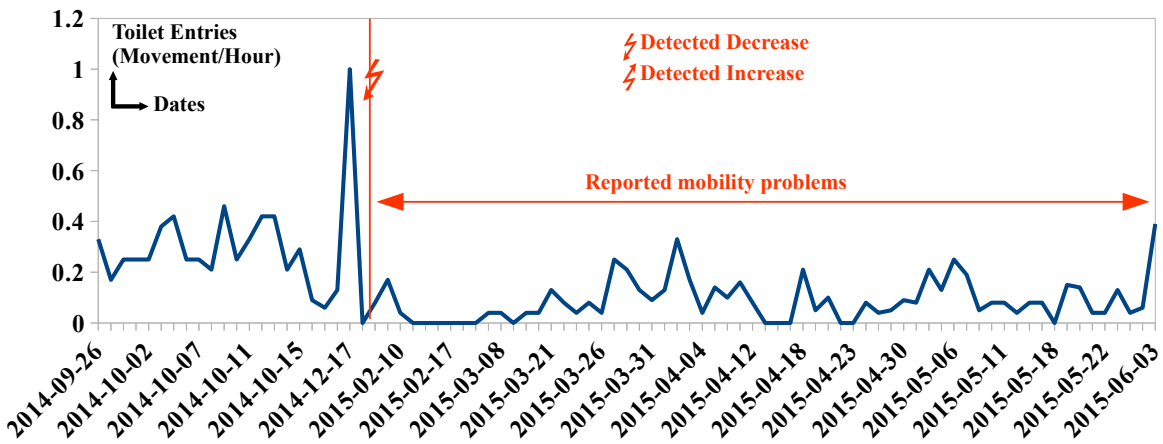


Fig. 5.20 Detected Changes in Toilet Entries of Participant H Due to Mobility Impairments

Table 5.11 Early Change Detection Examples for Participant H

Change Indicator	Change Date	Mean Before	Mean After	Direction
Toilet Entries	2015-01-16	0.31	0.09	Decrease

Table 5.12 Early Change Detection Examples for Participant I

Change Indicator	Change Date	Mean Before	Mean After	Direction
Toilet Entries	2015-09-13	1.33	1.82	Increase
Toilet Entries	2016-05-05	1.82	2.31	Increase
Toilet Entries	2016-05-17	2.31	6.94	Increase

5.2.8 Detected Health Changes for Participants J and K

Daily evolution of received visit duration changes over time for participant J (Fig 5.21). An increase in received visits occurs on 2015-05-22, which is followed by a subsequent decrease 2015-06-16. Participant J lives alone at home. Her sons frequently visit her between 2015-05-22 and 2015-06-16. She was very sick and requires help. Detected changes in visits are related to social life changes.

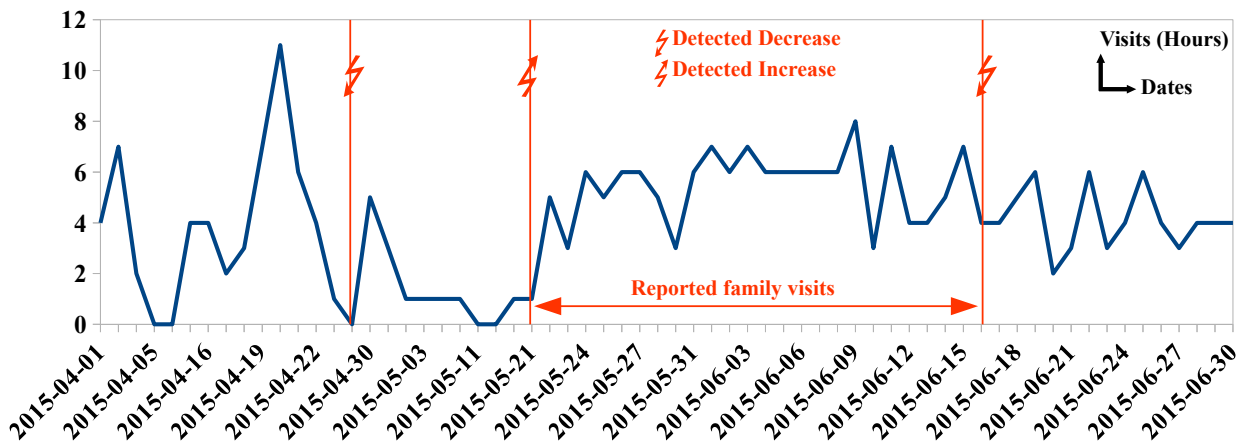


Fig. 5.21 Detected Changes in Visits of Participant J Due to Family Visits

Table 5.13 Early Change Detection Examples for Participant J

Change Indicator	Change Date	Mean Before	Mean After	Direction
Visits	2015-04-28	3.94	1.25	Decrease
Visits	2015-05-22	1.25	5.54	Increase
Visits	2015-06-16	5.54	4.13	Decrease

Participant K also lives alone at home. An increase in received visit duration occurs on 2016-12-08 (Fig 5.22). Due to severe cognitive impairments (*e.g.*, hallucination and

memory troubles), formal caregiver and daughter frequently visit participant K for urgent assistance. Two consecutive decreases in visit frequency occur on 2017-01-01 and 2017-01-17. Daughter visits become less frequent starting from 2017-01-01 after treating observed cognitive problems and recruiting formal caregiver. Developed monitoring system detects changes in visit routine that are associated with social habits.

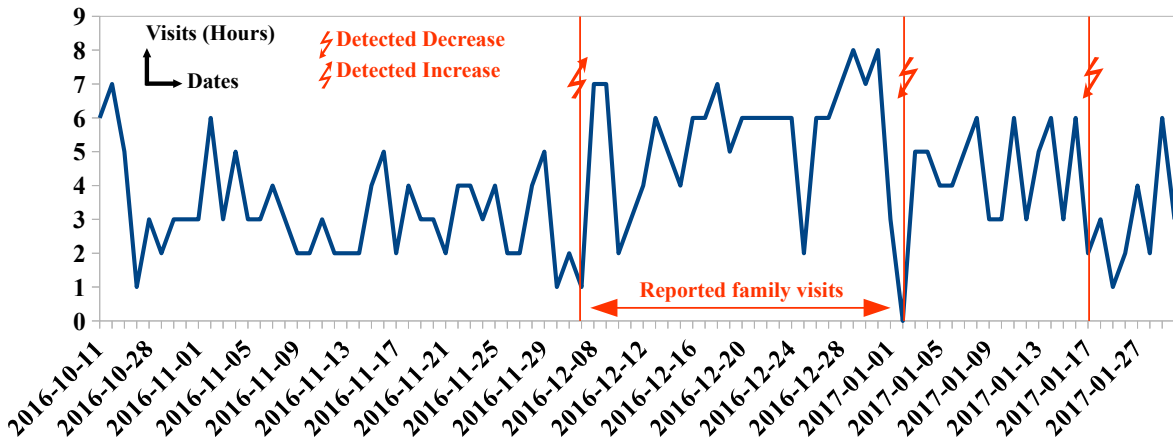


Fig. 5.22 Detected Changes in Visits of Participant K Due to Family Visits

Table 5.14 Early Change Detection Examples for Participant K

Change Indicator	Change Date	Mean Before	Mean After	Direction
Visits	2016-12-08	3.2	5.67	Increase
Visits	2017-01-01	5.67	4.75	Decrease
Visits	2017-01-17	4.57	2.88	Decrease

Detected increases in received visit duration for participant J between 2015-05-22 and 2015-06-16, and participant K between 2016-12-08 and 2017-01-01 indicate real increase in family visits (Tables 5.13 and 5.14). Both participants live alone at home and have physical or cognitive problems. Family members and caregivers frequently visit them for help and assistance. Analyzing visit duration indicates possible changes in social life.

5.2.9 Detected Health Changes for Participants L and M

Fig. 5.23 shows daily evolution of global activity level for participant M. Developed analysis algorithms detect 3 consecutive decreases on 2017-02-15, 2017-06-20 and 2017-10-25. Participant M and family doctor confirm mobility impairments and increased risk of dependence

in managing activities of daily living. Professional caregiver helps with medication taking and household from 2017-05-04. Analysis algorithms detect mobility impairments even before initializing home aid.

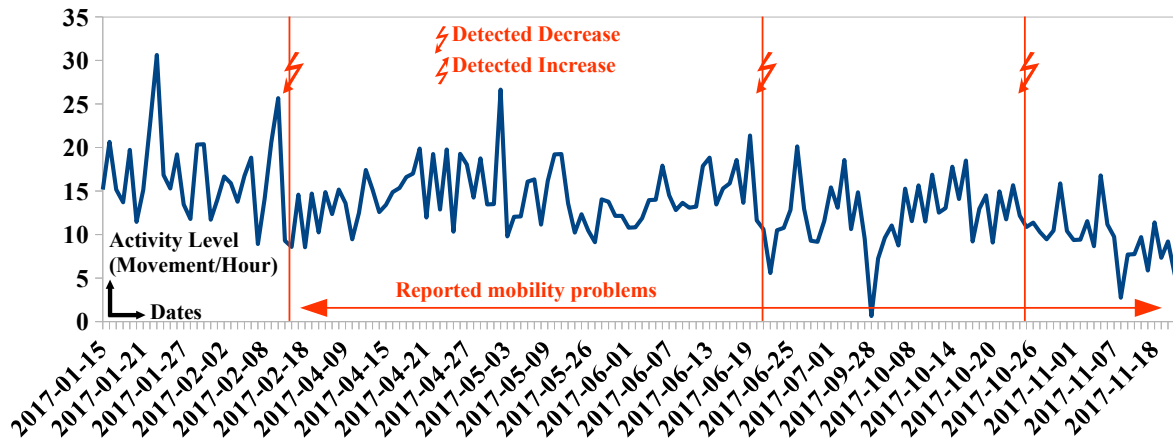


Fig. 5.23 Detected Changes in Activity Level of Participant M Due to Mobility Impairments

Table 5.15 Early Change Detection Examples for Participant M

Change Indicator	Change Date	Mean Before	Mean After	Direction
Activity Level	2017-02-15	16.98	14.37	Decrease
Activity Level	2017-06-20	14.37	12.29	Decrease
Activity Level	2017-10-25	12.29	11.11	Decrease

Fig. 5.24 illustrates daily evolution of indoor activity level of participant L. First detected decrease occurs on 2017-05-27. Nurses report knee problems in 2017-06. Observed mobility impairments reduce activity level of participant L. After treating knee problems, monitoring system detects two consecutive positive increases in activity level on 2017-07-23 and 2017-12-24. Nurses observe considerable improvement in physical health status in 2017-09. Sensor observations confirm positive treatment impact, even one month before nurses' observations.

Participants L and M live in nursing home and individual home respectively. Analyzing their activity level identifies changes in 2017 (Tables 5.15 and 5.16). After detecting decrease in activity level in 2017-05 due to knee problems, participant L shows two positive increases in 2017-07 and 2017-12. Observed changes confirm knee relief and positive treatment impact. Physical health status of participant M declines. Three consecutive decreases in global activity level occur between 2017-02 and 2017-10. Participant M confronts increased risk of dependence and requires professional assistance. He recruits professional caregiver

from 2017-05. Analysis algorithms detect physical health decline or improvement, even one month before medical observations of nursing home team and three months before initializing home aid.

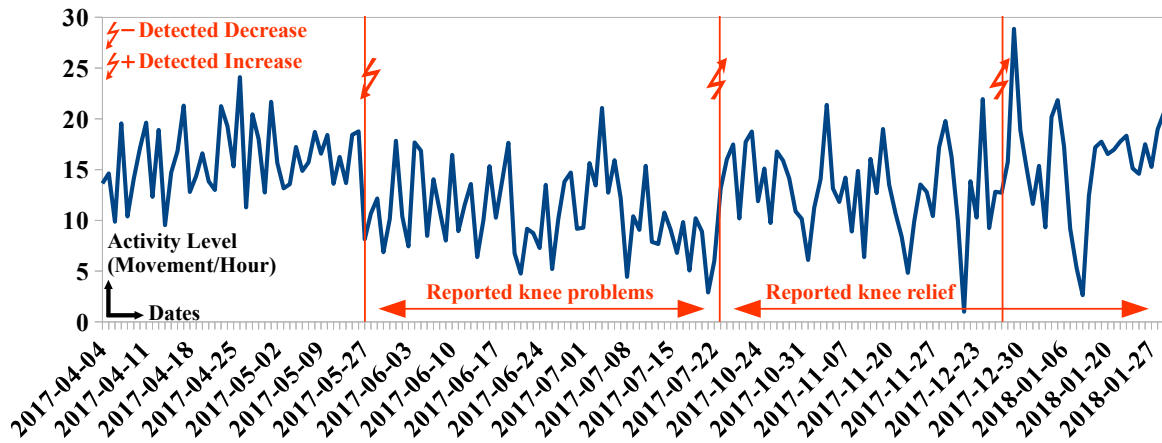


Fig. 5.24 Detected Changes in Activity Level of Participant L Due to Knee Problems

Table 5.16 Early Change Detection Examples for Participant L

Change Indicator	Change Date	Mean Before	Mean After	Direction
Activity Level	2017-05-27	16.0	10.73	Decrease
Activity Level	2017-07-23	10.73	12.86	Increase
Activity Level	2017-12-24	12.86	15.57	Increase

5.2.10 Detected Health Changes for Participants N and O

Participant N is healthy and active. She manages independently activities of daily living. Developed monitoring system detects no changes in sleep interruptions between 2016-10-10 and 2018-04-17 (Fig 5.25). Sleep interruptions have an average of 4 movements per hour and a maximum of 12 movements per hour. Monitored average is normal due to body movements on bed. Participant N confirms having good sleep quality with few sleep interruptions. Detecting no changes in sleep interruptions of participant N proves healthy physical status and good sleep quality.

Similar observations occur for participant O. No changes in sleep interruptions are detected for several months between 2017-04-15 and 2017-12-09 (Fig 5.26). Sleep interruptions do not go beyond 2 movements per hour on average and 7 movements per hour in maximum.

This low sleep interruption level indicates low body movement frequency on bed and stable sleep. Participant O has severe mobility impairments, walks with medical walker and sleeps for long periods during day and night. Detecting no changes in sleep interruptions of participant O confirms physical health decline related to long inactivity and sleep periods.

