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Moustafa Fayad

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Health care platform development based on multimedia sensors

Thèse de doctorat de Université de Paris
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*To my dearest ones,
in gratitude,
for their love and sacrifices:
my family.*

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Résumé étendu

Introduction

Le monde est confronté à des changements démographiques importants à une échelle sans précédent. Les personnes âgées constituent le segment de la population mondiale qui augmente le plus rapidement. L'Organisation mondiale de la santé (OMS) estime que le nombre de personnes âgées de plus de 60 ans passera de 605 millions à 2 milliards, ce qui correspond à une augmentation de 11% à 22% dans la population mondiale. Une étude suggère que la population âgée de l'Europe devrait augmenter rapidement de 58 millions entre 2004 et 2050. D'ici 2050, le nombre de personnes âgées de 65 ans et plus aux États-Unis devrait atteindre 83,7 millions, soit presque le double de la population de 43,1 millions en 2012. On prévoit qu'elle sera de 487 millions en Chine, soit près de 35% de la population totale de la Chine. En France, le taux de vieillissement continue d'augmenter de manière significative. Selon l'Insee, en 2050, 2,5 millions de personnes âgées perdront leur autonomie (15,3% des 60 ans et plus). Ces statistiques montrent que le vieillissement dans les pays occidentaux est une évidence. Ainsi, le nombre de personnes âgées fragiles et dépendantes augmenterait. La fragilité se caractérise par des limitations fonctionnelles et un déclin des capacités d'adaptation, ce qui engendre un besoin d'aide pour effectuer les activités quotidiennes et nécessite un suivi régulier.

Selon l'OMS, le vieillissement se caractérise par une détérioration progressive des capacités physiques et mentales. Ce changement structurel et fonctionnel entraîne souvent une perte d'autonomie et des maladies chroniques (diabète, Alzheimer, maladies cardiovasculaires, pathologie, etc.). Avec le temps, il limite considérablement l'autonomie et augmente les risques d'accidents domestiques. Parmi les risques inhérents aux personnes âgées, la chute reste la plus critique et la plus problématique. Plusieurs facteurs augmentent le risque de chute : (a) l'état de santé de la personne (i.e., détérioration de la condition physique, etc.), (b) l'environnement (obstacle, faible luminosité, logement mal adapté, etc.) ou (c) comportements (abus d'alcool, oubli d'utiliser un appareil fonctionnel, etc.). Les chutes engendrent des conséquences graves (fractures, perte de confiance en soi, voire décès). Chaque année, environ 28 à 35% des personnes de plus de 65 ans sont victimes de chutes et 32 à 42% de plus de 70 ans. Selon la santé publique en France, chaque année, 13 des personnes âgées chutent accidentellement, dont 2/3 des chutes surviennent à domicile. Les chutes accidentelles causent la mort de plus de 9 300 personnes âgées chaque

année et l'hospitalisation d'environ 76 000 personnes pour des fractures du col du fémur. Ainsi, les chutes augmentent considérablement la mortalité et la morbidité. Cependant, une intervention rapide après une chute réduit la possibilité d'hospitalisation de 26% et de décès de plus de 80%.

Au-