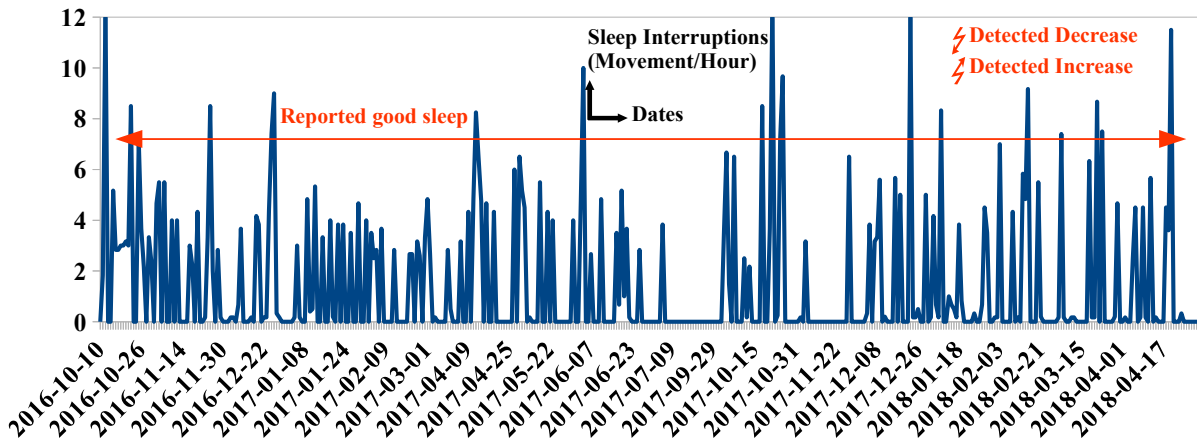


Fig. 5.25 Stable Daily Evolution of Sleep Interruptions for Participant N Confirming Good Sleep

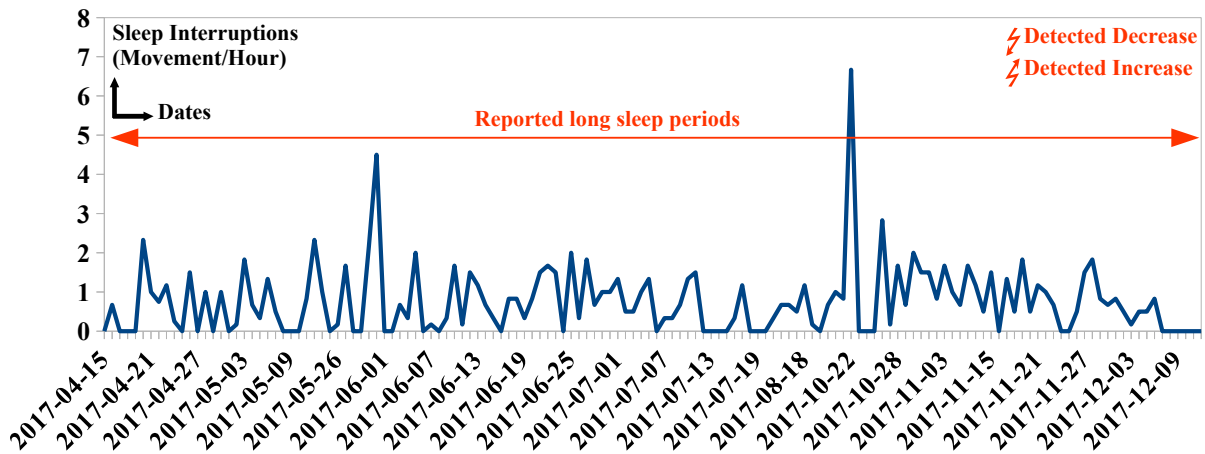


Fig. 5.26 Stable Daily Evolution of Sleep Interruptions for Participant O Confirming Long Sleep

5.2.11 Detected Health Changes for Participants T and U

Fig. 5.27 illustrates stable evolution of sleep interruptions for participant T. She is healthy and active person. Participant T regularly receives friend visits and go outside for shopping. Daily

and weekly habits are very regular. Detecting no changes in sleep interruptions confirms stable health status and reported good sleep quality for participant T.

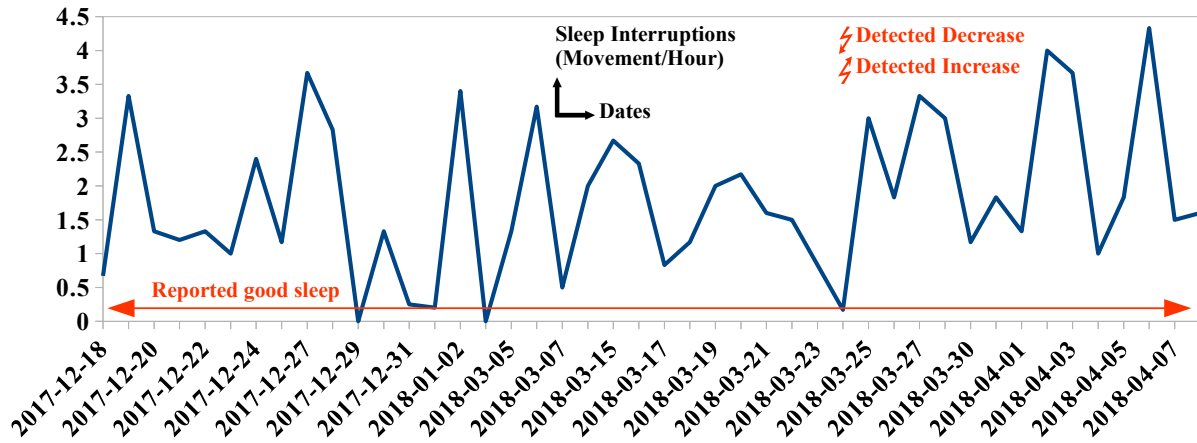


Fig. 5.27 Stable Daily Evolution of Sleep Interruptions for Participant T Confirming Good Sleep

Fig. 5.28 shows daily evolution of toilet entries for participant U. Developed analysis algorithms detect two consecutive increases on 2017-09-16 and 2017-11-06 (Table 5.17). Participant U notices significant increase in toilet entries on 2017-10-01. Family doctor confirms urinary infection two weeks after. Developed analysis algorithms detect urinary infection even before personal observation of participant U and family doctor diagnosis. Participant U is positively impressed after detecting decrease in toilet entries on 2017-12-02. This decrease is related to remedy for urinary infection after its treatment.

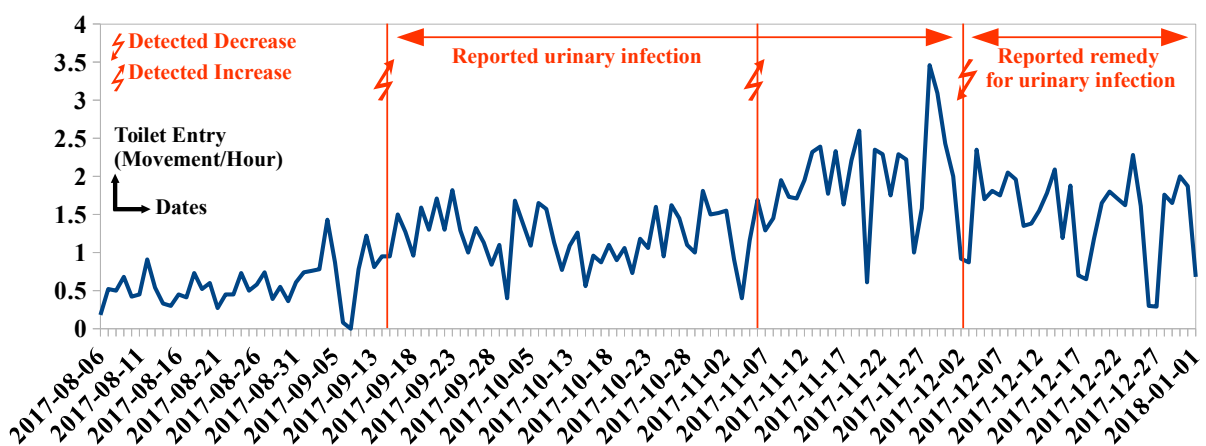


Fig. 5.28 Detected Changes in Toilet Entries of Participant U Due to Urinary Infection

Table 5.17 Early Change Detection Examples for Participant U

Change Indicator	Change Date	Mean Before	Mean After	Direction
Toilet Entries	2017-09-16	0.78	1.2	Increase
Toilet Entries	2017-11-06	1.2	2.0	Increase
Toilet Entries	2017-12-02	2.0	1.53	Decrease

5.2.12 Detected Health Changes for Participants V, X and Y

Participants V, X and Y are Parkinson patients of medical clinic geriatrician Dr Émilie Guettard. They consult Dr Émilie a couple of months before experimentation begin. After establishing ethical approval, involved participants take part of first interview session. This first diagnosis identifies medical health status at experimentation begin. Monitored participants continue consulting medical clinic geriatrician each 2 months, and earlier if required. Dr Émilie Guettard validates medical relevance of technological observations based on advanced geriatric diagnosis and personal participant observations.

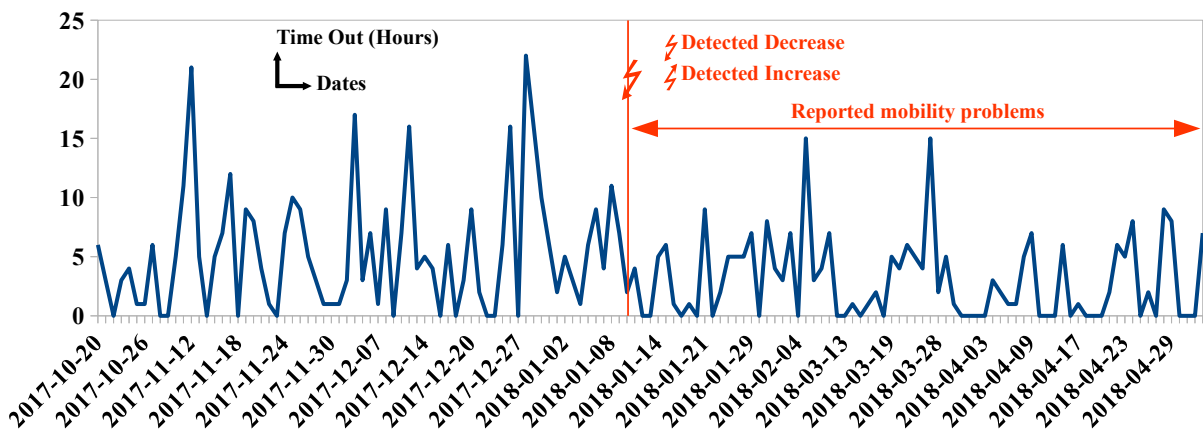


Fig. 5.29 Detected Changes in Time Out of Participant V Due to Parkinson

Table 5.18 Early Change Detection Examples for Participant V

Change Indicator	Change Date	Mean Before	Mean After	Direction
Time Out	2018-01-10	5.43	3.03	Decrease

Daily evolution of time out home indicates important decrease for participant V (Fig. 5.29). He goes less frequently outside starting from 2018-01-10. Participant V has Parkinson disease since a couple of years and takes regular treatments. At the beginning of monitoring

period (2017-10), health status is quite stable. First interview reports regular engagement in outdoor activities a couple of days per weeks, such as tango, theatre and flamenco. Recently (starting from 2018-04), medical clinic geriatrician diagnoses serious health decline. Participant V has frequent freezing periods in 2018-01, frequent trembling in fingers and legs in 2018-04, and reduces his outdoor activities. Technological observations early identify serious decrease in go out routine due to physical Parkinson-related health decline, even before geriatrician diagnosis.

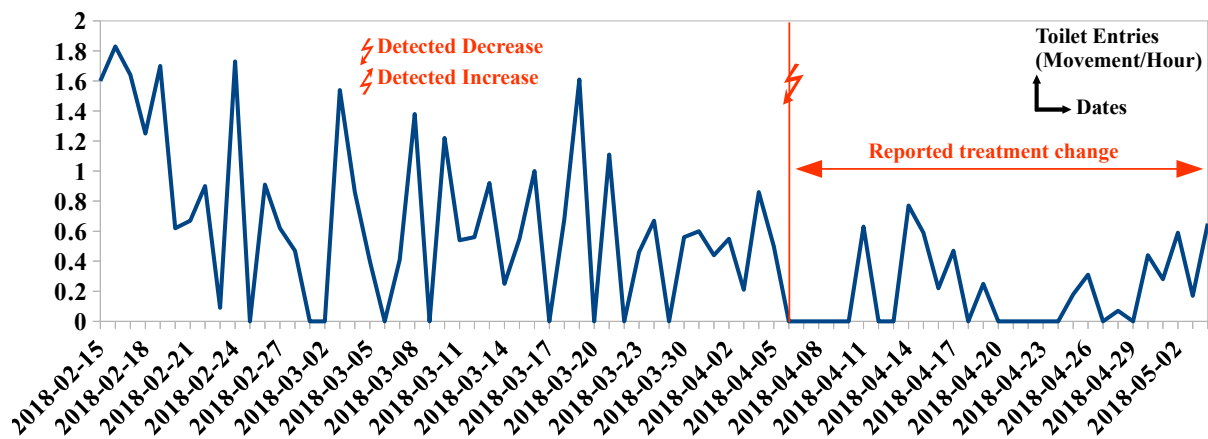


Fig. 5.30 Detected Changes in Toilet Entries of Participant X Due to Treatment Change

Table 5.19 Early Change Detection Examples for Participant X

Change Indicator	Change Date	Mean Before	Mean After	Direction
Toilet Entries	2018-04-06	0.61	0.19	Decrease

Participant X has mobility problems related to Parkinson disease. Daily evolution of toilet entries decreases on 2018-04-06 (Fig 5.30). On 2018-06-21, participant X confirms that she really consumes less toilet papers and wakes-up less frequently at night for urinary elimination (compared to monitoring period begin on 2018-02-02). Geriatrician and participant X explain detected decrease in toilet entries by treatment change. Technological monitoring early detects toilet entry changes that are associated with treatment change, even 2 months before personal observation of monitored participant and geriatrician diagnosis.

Fig 5.31 shows daily evolution of activity level at home for participant Y. Abnormal increase in activity level occurs between 2018-02-24 and 2018-03-09. Participant Y experiences abnormal hyperactivity periods (*i.e.*, agitation periods) in 2018-03 after treatment change. Prescribed treatment causes side effects. Geriatrician prescribes new treatment a

couple of weeks after. Detected changes in activity level of participant Y early identify treatment side effects.

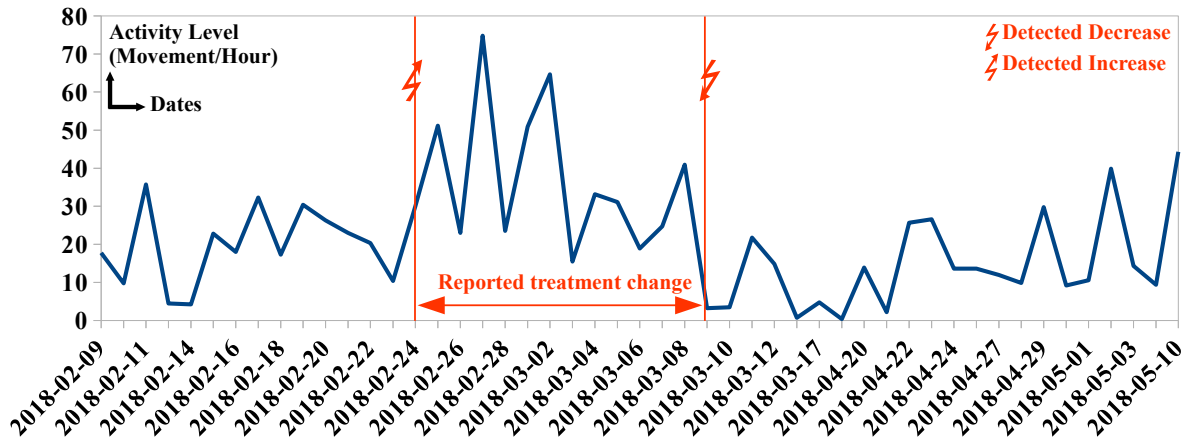


Fig. 5.31 Detected Changes in Activity Level of Participant Y Due to Treatment Change

Table 5.20 Early Change Detection Examples for Participant Y

Change Indicator	Change Date	Mean Before	Mean After	Direction
Activity Level	2018-02-24	19.3	36.22	Increase
Activity Level	2018-03-09	36.22	7.9	Decrease

Tables 5.18, 5.19 and 5.20 present detected changes for 3 Parkinson patients. Compared to monitoring period begin, participant V experiences serious physical health decline in 2018-01, and participants X and Y test new treatments in 2018-04 and 2018-02 respectively. Proposed monitoring system early identifies abnormal changes in time out home, toilet entries and activity level that are associated with mobility impairments and treatment changes, even a couple of months before participant observations and geriatrician diagnosis.

5.3 Health Change Cause Investigation and Medical Relevance Validation

Evaluating medical relevance of detected changes requires continuous collection of personal, context and medical information. Personal interviews with monitored elderly people enable investigation of possible causes explaining observed changes; e.g., detected changes in activity patterns correlate with personal feelings of slowness in physical movements and

trembling in fingers related to Parkinson, and detected changes in preparing meal duration correlate with forgetting recent events related to cognitive impairments.

Context information provide better understanding of detected changes; e.g., going out less frequently during heavy snow periods, and moving across rooms decrease after moving television to bedroom. Medical information validate relevance of detected changes based on advanced medical assessment during geriatrician's visit; e.g., geriatric scale results confirm detected changes in activity level.

5.3.1 Personal, Context and Medical Information Collection

Personal, context and medical information validate technologically-detected changes in monitored health change indicators. Collecting these information in parallel with monitoring period is essential to validate medical relevance of detected changes. Medical nursing home team records all significant observations on a daily basis using dedicated tablets (Fig 5.32 and 5.33). Real-time notifications per SMS and email enable early investigation of detected change cause from 2 to 10 days after change occurrence. Developed web-based application ChangeTracker provides more information about monitored geriatric indicators and detected changes. Regular review meetings allow to accurately investigate possible causes and investigate mutli-dimensional correlations.



Fig. 5.32 Correlation of Detected Changes with Medical Observations

Nursing home team continuously collects **electronic health records** using dedicated tablets (Fig 5.33). Nurses visit monitored participants a couple of times per day for medicine taking, toilet entry assistance, room cleaning and nutritional services. Nursing home residents use emergency button to call nurses if required. Nurses report all interventions, formal and informal observations, special health events and social habits in developed software. These electronic health records include geriatric assessment results, hospitalizations, treatments, physical, emotional and cognitive problems.

Developed monitoring system ChangeTracker sends **change notifications** from 2 to 10 days after change occurrence. These notifications inform about change date, monitored

participant ID, and means before and after detected change. Change notifications provide opportunity to confirm that detected changes are really permanent and investigate possible correlations with geriatric observations. ChangeTracker gives more information about notified changes by showing all historical monitoring data if required, and highlighting detected long-term changes in all monitored health change indicators.

13/08/2015	
05:32	DESORIENTEE LEVEE 1 FOIS RECOUCHEE SANS SOUCIS
11:10	PAS LE MORAL CE MATIN - PLEURE - SE DEMANDE POURQUOI ELLE N'EST PAS RESTE CHEZ ELLE - PREVENU ET A ETAIT LUI PARLER
16:30	ENTRETIEN AVEC ELLE CE MATIN A LA DEMANDE DE N'AVAIT PAS LE MORAL, SE SENTAIT EN PRISON, JE LUI AI EXPLIQUE DE NOUVEAU LE FONCTIONNEMENT DE LA MAISON DE RETRAITE ET LES SORTIES QU'ON POUVAIT LUI PROPOSER AINSI QUE LES SORTIES QU'ELLE POUVAIT FAIRE AVEC SES ENFANTS. MIEUX A LA SUITE DE L'ENTRETIEN.
14/08/2015	
11:30	EN PLEURE CE MATIN DANS SA CHAMBRE. DIT NE PAS ACCEPTER D'ETRE ICI
12:01	FAIS DEPISTAGE CANCER CUTANE MIS DANS SON DOSSIER. N A PAS TROP LE MORAL CE MATIN
15/08/2015	
10:43	EN PLEURE CE MATIN AU REVEIL A PEUR DE PERDRE LA TETE DIT ELLE N ARRIVE PAS ENCORE A TROUVER SES REPERES
16/08/2015	
14:22	SOURIANTE CE MATIN AU LEVER A FAIT SA TOILETTE SEULE SE LIE D AMITIE AVEC A TRES BIEN MANGE CE MIDI LEGUMES ET VIANDE PAR CONTRE MIXEE

Fig. 5.33 Electronic Health Record Example

Regular review meetings with elderly people, family members and family doctors (each 4 months with nursing home and each 2 months with individual houses) allow to accurately investigate possible causes of detected changes. Medical clinic geriatrician evaluates medical relevance of investigated change explications, by reviewing all past detected changes and correlating them with medical records (*e.g.*, geriatric scales, cognitive diagnosis and prescribed treatments). Review meetings investigate mutli-dimensional correlations of detected changes, such as identifying simultaneous decreases in activity level and time out home related to mobility impairments, and consecutive increases in sleep interruptions and toilet entries after treatment change.

5.3.2 Possible Health Change Cause Categories and Rates

In total, developed analysis algorithms detect 340 changes for all participants with an average of 0.97 change per month for those living at home and 1.14 change per month for those living in nursing home. Nursing home participants have higher change frequency related to their increased risk of dependence. Medical correlations confirm that 36% of detected changes are related to health improvements (*e.g.*, participant U retrieves normal frequency of toilet entries after remedy for urinary infection (Fig. 5.28)). Health problems justify 64% of detected changes (*e.g.*, participant M shows 3 consecutive decreases in global activity level after experiencing mobility problems (Figure 5.23)).

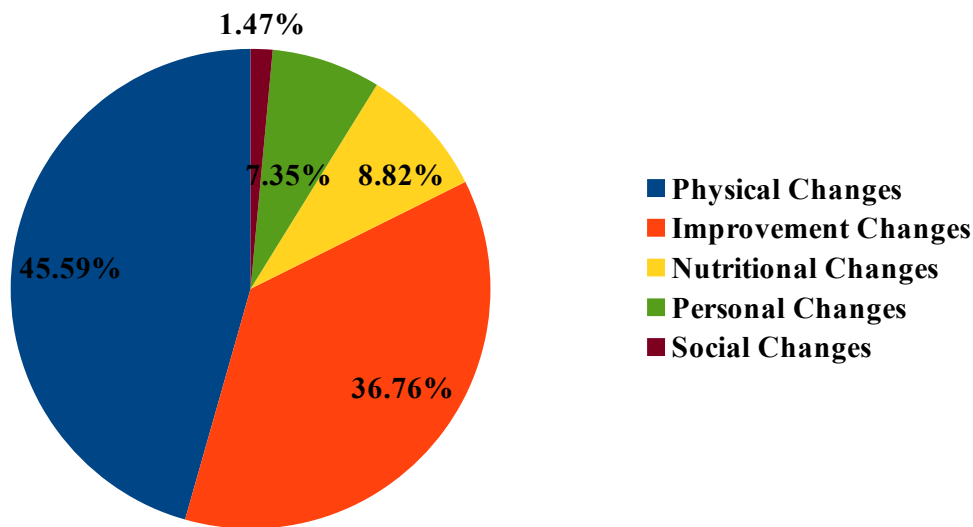


Fig. 5.34 Possible Cause Rates of Detected Changes in Individual Houses

Table 5.21 Possible Causes of Detected Changes in Individual Houses

Cause	Rate	Example
Physical problems	45.59%	Participant V sleeps longer with fewer interruptions correlated with Parkinson freezing periods
Health improvements	36.76%	Participant N has fewer sleep interruptions correlated with improvement in sleep habits and toilet entries
Nutritional problems	8.82%	Participant J enters less frequently to toilet while experiencing constipation and digestive problems

Personal changes	7.35%	Participant M sleeps and wakes-up earlier after changing daily habits
Social problems	1.47%	Participant M receives less visits at home due to social isolation

Individual house participants show diverse changes in monitoring period that are associated with diverse medical reasons, such as physical problems, health improvements, nutritional problems, personal changes and social problems (Fig 5.34 and Table 5.21). Health improvements justify 36.76% of detected changes; e.g., participant N has fewer sleep interruptions correlated with improvement in sleep habits and toilet entries. Physical health problems present main detected change cause for individual house participants with a percentage of 45.59%; e.g., participant V sleeps longer with fewer interruptions correlated with Parkinson freezing periods. Nutritional, personal and social changes influence monitored health status with respective rates of 8.82%, 7.35% and 1.47%; e.g., participant M receives less visits at home due to social isolation.

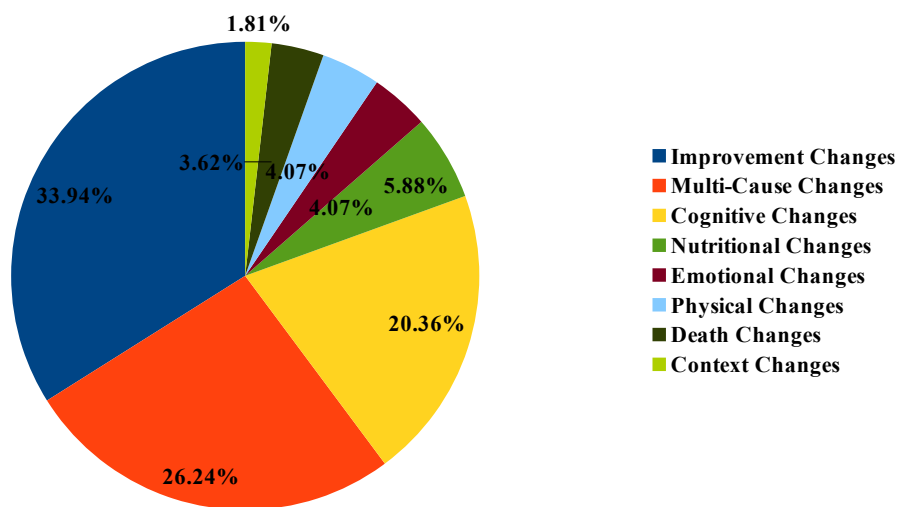


Fig. 5.35 Possible Cause Rates of Detected Changes in Nursing Home

Table 5.22 Possible Causes of Detected Changes in Nursing Home

Cause	Rate	Example
Health improvements	33.94%	Participant L retrieves normal activity level after treating knee problems

Multiple health problems	26.24%	Participant G has global activity level decreases correlated with cough, toothache and respiration difficulties
Cognitive problems	20.36%	Participant E shows abnormal activity level increases and decreases during Alzheimer disorientation periods
Nutritional problems	5.88%	Participant E has more frequent toilet entries as result of diarrhea
Emotional problems	4.07%	Participant F has more sleep interruptions after husband's death
Physical problems	4.07%	Participant D goes out less frequently due to foot problems
Death	3.62%	Participant A experiences relevant decreases in activity and time out of room few months before death
Context changes	1.81%	Participant C shows more sleep interruptions after room change

Nursing home residents have less stable health conditions than those living independently at home. Detected changes are correlated with diverse health problems, such as cognitive, nutritional, emotional and physical impairments (Fig. 5.35 and Table 5.22). Early and advanced stages of Alzheimer disease explain 20.36% of detected changes; e.g., participant E shows abnormal activity level increases and decreases during Alzheimer disorientation periods. Nutritional, emotional and physical problems influence health status with respective rates of 5.88%, 4.07% and 4.07%; e.g., participant D goes out less frequently due to foot problems and participant E has more frequent toilet entries as result of diarrhea. After treating diagnosed health problems, proposed monitoring system detects possible health improvements explaining 33.94% of detected changes; e.g., participant L retrieves normal activity level after treating knee problems.

5.3.3 Health Change Detection Ontology

Collected medical interpretations of detected changes in all monitored health change indicators (e.g., activity level, sleep interruptions, toilet entries, received visits and time out of home) define global health change detection ontology (Fig. 5.36). This ontology identifies possible cause categories and sub-categories for detected health changes. Electronic health

records, personal interviews and regular review meetings with elderly people, family members and family doctor investigate possible causes of detected changes. Main health change causes are physical problems, nutritional problems, emotional problems, context changes, social problems, health improvements, cognitive problems and death.

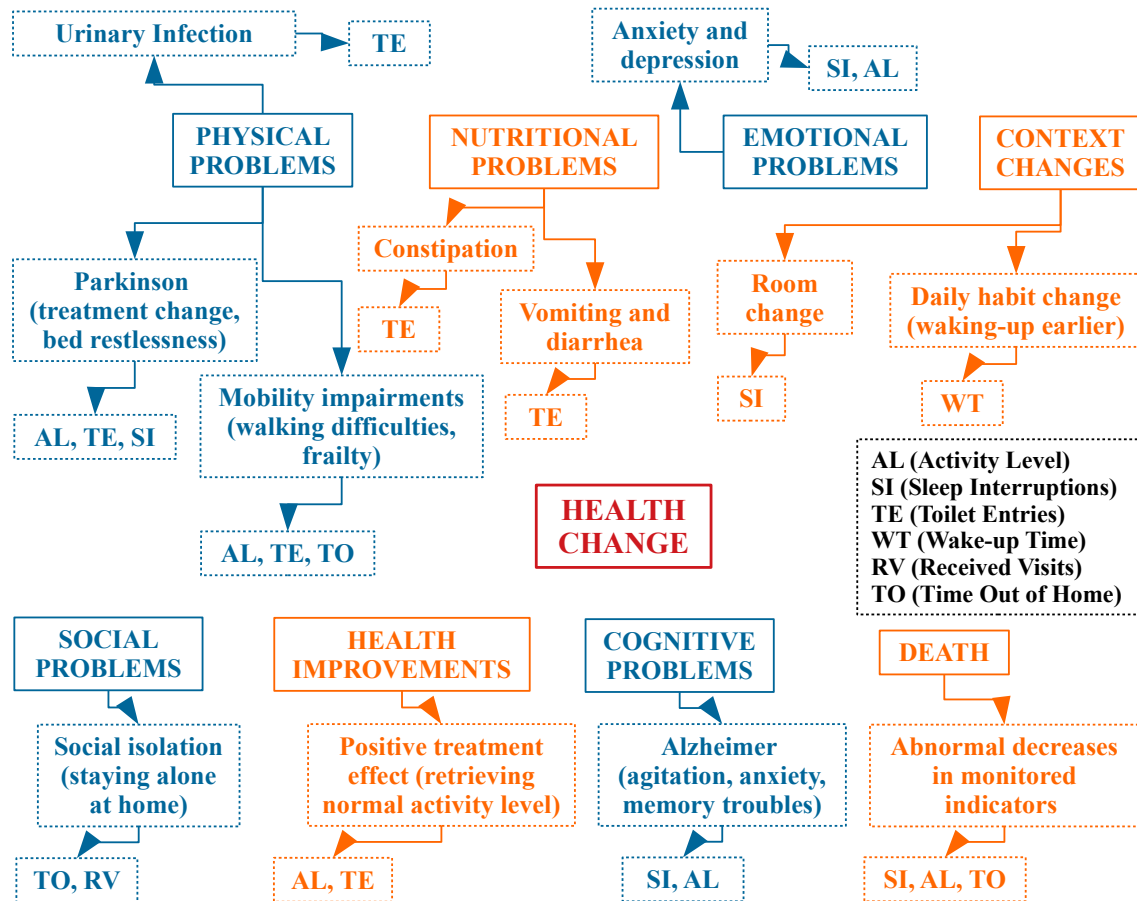


Fig. 5.36 Health Change Detection Ontology

Aging process is associated with **physical health problems**. Developed monitoring system detects changes in activity level, toilet entries and sleep interruptions that are related to hyperactivity periods and disrupted sleep-wake cycle due to Parkinson disease (*e.g.*, participants V, X and Y experience frequent sleep interruptions in association with their Parkinson-related bed restlessness). Participants L and B show decreases in activity level and toilet entries due to their mobility impairments, walking difficulties and knee problems. Participants H and M are less active at home and go less frequently out due to their increased risk of dependence in managing activities of daily living. Urinary infection explains detected increases in toilet entries for participants I and U.

Developed monitoring system identifies **nutritional health problems** for participant J. She goes less frequently to toilet due to constipation. Vomiting and diarrhea cause significant increases in toilet entries for participants M and E. Elderly people often show **emotional health problems**. Detected changes in sleep interruptions and activity level explain anxiety and depression felt by participants C and F. **Context changes** have influence on monitoring data. Whereas participant C experiences more sleep interruptions after room change, participant M wakes-up earlier after changing daily habits. Both participants go out less frequently and receive less visits. They stay often alone at home because of their **social isolation**.

Detecting changes in monitored indicators does not only result from negative health problems, but also positive **health improvements**. After treating their knee problems and urinary infection, participants L and U retrieve their normal activity level and toilet entry frequency. Participants B, J and K receive more visits, which is related to positive change in their social habits. **Cognitive problems** are common among elderly people. Agitation, anxiety periods, wandering at night and memory troubles related to Alzheimer disease abnormally affect activity level and sleep interruptions of participants D, E, F and G. Abnormal decreases in all monitored indicators affect elderly people a couple of months before **death**.

5.3.4 Change Detection Technique Performance Evaluation

Statistical, probabilistic and machine-learning change detection techniques do not provide same performance in terms of change detection precision. Applying these techniques on real monitoring data enables effective performance evaluation, including all monitored health change indicators (*e.g.*, activity level, toilet entries, sleep interruptions, received visits and time out of home) for same monitored participants. Change detection techniques do not detect same change points for tested inferred data. Correlating detected change points with medical observations is essential to evaluate their medical relevance.

Change detection precision refers to percentage of detected changes with retrieved medical explication (*i.e.*, changes related to health status based on medical correlations). Unexplained changes are either related to false alarms or undiagnosed health problems (*e.g.*, participant N wakes-up earlier, but does not feel this change and does not find explication). Fig. 5.37 shows measured precision for investigated change detection techniques. Bootstrap technique provides best precision of 83,87%; *i.e.*, bootstrap technique detects significant changes that are highly related to physical and health problems.

Table 5.23 presents best precision of each change detection technique and its corresponding configuration. Machine learning techniques (*e.g.*, One-Class SVM, Affinity Propagation,

K-Means and Mean Shift) are sensitive to outliers. Statistical and probabilistic techniques (e.g., Z-Score, Naive Bayes Classifier, Bayesian and ULSIF) are sensitive to threshold.

All techniques (except Bayesian) analyze data online with low execution time. Bootstrap, SD-Band, PELT and Bayesian techniques have high computational cost related to their recursive analysis of all past data. Bootstrap technique provides reasonable trade-off between precision, threshold selection, execution time and computational cost. It is more robust to outliers, threshold free and detects relevant changes that are missed by other techniques.

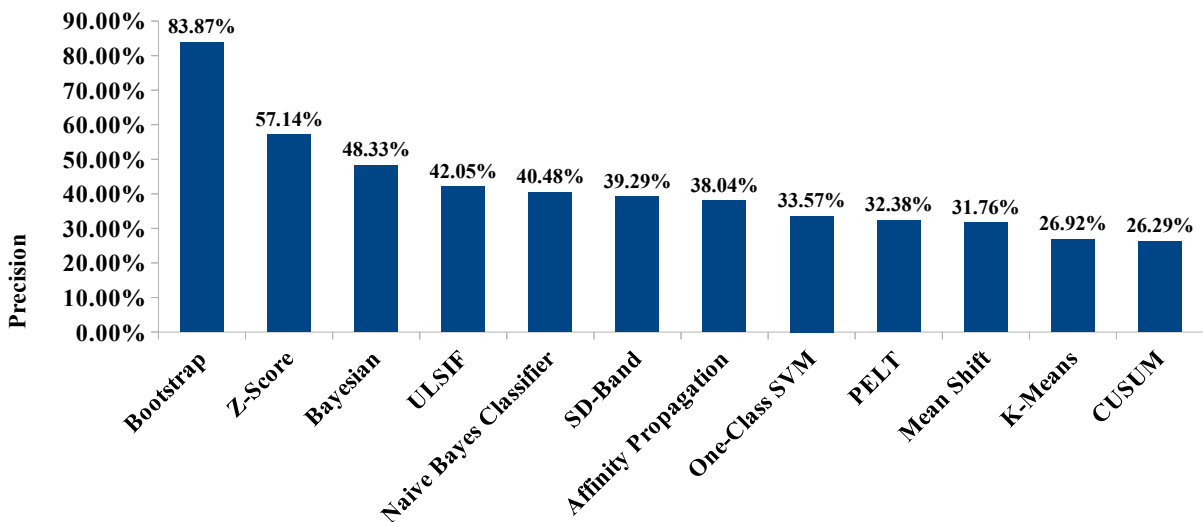


Fig. 5.37 Change Detection Technique Precision

Whereas **Bootstrap** technique randomly re-orders original data to confirm change occurrence without requiring additional threshold, **Z-Score** technique directly depends from selected threshold. Changing Z-Score threshold provides new change point groups, and consequently alters Z-Score change detection precision. Main advantage of Z-Score technique is online computation of change detection parameters (e.g., window mean and standard deviation) without requiring full storage of all past data. Main limitation of Bootstrap technique is recursive analysis of all past data for multiple change point detection, resulting in higher computational costs.

Bayesian technique accurately computes change probability for each data point. This provides high precision, but also high execution time due its recursive analysis compared to **ULSIF** technique. ULSIF efficiently computes probability ratio of moving window and past data, resulting in low execution time and computational costs. Main limitation of ULSIF technique is its dependence on selected threshold. Changing ULSIF threshold (i.e., probability ratio threshold) gives different change point selection, and changes final precision.

Both **Naive Bayes Classifier** and **SD-Band** techniques compute their change detection parameters online (*e.g.*, mean and standard deviation), resulting in low execution time and computational costs. Whereas Naive Bayes Classifier computes change probability for each new data point, SD-Band technique measures moving band of one standard deviation above and below past data mean. Both techniques are threshold dependent (*i.e.*, probability threshold or window length for consecutive deviation selection), which is their main limitation.

Table 5.23 Change Detection Technique Precision, Advantages, Disadvantages and Configuration (window length (W) and threshold (Th))

Technique	Configuration	Precision	Advantages	Disadvantages
Bootstrap	Threshold free	83.87%	Threshold free, robust to outliers, high precision	High computational costs due to recursive analysis
Z-Score	W=7, Th=2	57.14%	Applicable on seasonal signals, low online computational costs, low execution time	Sensitive to zscore threshold
Bayesian	Th=0.25	48.33%	Robust to outliers, high precision	Sensitive to probability threshold, high execution time, high computational costs due to recursive and offline analysis
ULSIF	W=7, Th=0.5	42.05%	Low online computational costs	Sensitive to defined threshold
Naive Bayes Classifier	W=5, Th=0.01	40.48%	Small number of reference data, low online computational costs	Sensitive to probability threshold
SD-Band	W=3	39.29%	Low execution time	Sensitive to window length, sensitive to outliers

Affinity Propagation	Th=10	38.04%	Threshold free, unsupervised clustering, low execution time, low online computational costs	Highly sensitive to outliers, high number of reference data
One-Class SVM	W=14	33.57%	Threshold free, unsupervised classification, low execution time, low online computational costs	Highly sensitive to outliers, high number of reference data
PELT	Threshold free	32.38%	Threshold free, low execution time	Sensitive to outliers, high computational costs due to offline analysis
Mean Shift	Th=10	31.76%	Threshold free, unsupervised clustering, low execution time, low online computational costs	Highly sensitive to outliers, high number of reference data
K-Means	Th=10	26.92%	Threshold free, unsupervised clustering, low execution time, low online computational costs	Highly sensitive to outliers, high number of reference data
CUSUM	W=7	26.29%	Low online computational costs, low execution time	Sensitive to decision parameter

Machine learning techniques are threshold free. One-Class SVM classifies new data points as normal or abnormal compared to reference data. Affinity Propagation, Mean Shift and K-Means compute data clusters, in order to detect possible changes between identified clusters. These clustering and classification techniques have low execution time and computational cost. Their main limitation is high sensibility to outliers, resulting in low change detection precision. Classification and clustering techniques require high number

of reference data. Collected monitored data over months and years remain insufficient to accurately train machine learning techniques.

PELT technique does not require threshold definition for change point selection. It analyzes all past data, and employs log-likelihood test for optimal change point selection. This generates more computational costs (*i.e.*, required storage of all past data) compared to **CUSUM** technique. CUSUM iteratively calculates sums of positive and negative deviations for change detection. Change decision parameter decides whether change occurs or not. Altering definition of this parameter (based on pre-defined tables or standard deviation) generates new change point groups, and influences output precision.

Table 5.24 Change Detection Technique Comparison

Technique	High Precision	Threshold Free	Low Execution Time	Low Computational Cost
Bootstrap	✓	✓	✓	
Z-Score	✓		✓	✓
Bayesian	✓			
ULSIF			✓	✓
Naive Bayes Classifier			✓	✓
SD-Band			✓	
Affinity Propagation		✓	✓	✓
One-Class SVM		✓	✓	✓
PELT		✓	✓	
Mean Shift		✓	✓	✓
K-Means		✓	✓	✓
CUSUM			✓	✓

Bootstrap technique provides reasonable trade-off between precision, execution time and computational costs (Table 5.24). This technique changes original data order to accurately investigate change occurrence, without requiring variable threshold (*i.e.*, fixed threshold for any input data). Generating bootstraps and comparing their change magnitude to original data considerably reduces false positive rate. Bootstrap additionally splits analyzed data

into new sets (separated by identified change point) for multiple change point detection. Recursive investigation of change points considerably reduces false negative rate.

5.4 Conclusion and Discussion

Real deployments in 3 French cities validate proposed technological approach in this thesis. In total, 25 elderly people living alone at home or nursing home participate in experimentation. Local partners help with **recruitment process**, such as medical clinic, nursing home, geriatric organization and metropolis council. Movement and contact sensors are deployed in each room and on main house entries to detect presence and absence of movements, and door opening and closings. Despite the basis information collected by these sensors, developed **data processing algorithms** extract diverse geriatric indicators (*e.g.*, activity level, sleep interruptions, toilet entries, received visits and time out of home). Data processing algorithms provide input for change detection techniques. These techniques analyze monitored indicators on a daily basis, and distinguish between temporary and permanent changes.

Medical clinic geriatrician Dr. Émilie Guettard [36] and **nursing home team** [37] validate **medical relevance** of detected changes in this thesis. **Medical diagnosis** provided by geriatrician, and **electronic health records** provided by nursing home investigate possible change causes. Detected changes do not only correlate with health problems (*e.g.*, physical and cognitive problems), but also with health improvements (*e.g.*, positive treatment effect). Among evaluated and adapted change detection techniques, **Bootstrap technique** provides reasonable trade-off between precision, time execution and computational costs. This technique reduces false positives by identifying medically-relevant changes in health status, and reduces false negatives by detecting changes that are missed by other techniques.

Conclusion and Future Work

In this thesis, **proposed methodology** identifies **real needs** of elderly people, family members and family doctors. They need to **early** detect possible changes in health status **without intrusive monitoring**. Geriatricians are interested in integrating new technological observations, in order to complete their medical observations. Family members and nursing home team need to establish new link between them and elderly people living alone at home. Compared to existing methodologies, proposed methodology in this thesis targets detection of long-term changes in monitored behavior via unobtrusive technologies on a daily basis and at temporal scale.

Effective translation of geriatric needs requires identification of **health change indicators**. This thesis uses validated geriatric references to define activities of daily living that are associated with physical and health problems, and can be monitored via unobtrusive technologies. Physical, cognitive, social, nutritional and emotional activities of daily living highly correlate with aging-related health problems.

Employed technologies in this thesis discretely operate in the environment, in order to measure real behavior evolution. Environmental sensors, sensor-enhanced devices and in-phone-embedded sensors **unobtrusively** monitor elderly people behavior without changing their daily habits. Analyzing monitored indicators on a daily basis enables early change detection in health status. Correlating technological observations with medical and personal observations is essential to validate **medical relevance** of detected changes.

This thesis develops web-based application **ChangeTracker** that provides elderly people, family members and family doctor with **online behavior analysis** and **continuous change detection**. This application is integrated in ambient assisted living platform UbiSMART. UbiSMART acquires sensor observations and infers activities of daily living in real time. This platform does not detect changes in inferred activities. ChangeTracker implements new change detection service, by converting sensor observations into geriatric indicators and analyzing them online for long-term change identification.

Implemented **data processing algorithms** in this thesis compute health change indicators, such as **activity level** based on activity periods, **sleep interruptions** based on activity

periods at night, **toilet entries** based on toilet sensor observations, **received visits** based on parallel activity periods and **time out of home** based on inactivity periods. All computed indicators are weighted to presence time alone at home. Discarding go out periods and visit periods is essential to avoid detecting irrelevant changes, such as toilet entry decreases after going out more frequently and activity level increases during presence of multiple persons.

This thesis **evaluates** 12 **change detection techniques** by applying them on real data. Among evaluated techniques, this thesis **adapts** 9 statistical, probabilistic and machine-learning techniques, in order to enable **multiple long-term change detection**. These techniques apply different filters on detected deviations and identify changes with different granularity. Z-Score, Naive Bayes Classifier, ULSIF and One-Class SVM detect changes based on static or single reference phase. **Proposed adaptation** in this thesis defines **moving reference phase**. This allows to re-initialize reference phase after change detection, in order to detect future changes. SD-Band technique identifies short-term changes. Proposed adaptation to SD-Band defines **moving window** of consecutive deviations for long-term change detection. Affinity propagation, K-Means and Mean Shift classify data into clusters. Proposed adaptation to these clustering techniques computes **rate** of cluster including current data point to identify possible change point.

Real deployments in 3 French cities validate proposed technological approach in this thesis. In total, 25 elderly people living alone at home or nursing home participate in experimentation. Local partners help with **recruitment process**, such as medical clinic, nursing home, geriatric organization and metropolis council. Movement and contact sensors are deployed in each room and on main house entries to detect presence and absence of movements, and door opening and closings. Despite the basis information collected by these sensors, developed **data processing algorithms** in this thesis extract diverse geriatric indicators (*e.g.*, activity level, sleep interruptions, toilet entries, received visits and time out of home). Data processing algorithms provide input for change detection techniques. These techniques analyze monitored indicators on a daily basis, and distinguish between temporary and permanent changes.

Medical clinic geriatrician Dr. Émilie Guettard [36] and **nursing home team** [37] validate **medical relevance** of detected changes in this thesis. **Medical diagnosis** provided by geriatrician, and **electronic health records** provided by nursing home investigate possible change causes. Detected changes do not only correlate with health problems (*e.g.*, physical and cognitive problems), but also with health improvements (*e.g.*, positive treatment effect). Among evaluated and adapted change detection techniques, **Bootstrap technique** provides reasonable trade-off between precision, time execution and computational costs. This

technique reduces false positives by identifying medically-relevant changes in health status, and reduces false negatives by detecting changes that are missed by other techniques.

- **Thesis Challenges and Proposed Solutions**

This thesis confronts **technological, medical and social challenges**. **Recruiting** elderly people is difficult, especially if they are not used to integrate technologies at home. **Proposed solution** in this thesis selects **unobtrusive technologies** that do not change daily habits and do not affect individual privacy. Main challenge is how to **validate technological observations**. Proposed solution in this thesis achieves **real deployments** with continuous collection of **medical feedbacks**. Medical feedbacks are essential to define analysis parameters, develop analysis algorithms and evaluate them.

Proposed solution to **recruitment process difficulties** is cooperating with **medical partners**. These institutions have experience with elderly people, understand their needs and better communicate with them. Convincing elderly people to participate in technological experimentations is challenging, especially if they are afraid of using new technologies. This thesis conducts long-term experimentation by involving geriatric experts in addition to technological experts.

Employed **unobtrusive technologies** in this thesis have more acceptance rate than wearable and intrusive technologies. Elderly people refuse cameras and microphones that affect individual privacy. They easily forget to wear smart watch or bracelet while performing activities of daily living. Movement and contact sensors discretely operate in the environment and do not require any direct interaction with end-users.

Real deployments provide real validation. Applying thesis approach in research laboratory or in experimental house is not sufficient. Proposed solution is conducting real deployments that require **prior testing** of employed technologies, **moving and travelling** to deployment sites, easy **installation and integration** in living environment and **financial budget**. Stable background server is essential to collect monitoring data with minimum interruption periods (*e.g.*, system shutdowns due to internet connection problems or hardware failures).

Medical observations validate relevance of technological observations. This thesis collects medical observations based on **regular phone calls, personal interviews and review meetings**. Collected information investigate possible causes of detected changes. Automating medical observation collection reduces manual investigation efforts via phone applications and personal tablets.

Further challenge is how to **quantify health status** based on **sensor observations**. **Developed analysis algorithms** in this thesis extract **geriatric indicators** from collected sensor

data, and investigate possible changes. Medical observations confirm that detected changes correlate with physical and cognitive problems.

Effective geriatric need translation is challenging. Engaged elderly people and geriatricians appreciate thesis work. **Technological observations** are of great help for them, because detected changes correlate with health status. Elderly people accept employed technological solutions becoming part of their homes. Employed movement sensors have limitations in terms of **sensing vital signs** and **monitoring elderly people not living alone at home**. Family members have future concerns about **who collects and pays for monitoring data**.

- **Short-term Future Work**

This thesis provides insight into short-term perspectives. These perspectives target integration of new monitoring technologies and analysis of further geriatric indicators.

Integrating **new technologies** provides more information about monitored behavior. **Bed sensors** discretely measure heart beats and respiratory rhythm. These sensors accurately follow-up sleep habits, by identifying wake-up and sleep times. **Sensor-enhanced fridge and oven** notify about preparing and taking meals. Nutritional habits are associated with physical and cognitive problems. **Smart scale** measures weight and burned calories. **WIFI-based devices** follow-up body movements even with multiple person presence, based on body reflection in WIFI-zone. This technology monitors heart beats and respiratory rhythm during day.

Computing further **geriatric indicators** enables more accurate change detection. Movement sensors measure **room changes**. Moving between rooms correlates with physical and cognitive health (*e.g.*, repetitive wandering between rooms indicates frontal lobe disorder). Movement and contact sensors identify **freezing and instability periods**. **Falls** are highly associated with walking difficulties. Sensor-enhanced land-line phone and smart phone applications follow-up **incoming and outgoing calls**. Verbal communication is related to cognitive health.

- **Long-term Future Work**

This thesis opens long-term perspectives regarding outdoor behavior analysis, large-scale deployments and proactive intervention.

Analyzing **outdoor activities** investigates **social life** changes. **City beacons** deployed in diverse points of interest (*e.g.*, cinema, theater, shopping center, tramway station, working areas, restaurants and parks) follow-up outdoor activities. Detected changes in social habits, cultural engagement and entertainment activities indicate possible health problems. Completing indoor behavior analysis with outdoor behavior analysis provides more accurate change cause investigation.

Large-scale deployments enable **deeper understating of change characteristics** related to specific aging diseases, such as Alzheimer, Parkinson and Frailty. Correlating technological observations with medical observations of large elderly populations allows to compute accurate **health change probabilities**. Associating detected changes with possible disease probability supports geriatricians in their medical assessment. This improves medical diagnosis reliability based on iterative learning of past case studies. **Involving geriatricians** and integrating their feedbacks in change detection process improves its impact.

Early health change detection enables **proactive intervention**. A good philosophy of intervention changes the environment, instead of asking elderly people to change the environment. **Engaging caregivers with elderly people** in intervention process avoids reducing their quality of life. Sending notifications to elderly people about going out in case of social isolation is never helpful. Intervention should be personalized; i.e., it takes into account living environment characteristics, personal preferences and health status. Initializing behavior change requires convincing arguments, strong belief about health problems, and perceived benefits of actions and barriers to action. A good philosophy of intervention does not only creates behavior changes, but also maintains them over long period.

List of Figures

1.1	Positive Impact of Early Health Change Detection on Intervention Services for Elderly People	14
1.2	European Project City4Age Strategy and Objectives [38]	20
3.1	Stakeholders and Geriatric Needs	43
3.2	Health Change Indicator Categories	48
3.3	Examples of Environmental Sensors	54
3.4	Examples of Sensor-Enhanced Devices	55
3.5	Examples of In-Phone-Embedded Sensors	56
4.1	Implementation Architecture of ChangeTracker Service in UbiSMART Platform	62
4.2	Application of Time At Home Algorithm Based on Movements and Door Openings	64
4.3	Application of Visit Detection Algorithm Based on Parallel Activity Periods	66
4.4	Application of Wake-Up and Sleep Time Detection Algorithm Based on Activity Level Changes	66
4.5	Application of Weighted Toilet Entry Algorithm	68
4.6	Application of Weighted Sleep Interruption Algorithm	69
4.7	Application of Weighted Movement Number Algorithm	70
4.8	PELT Change Detection Technique	77
4.9	Bayesian Log-Likelihood of Datasequence [t, s]	78
4.10	Bayesian Log-Likelihood of Data [t, n]	78
4.11	ULSIF Change Detection Technique	79
4.12	Client-Server Implementation Architecture of ChangeTracker Service	82
4.13	MQTT-Communicated Sensor Event Example	85
4.14	Sensor Event Table in PostgreSQL Database	85
4.15	Index Page View of ChangeTracker Service	88
4.16	Toilet Entry View of ChangeTracker Service	89
4.17	Daily Information View of ChangeTracker Service	89

4.18	Implementation Architecture of UbiSMART Platform	91
4.19	Graphical User Interface of HomeDesc Service	92
4.20	Graphical User Interface of SensLog Service	93
4.21	Graphical User Interface of Life Service	95
5.1	Cooperating Partners in Recruitment Process	99
5.2	Local Medical Events Promoting Recruitment Process	100
5.3	Experimental House in Lattes and Tested Technologies	101
5.4	Nursing Home Deployments and Employed Technologies	103
5.5	Individual House Deployments and Employed Technologies	104
5.6	Detected Changes in Activity Level of Participant A Due to Death	114
5.7	Detected Changes in Time Out of Participant A Due to Death	114
5.8	Detected Changes in Sleep Interruptions of Participant A Due to Death	115
5.9	Detected Changes in Time Out of Participant B Due to Frequent Family Invitations	116
5.10	Detected Changes in Activity Level of Participant B Due to Mobility Impair- ments	116
5.11	Detected Changes in Activity Level of Participant C Due to Depression and Room Change	117
5.12	Detected Changes in Sleep Interruptions of Participant C Due to Depression and Room Change	118
5.13	Detected Changes in Sleep Interruptions of Participant D Due to Alzheimer	119
5.14	Detected Changes in Activity Level of Participant D Due to Alzheimer	120
5.15	Detected Changes in Activity Level of Participant E Due to Alzheimer	121
5.16	Detected Changes in Toilet Entries of Participant E Due to Vomiting and Diarrhea	121
5.17	Detected Changes in Activity Level of Participant G Due to Alzheimer	123
5.18	Detected Changes in Sleep Interruptions of Participant F Due to Anxiety	123
5.19	Detected Changes in Toilet Entries of Participant I Due to Urinary Infection	125
5.20	Detected Changes in Toilet Entries of Participant H Due to Mobility Impair- ments	125
5.21	Detected Changes in Visits of Participant J Due to Family Visits	126
5.22	Detected Changes in Visits of Participant K Due to Family Visits	127
5.23	Detected Changes in Activity Level of Participant M Due to Mobility Impair- ments	128
5.24	Detected Changes in Activity Level of Participant L Due to Knee Problems	129

5.25	Stable Daily Evolution of Sleep Interruptions for Participant N Confirming Good Sleep	130
5.26	Stable Daily Evolution of Sleep Interruptions for Participant O Confirming Long Sleep	130
5.27	Stable Daily Evolution of Sleep Interruptions for Participant T Confirming Good Sleep	131
5.28	Detected Changes in Toilet Entries of Participant U Due to Urinary Infection	131
5.29	Detected Changes in Time Out of Participant V Due to Parkinson	132
5.30	Detected Changes in Toilet Entries of Participant X Due to Treatment Change	133
5.31	Detected Changes in Activity Level of Participant Y Due to Treatment Change	134
5.32	Correlation of Detected Changes with Medical Observations	135
5.33	Electronic Health Record Example	136
5.34	Possible Cause Rates of Detected Changes in Individual Houses	137
5.35	Possible Cause Rates of Detected Changes in Nursing Home	138
5.36	Health Change Detection Ontology	140
5.37	Change Detection Technique Precision	142
5.38	Wireless Marmitek MS13E Movement Sensors	158
5.39	Wireless Marmitek DS90 Contact Sensors	160
5.40	Raspberry-Pi V3 and CM19 X10 Receiver	162
5.41	Event and House Table Query Examples	168

List of Tables

1.1	Proposed Methodological Contributions	17
1.2	Proposed Technical Contributions	18
1.3	European Project City4Age Deployment Sites [38]	20
2.1	Existing and Proposed Behavior Definitions and Models	25
2.2	Existing Behavior Change Initiation and Maintenance Models	26
2.3	Comparison of Psycho-Geriatric Scales	28
2.4	Examples of Psycho-Geriatric Scales	30
2.5	Comparison of Health Change Detection Approaches	39

3.1	Comparison of Geriatric Stakeholder Needs	47
3.2	Activity of Daily Living (ADL) Indicators	49
3.3	Mobility Indicators	50
3.4	Cognitive Indicators	51
3.5	Social Life Indicators	51
3.6	Nutritional Indicators	52
3.7	Emotional Indicators	52
3.8	Raw and Inferred Data of Environmental Sensors	54
3.9	Raw and Inferred Data of Sensor-Enhanced Devices	55
3.10	Raw and Inferred Data of In-Phone-Embedded Sensors	57
3.11	Examples of Health Change Metrics	57
3.12	Examples of Personal, Context and Medical Observations	59
4.1	Case Study Raw and Inferred Data	63
4.2	Evaluated and Adapted Change Detection Techniques	71
5.1	Participant ID, Gender, Monitoring Start, End and Place at Nursing Home (NH) and Individual Houses (IH)	105
5.2	Regular Participant Habits and Reported Health Information Related to Cognitive Impairments (CG), Physical Impairments (PH), Diabetes (DB), Frequent Visits (FV) and Go Out (FG)	106
5.3	Analyzed Health Change Indicators	112
5.4	Early Change Detection Examples for Participant A	115
5.5	Early Change Detection Examples for Participant B	117
5.6	Early Change Detection Examples for Participant C	118
5.7	Early Change Detection Examples for Participant D	120
5.8	Early Change Detection Examples for Participant E	122
5.9	Early Change Detection Examples for Participant F	124
5.10	Early Change Detection Examples for Participant G	124
5.11	Early Change Detection Examples for Participant H	125
5.12	Early Change Detection Examples for Participant I	126
5.13	Early Change Detection Examples for Participant J	126
5.14	Early Change Detection Examples for Participant K	127
5.15	Early Change Detection Examples for Participant M	128
5.16	Early Change Detection Examples for Participant L	129
5.17	Early Change Detection Examples for Participant U	132
5.18	Early Change Detection Examples for Participant V	132

5.19	Early Change Detection Examples for Participant X	133
5.20	Early Change Detection Examples for Participant Y	134
5.21	Possible Causes of Detected Changes in Individual Houses	137
5.22	Possible Causes of Detected Changes in Nursing Home	138
5.23	Change Detection Technique Precision, Advantages, Disadvantages and Configuration (window length (W) and threshold (Th))	143
5.24	Change Detection Technique Comparison	145
5.25	Technical Movement Sensor Specifications	159
5.26	Technical Contact Sensor Specifications	160
5.27	Technical Raspberry-Pi Specifications	162

List of Listings

4.1	SensorML Template for Modeling Sensor Network	83
4.2	O&M Data Format Template	84
4.3	JavaScript Service Prototype	85
4.4	Database Access Example	86
4.5	Toilet Entry Computation Example	86
4.6	Toilet Entry Change Detection Example	87
4.7	Mail and SMS Change Notification Example	90
5.1	Main Function Prototypes of ChangeTracker	164
5.2	HTML, CSS and JavaScript Example	165
5.3	Event Model Definition Script	166
5.4	Event Table Migration Script	166
5.5	SensorML Movement Sensor Model	169
5.6	O&M Movement Sensor Example	170
5.7	MQTT Publish and Subscribe Implementation	171
5.8	Google Mail and Twilio SMS Notification Implementation	172

List of Algorithms

1	Time at Home Algorithm	64
2	Visit Detection Algorithm	65
3	Wake-up and Sleep Time Detection Algorithm	67
4	Weighted Toilet Entry Algorithm	68
5	Weighted Sleep Interruption Algorithm	69
6	Weighted Movement Number Algorithm	70
7	Z-Score Change Detection Technique	72
8	Bootstrap Change Detection Technique	74
9	CUSUM Change Detection Technique	75
10	SD-Band Change Detection Technique	76
11	Naive Bayes Classifier Change Detection Technique	78
12	One-Class SVM Change Detection Technique	80
13	Clustering Change Detection Technique	81

Appendix

- **Wireless Movement Sensors**

Wireless Marmitek MS13E movement sensors detect presence and absence of movements (Fig. 5.38). These commercial sensors are often used for house intrusion detection and automatic light switching. Deploying movement sensors at home collects minimal information about activities of daily living and enables inference of significant information highly related to physical and cognitive problems, such as activity periods at night associated with sleep interruptions, global activity level associated with mobility impairments and toilet entries associated with urinary infection.



Fig. 5.38 Wireless Marmitek MS13E Movement Sensors

Marmitek MS13E movement sensors communicate via X10 protocol [116]. Sensor IDs consist of one alphabetic letter (from A to P) followed by one numerical value (from 1 to 16); e.g., living room sensor has ID "A1" and bedroom sensor has ID "A2". Range of Marmitek sensors is 80 meters depending on local circumstances, such as PC monitors, old televisions

and fluorescent lights. Movement detection operates at day and night. These sensors also detect transition from dark to light and vice versa.

Locally-deployed X10 receiver collects sensor events at home. Movement sensors investigate presence of movements each 10 seconds, and send "On" events if movements occur (Table 5.25). They notify absence of movements 1 minute after last detected movement by sending "Off" event. Marmitek sensors use 2 AAA batteries for several months up to 1 year.

Table 5.25 Technical Movement Sensor Specifications

Technical Characteristic	Specifications
Power supply	Two AAA batteries
Motion sensing range	Up to 80m (dependently of local conditions)
Observation type	Boolean, "On" indicates movements, "Off" indicates no movements
Observation frequency	"On" events each 10s if movements occur, "Off" event 1 minute after last detected movement
Radio signal protocol	X10
Radio signal frequency	433.92 MHz
Radio signal range	Up to 30m free field, up to 20m through walls and ceilings
Operating temperature	From -10°C to +30°C
Dimensions	67x67x27mm

- **Wireless Contact Sensors**

Wireless Marmitek DS90 contact sensors detect object openings and closing (Fig. 5.39). These commercial sensors often identify window and door openings for house intrusion detection. Installing contact sensors on objects of daily living collects information on activities of daily living, such as following-up going out and coming back home by fixing contact sensors on main house entries, preparing meals by fixing contact sensors on fridge, microwave and oven, and wearing one's clothes by fixing contact sensor on wardrobe.



Fig. 5.39 Wireless Marmitek DS90 Contact Sensors

Table 5.26 Technical Contact Sensor Specifications

Technical Characteristic	Specifications
Power supply	Two AAA batteries
Observation type	Boolean, "Alert" indicates opening, "Normal" indicates closing
Observation frequency	Sending events if openings and closings occur
Radio signal protocol	X10
Radio signal frequency	433.92 MHz
Radio signal range	Up to 100m free field, up to 30m through walls and ceilings
Dimensions	44x86x20mm

Contact sensors consist of magnet contact and transmitter part [117]. Initial position requires attaching both parts to each other as close as possible. Opening associated object

causes disconnection of both parts and generates "Alert" event. Closing associated object re-connects both parts and generates "Normal" event.

Power supply consists of 2 AAA batteries (Table 5.26). These batteries last for several months up to 1 year. Locally-deployed X10 receiver collects generated sensor events. Sensor IDs are random combination of 6 alpha-numerical values; e.g., main door sensor has ID "C6F280".

- **Local Raspberry-Pi Gateway**

Raspberry-Pi is a small and affordable computer [118]. Users take advantage of its small size and reasonable performance for managing local sensor networks, smart devices and multimedia contents. Integrating this device in local sensor deployments allows to collect and transfer sensor events in real-time. Installed scripts and softwares enable remote control and continuous management of home sensor deployment.



Fig. 5.40 Raspberry-Pi V3 and CM19 X10 Receiver

Table 5.27 Technical Raspberry-Pi Specifications

Technical Characteristic	Specifications
Processor	Broadcom BCM2837B0, Cortex-A53 64-bit SoC @ 1.4 GHz
Memory	1GB LPDDR2 SDRAM
Connectivity	WLAN, Bluetooth, Ethernet, 4x USB
SD card	Micro SD format for loading operating system and data storage
Power supply	5V/2.5A DC via micro USB connector

Raspberry-Pi gateway is equipped with CM19 X10 receiver (Fig. 5.40). This receiver collects sensor events at home via X10 protocol and transmits them via USB connection [119]. Installing X10 software and configuring Python scripts allows to parse received events, identify sensor IDs, read event values and adapt JSON data format.

Additional Internet access point is essential to transmit sensor events in real-time. Raspberry-Pi gateways is equipped with Ethernet port for wired connections. It supports wireless connection to local WLAN networks. Embedded configuration file defines WIFI

access credentials. UbiGate component of UbiSMART implements Python scripts to manage Internet disconnections. Raspberry-pi gateway retains sensor events during Internet disconnections, and re-transfers them after Internet re-connection. Implemented scripts send continuous "KeepAlive" notifications to identify Internet disconnections.

Micro-SD card of Raspberry-PI supports installation of Linux operating system (Table 5.27). Control unit and internal memory execute required scripts with good performance. Power consumption is reasonable during months of non-interrupted functioning. Raspberry-Pi gateway accesses smart home devices for possible intervention, such as accessing smart television via Bluetooth and accessing social robots via WLAN.

- **NodeJS for Back-End and Front-End Development**

NodeJS is a JavaScript runtime environment [120]. JavaScript is main programming language of ChangeTracker. NodeJS implements data processing algorithms and change detection techniques (Listing 5.1). It manages communication with database and view layers. JavaScript code runs in dedicated application server Sails [121]. Sails enables execution in normal and debugging modes; i.e., normal execution in production server and debugging execution in development server. Debugging activates logging services for error investigation and correction. Sails enables execution and testing in real-time; i.e., during development phase.

```
//Views
service.index = function (params , res );
service.getIndexInformation = function (params , res , opt_cb );
service.toilet = function (params , res );
service.getToiletInformation = function (params , res , opt_cb );

//Data Processing Algorithms
function getDayMovementBlocks ( events );
function getDayAtHomeBlocks ( dayMovementBlocks );
function getDayActivityPeriods ( house , dayEvents , delta );
function getDayVisitBlocks ( dayActivityPeriods );

//Change Detection Techniques
function applyChangeDetectionAlgorithm ( data );
function getFirstPointAfterChange ( data , indexes );
function average ( data );
function standardDeviation ( values );
```

Listing 5.1 Main Function Prototypes of ChangeTracker

View layers include JavaScript, HTML and CSS codes (Listing 5.2). HTML defines view layouts, such as buttons, texts and graphs. CSS specifies component formats, such as colors, size and position. Embedding JavaScript in Front-End is essential to integrate dynamic features, such as loading house description "<%= houseDescription %>" from database through controller layer. Flotr2 is a JavaScript library for drawing dynamic HTML graphs [122]. Graphs show daily evolution of computed geriatric indicators and metrics. Flotr2 enables drawing of curves, points, lines and bars.

```
<!DOCTYPE html>
<style type="text/css">
  #toiletGraph {
    width : 1500px;
    height: 384px;
    margin: 8px auto;
  }
</style>
<script src="/servicesRepository/changetracker/js/flotr2.min
.js"></script>

<div class="container">
  

  <div class="text-center">
    <h1> Change Tracker </h1>
    <h3> <%= houseDescription %></h3>
  </div>
</div>
```

Listing 5.2 HTML, CSS and JavaScript Example

- **Waterline for Object Relational Mapping**

Waterline is an Object Relational Mapping (ORM) interface for NodeJS. This library intervenes between back-end functions and database queries. Waterline defines models representing main objects and their attributes, such as defining "event" object for sensor events with their date, house, sensor and value attributes (Listing 5.3). Full object description is required to correctly parse corresponding instances and store them in dedicated tables. Accessing database uses Waterline API for read and write operations, such as loading sensor event for given house "sails.models.event.find().where(conditions)".

```
module.exports = {
  attributes: {
    date: {type: 'datetime', required: true},
    house: {type: 'integer', required: true},
    sensor: {type: 'string', required: true},
    value: {type: 'string', required: true}
  }
};
```

Listing 5.3 Event Model Definition Script

Waterline supports creation of relational tables, their modification and their removal if required (Listing 5.4). Corresponding migration scripts are essential to follow-up table creations and modifications in time. Declared model attributes completely match created table columns, such as matching "event" model and migration scripts. Waterline supports dropping out tables or retrieving previous table versions.

```
exports.up = function(knex, Promise) {
  return knex.schema
    .createTable('event', function(table) {
      table.increments();
      table.timestamp('createdAt');
      table.timestamp('updatedAt');
      table.timestamp('date');
      table.integer('house');
      table.text('sensor');
      table.text('value');
    });
};
```

```
exports.down = function(knex, Promise) {  
  return knex.schema.dropTable('event');  
};
```

Listing 5.4 Event Table Migration Script

- **PostgreSQL for Data Storage**

PostgreSQL is a relational database [109]; i.e., objects and attributes have corresponding tables and columns. Accessing database requires administrator credentials. PostgreSQL does not only allow database access from controller layer, but also direct user access through terminal interface (Fig. 5.41). Classical "select", "update" and "delete" queries perform read and write operations, such as retrieving specific house sensor event and house description.

```
ubidb=# select * from event order by date desc limit 1;
 id |      createdAt      |      updatedAt      |      date      | house | sensor | value
-----+-----+-----+-----+-----+-----+-----
2915970 | 2018-07-31 10:44:26+00 | 2018-07-31 10:44:26+00 | 2018-07-31 10:43:40+00 | 42 | A1 | on
(1 row)

ubidb=# select id, "description" from house where id=42;
 id | description
-----+-----
 42 | House Citizen 42
(1 row)
```

Fig. 5.41 Event and House Table Query Examples

PostgreSQL database is consistent and reliable. It supports diverse data types, such as integers, strings, timestamps and booleans. Raw identifiers are unique for each table. Foreign keys define relationships between tables, such as linking "house" attribute in "event" table with corresponding identifier in "house" table. Concurrency rules manage multiple database access by prioritizing write on read operations for higher data integrity, and parallelizing read operations for lower execution time.

- **SensorML for Modeling Sensor Network**

Sensor Model Language (SensorML) describes sensor network, types and locations in XML format [92]. Main focus of SensorML is enhancing interoperability between heterogeneous sensor networks. Standardizing sensor models enables automatic recognition of sensing processes for correct data collection and analysis.

```
<sml:position>
  <gml:Point gml:id="stationLocation" srsName="http://
    www.opengis.net/def/crs/EPSSG/0/4326">
    <gml:coordinates>Room_livingRoom</gml:
      coordinates>
  </gml:Point>
</sml:position>
<sml:output name="MotionDetection">
  <sml:ObservationType name="TruthObservation">
    <swe:uom definition="http://sensorml.com/ont
      /swe/property/contact">Boolean</swe:uom>
  </sml:ObservationType>
</sml:output>
```

Listing 5.5 SensorML Movement Sensor Model

SensorML defines generic ontology for diverse sensor types and sensing processes, such as temperature, vibration, pressure and contact sensors. Defining sensor position and observation type is essential to identify received events and correctly parse them; e.g., Listing 5.5 specifies movement sensor located in "Living Room" and emitting "Boolean" events.

- **Observation and Measurement Data Format**

Observation and Measurement (O&M) standard defines common data format. Standardizing sensor event format enables unified data transmission independently from observation types and measurement values, such as movement and temperature sensors sending Boolean or numerical values. O&M specifies key observation attributes including feature of interest, observed property, result, procedure, phenomenon time and result time (Listing 5.6).

```
{
  "id": "Raspberry_Pi/b8:27:eb:80:c1:a6/
    MS13E_A1_46_Room_livingRoom/2018-04-06T13:06:11",
  "type": "TruthObservation",
  "phenomenonTime": {
    "instant": "2018-04-06T13:06:11+02:00"
  },
  "observedProperty": {
    "href": "http://sensorml.com/ont/swe/property/Motion"
  },
  "procedure": "MS13E_A1_46_Room_livingRoom",
  "featureOfInterest": {
    "href": "46"
  },
  "resultTime": "2018-04-06T13:06:11+02:00",
  "result": {
    "uom": "Boolean",
    "value": "on"
  }
}
```

Listing 5.6 O&M Movement Sensor Example

Feature of interest refers to observation concerns, such as deploying movement sensor in living room and deploying temperature sensor in bathroom. Observed property and procedure refer to corresponding sensor model and sensing process in SensorML ontology. Result contains observation value and type, such as Boolean "On" event or numerical "19" value. Phenomenon and result times differentiate between real-world time associated with result, and time when result is generated.

- **Message Queuing Telemetry Transport (MQTT)**

Message Queuing Telemetry Transport (MQTT) protocol controls data communication between local gateways and remote server [108]. MQTT is a publish-subscribe-based communication protocol (Listing 5.7). Pre-defined topics define communication channels, such as `"/sensor/event/<houseId>"` topic for sending sensor events, and `"/sensor/configuration/<houseId>"` for sending sensor configurations.

```
messages = {}
def main():
    client = mqtt.Client()
    client.on_connect = on_connect
    client.on_publish = on_publish
    client.on_message = on_message
def on_connect(client, userdata, flags, rc):
    print("CONNECTED")
    client.subscribe("a/b")
def on_publish(client, userdata, mid):
    print("SENT: EVENT %s" % messages.pop(mid))
def on_message(client, userdata, msg):
    print("RECEIVED: " + str(msg.payload))
```

Listing 5.7 MQTT Publish and Subscribe Implementation

Central broker manages client and server subscriptions and publications; e.g., local gateways publish sensor events on corresponding topic and remote server subscribes to same topic for sensor event reception. Quality of Service (QoS) levels define data delivery priorities, such as "0" level sends messages without checking their reception, "1" level demands reception acknowledgment, and "2" level guarantees data delivery only once.

- **Mail and SMS Notification Services**

Google Mail provides free API for sending mail notifications [110]. Mail notifications inform about detected changes in monitored health change indicators. Google API requires creation of Google Mail account. Simple Mail Transfer Protocol (SMTP) enables configuration of sender mail, receiver mail, subject and text (Listing 5.8). Users prefer mail notifications on a monthly basis informing about health status and possible changes.

```
//Mail Notifications
module.exports = function(senderEmail, receiverEmail,
  receiverSubject, receiverText) {
  smtpTransport.sendMail({
    from: senderEmail,
    to: receiverEmail,
    subject: receiverSubject,
    text: receiverText
  });
};

//SMS Notifications
module.exports = function(senderPhone, receiverPhone,
  receiverText) {
  var client = new twilio.RestClient();
  client.messages.create({
    body: receiverText,
    to: receiverPhone,
    from: senderPhone
  });
};
```

Listing 5.8 Google Mail and Twilio SMS Notification Implementation

Twilio provides chargeable service for sending SMS notifications [111]. Twilio account requires creation of new sender phone number and prior-activation of receiver phone numbers (Listing 5.8). Users receive SMS notifications from 2 to 10 days after change occurrence. This allows to confirm that detected changes really persist, early investigate their origin and take actions.

References

- [1] United Nations Population Division. United nations population division: World population prospects. *available as <https://esa.un.org/unpd/wpp/>*, 2018.
- [2] World Health Organization. Towards an age-friendly world. *preprint, available as <http://www.who.int/ageing/age-friendly-world/en/>*, 2018.
- [3] United States Census Bureau. United states census bureau: International data base. *available as <https://www.census.gov/programs-surveys/international-programs/about/idb.html>*, 2018.
- [4] Fanny Buckinx, Yves Rolland, Jean-Yves Reginster, Céline Ricour, Jean Petermans, and Olivier Bruyère. Burden of frailty in the elderly population: perspectives for a public health challenge. *Archives of Public Health*, 73(1):19, 2015.
- [5] Andrew Clegg, John Young, Steve Iliffe, Marcel Olde Rikkert, and Kenneth Rockwood. Frailty in elderly people. *The Lancet*, 381(9868):752–762, 2013.
- [6] World Health Organization. Dementia fact sheet n°362. *preprint, available as <https://web.archive.org/web/20150318030901/http://www.who.int/mediacentre/factsheets/fs362/en>*, 2018.
- [7] Philip D Sloane, Sheryl Zimmerman, Chirayath Suchindran, Peter Reed, Lily Wang, Malaz Boustani, and S Sudha. The public health impact of alzheimer’s disease, 2000–2050: potential implication of treatment advances. *Annual review of public health*, 2002.
- [8] Cleusa P Ferri, Martin Prince, Carol Brayne, Henry Brodaty, Laura Fratiglioni, Mary Ganguli, Kathleen Hall, Kazuo Hasegawa, Hugh Hendrie, Yueqin Huang, et al. Global prevalence of dementia: a delphi consensus study. *The lancet*, 366(9503):2112–2117, 2005.
- [9] J Lökk. Lack of information and access to advanced treatment for parkinson’s disease patients. *Journal of multidisciplinary healthcare*, 4:433, 2011.
- [10] AW Willis, M Schootman, BA Evanoff, JS Perlmutter, and BA Racette. Neurologist care in parkinson disease a utilization, outcomes, and survival study. *Neurology*, 77(9):851–857, 2011.
- [11] D Wilson, Sunny Consolvo, Ken Fishkin, and Matthai Philipose. In-home assessment of the activities of daily living of the elderly. In *Extended Abstracts of CHI 2005: Workshops-HCI Challenges in Health Assessment*, 2005.

- [12] Tracey Holsinger, Janie Deveau, Malaz Boustani, and John W Williams. Does this patient have dementia? *Jama*, 297(21), 2007.
- [13] Saxon Ridley. The recognition and early management of critical illness. *Annals of the Royal College of Surgeons of England*, 87(5):315, 2005.
- [14] Kenneth S Boockvar and Mark S Lachs. Predictive value of nonspecific symptoms for acute illness in nursing home residents. *Journal of the American Geriatrics Society*, 51(8):1111–1115, 2003.
- [15] Giovanni Acampora, Diane J Cook, Parisa Rashidi, and Athanasios V Vasilakos. A survey on ambient intelligence in healthcare. *Proceedings of the IEEE*, 101(12):2470–2494, 2013.
- [16] Marilyn Rantz, Marjorie Skubic, Steven Miller, and Jean Krampe. Using technology to enhance aging in place. In *International Conference on Smart Homes and Health Telematics*, pages 169–176. Springer, 2008.
- [17] Karen Dorman Marek and Marilyn J Rantz. Aging in place: A new model for long-term care. *Nursing administration quarterly*, 24(3):1–11, 2000.
- [18] Charith Perera, Rajiv Ranjan, Lizhe Wang, Samee U Khan, and Albert Y Zomaya. Big data privacy in the internet of things era. *IT Professional*, 17(3):32–39, 2015.
- [19] George Demiris, Marilyn J Rantz, Myra A Aud, Karen D Marek, Harry W Tyrer, Marjorie Skubic, and Ali A Hussam. Older adults’ attitudes towards and perceptions of ‘smart home’ technologies: a pilot study. *Medical informatics and the Internet in medicine*, 29(2):87–94, 2004.
- [20] Firas Kaddachi, Hamdi Aloulou, Bessam Abdulrazak, Philippe Fraise, and Mounir Mokhtari. Early and unobtrusive detection of possible health changes toward better translation of geriatric needs. *Pervasive and Mobile Computing*, 2018.
- [21] Firas Kaddachi, Hamdi Aloulou, Bessam Abdulrazak, Philippe Fraise, and Mounir Mokhtari. Long-term behavior change detection approach through objective technological observations toward better adaptation of services for elderly people. *Health and Technology*, 2018.
- [22] Firas Kaddachi, Hamdi Aloulou, Bessam Abdulrazak, Philippe Fraise, and Mounir Mokhtari. Technological approach for early and unobtrusive detection of possible health changes toward more effective treatment. *ICOST 2018*, 2018.
- [23] Firas Kaddachi, Hamdi Aloulou, Bessam Abdulrazak, Philippe Fraise, and Mounir Mokhtari. Unobtrusive technological approach for continuous behavior change detection toward better adaptation of clinical assessments and interventions for elderly people. *Enhanced Quality of Life and Smart Living. ICOST 2017.*, pages 21–33, 2017.
- [24] Firas Kaddachi, Hamdi Aloulou, Bessam Abdulrazak, Joaquim Bellmunt, Romain Endelin, Mounir Mokhtari, and Philippe Fraise. Technological approach for behavior change detection toward better adaptation of services for elderly people. *BIOSTEC 2017*, page 96, 2017.

- [25] Bonnie Kaplan and Kimberly D Harris-Salamone. Health it success and failure: recommendations from literature and an amia workshop. *Journal of the American Medical Informatics Association*, 16(3):291–299, 2009.
- [26] Richard Heeks. Health information systems: Failure, success and improvisation. *International journal of medical informatics*, 75(2):125–137, 2006.
- [27] É Tardieu, Rachid Mahmoudi, Jean-Luc Novella, Nadia Oubaya, Francois Blanchard, Damien Jolly, and Moustapha Drame. External validation of the short emergency geriatric assessment (sega) instrument on the safes cohort. *Geriatric et psychologie neuropsychiatrie du vieillissement*, 14(1):49–55, 2016.
- [28] Joseph R Cockrell and Marshal F Folstein. Mini-mental state examination. *Principles and practice of geriatric psychiatry*, pages 140–141, 2002.
- [29] Patricia A Parmelee and Ira R Katz. Geriatric depression scale. *Journal of the American Geriatrics Society*, 1990.
- [30] Pascale Barberger-Gateau, Daniel Commenges, Michèle Gagnon, Luc Letenneur, Claire Sauvel, and Jean-François Dartigues. Instrumental activities of daily living as a screening tool for cognitive impairment and dementia in elderly community dwellers. *Journal of the American Geriatrics Society*, 40(11):1129–1134, 1992.
- [31] S Lafont, P Barberger-Gateau, C Sourgen, and JF Dartigues. Relation entre performances cognitives globales et dépendance évaluée par la grille aggir. *Revue d'épidémiologie et de santé publique*, 47(1), 1999.
- [32] S Mathias, US Nayak, and Bernard Isaacs. Balance in elderly patients: the " get-up and go" test. *Archives of physical medicine and rehabilitation*, 67(6):387–389, 1986.
- [33] Bruno Vellas, Yves Guigoz, Philip J Garry, Fati Nourhashemi, David Bennahum, Sylvie Lauque, and Jean-Louis Albarede. The mini nutritional assessment (mna) and its use in grading the nutritional state of elderly patients. *Nutrition*, 15(2):116–122, 1999.
- [34] Barry Reisberg, Stefanie R Auer, and Isabel M Monteiro. Behavioral pathology in alzheimer's disease (behave-ad) rating scale. *International Psychogeriatrics*, 8(S3):301–308, 1997.
- [35] Jeffrey L Cummings, Michael Mega, K Gray, Susan Rosenberg-Thompson, Daniela Anne Carusi, and Jeffrey Gornbein. The neuropsychiatric inventory comprehensive assessment of psychopathology in dementia. *Neurology*, 44(12):2308–2308, 1994.
- [36] Languedoc Mutualite. Clinique beau soleil. *preprint, available as http://www.languedoc-mutualite.fr/Cliniques/Clinique-Beau-Soleil_374_.html*, 2018.
- [37] Ehpad d'Occagnes. Maison de retraite saint vincent de paul. *preprint, available as <https://www.facebook.com/Maison-de-Retraite-Saint-Vincent-de-Paul-Ehpad-dOccagnes-900630783327770/>*, 2018.

- [38] City4Age. Elderly-friendly city services for active and healthy aging. *available as <http://www.city4ageproject.eu/>*, 2018.
- [39] Vladimir Urosevic, Ana Kovacevic, Firas Kaddachi, and Milan Vukicevic. Temporal clustering for behavior variation and anomaly detection from data acquired through iot in smart cities. In *Recent Applications in Data Clustering*. IntechOpen, 2018.
- [40] Vladimir Urosevic, Ana Kovacevic, Firas Kaddachi, and Milan Vukicevic. Temporal clustering and anomaly detection in elderly friendly smart cities based on hidden markov models. *ICIST 2018*, 2018.
- [41] Longbing Cao. In-depth behavior understanding and use: the behavior informatics approach. *Information Sciences*, 180(17):3067–3085, 2010.
- [42] Edward O Wilson. *Sociobiology*. Harvard University Press, 2000.
- [43] Joanna Szwacka-Mokrzycka. Trends in consumer behaviour changes. overview of concepts. *Acta Scientiarum Polonorum. Oeconomia*, 14(3), 2015.
- [44] Lars Perner. *Consumer behaviour and marketing strategy*, 2008.
- [45] Jacqueline W Miller, Timothy S Naimi, Robert D Brewer, and Sherry Everett Jones. Binge drinking and associated health risk behaviors among high school students. *Pediatrics*, 119(1):76–85, 2007.
- [46] Hanna M Lavikainen, Tomi Lintonen, and Elise Kosunen. Sexual behavior and drinking style among teenagers: a population-based study in finland. *Health promotion international*, 24(2):108–119, 2009.
- [47] Jeanne Ellis Ormrod. *Educational Psychology: Pearson New International Edition: Developing Learners*. Pearson Higher Ed, 2013.
- [48] Irwin M Rosenstock. Historical origins of the health belief model. *Health Education & Behavior*, 2(4):328–335, 1974.
- [49] James O Prochaska and Charles C DiClemente. The transtheoretical approach. *Handbook of psychotherapy integration*, 2:147–171, 2005.
- [50] Ralf Schwarzer. Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. *Applied Psychology*, 57(1):1–29, 2008.
- [51] Thomas J Madden, Pamela Scholder Ellen, and Icek Ajzen. A comparison of the theory of planned behavior and the theory of reasoned action. *Personality and social psychology Bulletin*, 18(1):3–9, 1992.
- [52] Burrhus Frederic Skinner. *Verbal behavior*. BF Skinner Foundation, 2014.
- [53] Albert Bandura. *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall, Inc, 1986.
- [54] Albert Bandura and Richard H Walters. *Social learning theory*. 1977.

- [55] Edwin H Sutherland, Donald R Cressey, and David Luckenbill. The theory of differential association. *Deviance: a symbolic interactionist approach*. General Hall, Lanham, pages 64–68, 1995.
- [56] Teake P Ettema, Rose-Marie Dröes, Jacomine de Lange, Gideon J Mellenbergh, and Miel W Ribbe. Qualidem: development and evaluation of a dementia specific quality of life instrument—validation. *International journal of geriatric psychiatry*, 22(5):424–430, 2007.
- [57] Rebecca G Logsdon, Laura E Gibbons, Susan M McCurry, Linda Teri, et al. Quality of life in alzheimer’s disease: patient and caregiver reports. *Journal of Mental health and Aging*, 5:21–32, 1999.
- [58] Patrice Ratl, Elisabeth Jouvel, Gisèle Pickeringl, Laurent Donnarell, Louise Nguyenl, Micheline Michell, Françoise Capriz-Ribièrel, Sylvie Lefebvre-Chapirol, Frédérique Gauquelinl, and Sylvie Bonin-Guillaumel. Validation of an acute pain-behavior scale for older persons with inability to communicate verbally: Algoplus®. *European Journal of Pain*, 15(2):198–e1, 2011.
- [59] Sophie Pautex, François R Herrmann, Agnès Michon, Panteleimon Giannakopoulos, and Gabriel Gold. Psychometric properties of the doloplus-2 observational pain assessment scale and comparison to self-assessment in hospitalized elderly. *The Clinical journal of pain*, 23(9):774–779, 2007.
- [60] Jiska Cohen-Mansfield. Conceptualization of agitation: results based on the cohen-mansfield agitation inventory and the agitation behavior mapping instrument. *International Psychogeriatrics*, 8(S3):309–315, 1997.
- [61] Jules Rosen, Louis Burgio, Marcia Kollar, Michelle Cain, Mary Allison, Mary Fogleman, Mary Michael, and George S Zubenko. The pittsburgh agitation scale: a user-friendly instrument for rating agitation in dementia patients. *The American Journal of Geriatric Psychiatry*, 2(1):52–59, 1994.
- [62] Alan K Bourke, Jochen Klenk, Lars Schwickert, Kamiar Aminian, Espen AF Ihlen, Sabato Mellone, Jorunn L Helbostad, Lorenzo Chiari, and Clemens Becker. Fall detection algorithms for real-world falls harvested from lumbar sensors in the elderly population: A machine learning approach. In *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*, pages 3712–3715. IEEE, 2016.
- [63] Hamdi Aloulou, Mounir Mokhtari, Thibaut Tiberghien, Jit Biswas, and Philip Yap. An adaptable and flexible framework for assistive living of cognitively impaired people. *IEEE journal of biomedical and health informatics*, 18(1):353–360, 2014.
- [64] Hamdi Aloulou, Mounir Mokhtari, Thibaut Tiberghien, Jit Biswas, Clifton Phua, Jin Hong Kenneth Lin, and Philip Yap. Deployment of assistive living technology in a nursing home environment: methods and lessons learned. *BMC medical informatics and decision making*, 13(1):42, 2013.
- [65] Singtel. Monitor and watch you elderly family members’ daily activities with singtel’s smart home solutions. <https://www.singtelshop.com/smarthome-yuhua>, 2018.

- [66] SeniorHome. Eva est une plateforme logicielle qui fonctionne sur la base de capteurs repartis dans le domicile. <http://seniorhome.fr/>, 2018.
- [67] Phillippa Lally, Cornelia HM Van Jaarsveld, Henry WW Potts, and Jane Wardle. How are habits formed: Modelling habit formation in the real world. *European journal of social psychology*, 40(6):998–1009, 2010.
- [68] Matthew L Lee and Anind K Dey. Sensor-based observations of daily living for aging in place. *Personal and Ubiquitous Computing*, 19(1):27–43, 2015.
- [69] Gina Sprint, Diane J Cook, and Maureen Schmitter-Edgecombe. Unsupervised detection and analysis of changes in everyday physical activity data. *Journal of biomedical informatics*, 63:54–65, 2016.
- [70] Tamara L Hayes, Thomas Riley, Nora Mattek, Misha Pavel, and Jeffrey A Kaye. Sleep habits in mild cognitive impairment. *Alzheimer disease and associated disorders*, 28(2):145, 2014.
- [71] Jeffrey Kaye, Nora Mattek, Hiroko H Dodge, Ian Campbell, Tamara Hayes, Daniel Austin, William Hatt, Katherine Wild, Holly Jimison, and Michael Pavel. Unobtrusive measurement of daily computer use to detect mild cognitive impairment. *Alzheimer's & Dementia*, 10(1):10–17, 2014.
- [72] Tamara L Hayes, Nicole Larimer, Andre Adami, and Jeffrey A Kaye. Medication adherence in healthy elders: small cognitive changes make a big difference. *Journal of aging and health*, 2009.
- [73] Tamara L Hayes, Francena Abendroth, Andre Adami, Misha Pavel, Tracy A Zitzelberger, and Jeffrey A Kaye. Unobtrusive assessment of activity patterns associated with mild cognitive impairment. *Alzheimer's & Dementia*, 4(6):395–405, 2008.
- [74] Stephen M Thielke, Nora C Mattek, Tamara L Hayes, Hiroko H Dodge, Ana R Quiñones, Daniel Austin, Johanna Petersen, and Jeffrey A Kaye. Associations between observed in-home behaviors and self-reported low mood in community-dwelling older adults. *Journal of the American Geriatrics Society*, 62(4):685–689, 2014.
- [75] Johanna Petersen, Daniel Austin, Jon Yeargers, and Jeffrey Kaye. Unobtrusive phone monitoring as a novel measure of cognitive function. *Alzheimer's & Dementia: The Journal of the Alzheimer's Association*, 10(4):P366–P367, 2014.
- [76] Hiroko H Dodge, Jian Zhu, Nora C Mattek, Molly Bowman, Oscar Ybarra, Katherine V Wild, David A Loewenstein, and Jeffrey A Kaye. Web-enabled conversational interactions as a method to improve cognitive functions: Results of a 6-week randomized controlled trial. *Alzheimer's & dementia: translational research & clinical interventions*, 1(1), 2015.
- [77] Mark R Hodges, Ned L Kirsch, Mark W Newman, and Martha E Pollack. Automatic assessment of cognitive impairment through electronic observation of object usage. In *International Conference on Pervasive Computing*, pages 192–209. Springer, 2010.

- [78] SJ Allin, A Bharucha, John Zimmerman, D Wilson, MJ Robinson, Scott Stevens, H Wactlar, and CG Atkeson. Toward the automatic assessment of behavioral disturbances of dementia. 2003.
- [79] Marco Avvenuti, Christopher Baker, Janet Light, Dan Tulpan, and Alessio Vecchio. Non-intrusive patient monitoring of alzheimer's disease subjects using wireless sensor networks. In *Privacy, Security, Trust and the Management of e-Business, 2009. CONGRESS'09. World Congress on*, pages 161–165. IEEE, 2009.
- [80] EH Magill and Jesse Michael Blum. Personalised ambient monitoring: supporting mental health at home. *Advances in home care technologies: Results of the Match project*, pages 67–85, 2012.
- [81] Jesse Blum and Evan Magill. M-psychiatry: Sensor networks for psychiatric health monitoring. In *Proceedings of The 9th Annual Postgraduate Symposium The Convergence of Telecommunications, Networking and Broadcasting, Liverpool John Moores University*, pages 33–37. Citeseer, 2008.
- [82] Andrei Tolstikov, Jit Biswas, Chen-Khong Tham, and Philip Yap. Eating activity primitives detection—a step towards adl recognition. In *e-health Networking, Applications and Services, 2008. HealthCom 2008. 10th International Conference on*, pages 35–41. IEEE, 2008.
- [83] Yan Zhang, Georg Layher, Steffen Walter, Viktor Kessler, and Heiko Neumann. Visual confusion recognition in movement patterns from walking path and motion energy. In *International Conference on Smart Homes and Health Telematics*, pages 124–135. Springer, 2017.
- [84] Kalliopi Dalakleidi, Myriam Sarantea, and Konstantina S Nikita. A modified all-and-one classification algorithm combined with the bag-of-features model to address the food recognition task. In *HEALTHINF*, pages 284–290, 2017.
- [85] Akio Sashima, Mitsuru Kawamoto, and Koichi Kurumatani. A telecare system on smart watches that communicate with wireless bio sensors. In *HEALTHINF*, pages 429–434, 2017.
- [86] V Ramu Reddy, Anirban Dutta Choudhury, Srinivasan Jayaraman, Naveen Kumar Thokala, Parijat Deshpande, and Venkatesh Kaliaperumal. Perdmcs: Weighted fusion of ppg signal features for robust and efficient diabetes mellitus classification. In *HEALTHINF*, pages 553–560, 2017.
- [87] Haider Mshali, Tayeb Lemlouma, and Damien Magoni. Adaptive monitoring system for e-health smart homes. *Pervasive and Mobile Computing*, 43:1–19, 2018.
- [88] Jae Woong Lee, Seoungjae Cho, Sirui Liu, Kyungeun Cho, and Sumi Helal. Persim 3d: Context-driven simulation and modeling of human activities in smart spaces. *IEEE Transactions on Automation Science and Engineering*, 12(4):1243–1256, 2015.
- [89] Ya-Li Zheng, Xiao-Rong Ding, Carmen Chung Yan Poon, Benny Ping Lai Lo, Heye Zhang, Xiao-Lin Zhou, Guang-Zhong Yang, Ni Zhao, and Yuan-Ting Zhang. Unobtrusive sensing and wearable devices for health informatics. *IEEE Transactions on Biomedical Engineering*, 61(5):1538–1554, 2014.

- [90] Marilyn J Rantz, Karen Dorman Marek, and Mary Zwygart-Stauffacher. The future of long-term care for the chronically ill. *Nursing Administration Quarterly*, 25(1):51–58, 2000.
- [91] Andreas K Triantafyllidis, Carmelo Velardo, Dario Salvi, Syed Ahmar Shah, Vassilis G Koutkias, and Lionel Tarassenko. A survey of mobile phone sensing, self-reporting, and social sharing for pervasive healthcare. *IEEE journal of biomedical and health informatics*, 21(1):218–227, 2017.
- [92] OGC. Sensor model language. *preprint, available as <http://www.opengeospatial.org/standards/sensorml>*, 2018.
- [93] International Organization for Standardization. Geographic information - observations and measurements. *preprint, available as <https://www.iso.org/standard/32574.html>*, 2018.
- [94] Wayne A Taylor. Change-point analysis: a powerful new tool for detecting changes. *preprint, available as <http://www.variation.com/cpa/tech/changepoint.html>*, 2000.
- [95] Michèle Basseville. Statistical methods for change detection. *Control Systems, Robotics and Automation—Volume XVI: Fault Analysis and Control*, page 130, 2009.
- [96] Benoit Mesnil and Pierre Petitgas. Detection of changes in time-series of indicators using cusum control charts. *Aquatic Living Resources*, 22(2):187–192, 2009.
- [97] J Martin Bland and Douglas G Altman. Comparing methods of measurement: why plotting difference against standard method is misleading. *The lancet*, 346(8982):1085–1087, 1995.
- [98] Rebecca Killick, Paul Fearnhead, and Idris A Eckley. Optimal detection of change-points with a linear computational cost. *Journal of the American Statistical Association*, 107(500):1590–1598, 2012.
- [99] Kevin P Murphy. Naive bayes classifiers. *University of British Columbia*, 18, 2006.
- [100] Paul Fearnhead. Exact and efficient bayesian inference for multiple changepoint problems. *Statistics and computing*, 16(2):203–213, 2006.
- [101] Shohei Hido, Yuta Tsuboi, Hisashi Kashima, Masashi Sugiyama, and Takafumi Kanamori. Statistical outlier detection using direct density ratio estimation. *Knowledge and information systems*, 26(2):309–336, 2011.
- [102] Junshui Ma and Simon Perkins. Time-series novelty detection using one-class support vector machines. In *Neural Networks, 2003. Proceedings of the International Joint Conference on*, volume 3, pages 1741–1745. IEEE, 2003.
- [103] Delbert Dueck. *Affinity propagation: clustering data by passing messages*. Citeseer, 2009.
- [104] David Arthur and Sergei Vassilvitskii. k-means++: The advantages of careful seeding. In *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, pages 1027–1035. Society for Industrial and Applied Mathematics, 2007.

- [105] Dorin Comaniciu and Peter Meer. Mean shift: A robust approach toward feature space analysis. *IEEE Transactions on pattern analysis and machine intelligence*, 24(5):603–619, 2002.
- [106] Johannes Ledolter and Randy Kardon. Detecting the progression of eye disease: Cusum charts for assessing the visual field and retinal nerve fiber layer thickness. *Translational vision science & technology*, 2(6):2–2, 2013.
- [107] Golam Kibria. Cumulative sum and exponentially weighted moving average control charts. *preprint, available as <http://www2.fiu.edu/~kibriag/Stat5666/Handout/Chapter99.pdf>*, 2016.
- [108] MQTT. Mqtt connectivity protocol. *preprint, available as <http://mqtt.org/>*, 2018.
- [109] PostgreSQL. Postgresql: open source relational database. *preprint, available as <https://www.postgresql.org/>*, 2018.
- [110] Google. Gmail api: Sending email. *preprint, available as <https://developers.google.com/gmail/api/guides/sending>*, 2018.
- [111] Twilio. Twilio: Connect the world with the leading platform for voice, sms, and video. *preprint, available as <https://www.twilio.com/>*, 2018.
- [112] Joaquim Bellmunt, Mounir Mokhtari, Bessam Abdulzarak, and Hamdi Aloulou. Agile framework for rapid deployment in ambient assisted living environments. In *Proceedings of the 18th International Conference on Information Integration and Web-based Applications and Services*, pages 410–413. ACM, 2016.
- [113] Romain Endelin. *Mécanisme d’optimisation du raisonnement pour l’actimétrie: application à l’assistance ambiante pour les personnes âgées*. PhD thesis, Université Montpellier, 2016.
- [114] Montpellier Mediterranee Metropole. Montpellier mediterranee metropole. *preprint, available as <http://www.montpellier3m.fr/>*, 2018.
- [115] ETAPE. Pole autonomie sante. *preprint, available as <http://pole-autonomie-sante.org/>*, 2018.
- [116] Marmitek. Ms13e wireless motion sensor. *available as https://www.keene.co.uk/pages/downloads/dnl_files/pdfs/MS13Ei.pdf*, 2018.
- [117] Marmitek. Ds90 door/window sensor. *available as https://www.keene.co.uk/pages/downloads/dnl_files/pdfs/DS90i.pdf*, 2018.
- [118] Raspberry Pi. Raspberry pi: Small and affordable computer. *preprint, available as <https://www.raspberrypi.org/>*, 2018.
- [119] Authinx. Cm19a usb pc transceiver. *preprint, available as <http://www.authinx.com/manuals/X10/CM19A.pdf>*, 2018.
- [120] Node.js. Node.js: Javascript runtime. *preprint, available as <https://nodejs.org/en/>*, 2018.

-
- [121] Sails. Sails makes it easy to build custom, enterprise-grade node.js apps. *preprint, available as <https://sailsjs.com/>*, 2018.
- [122] Humble Software. Flotr2. *preprint, available as <http://www.humblesoftware.com/flotr2/>*, 2018.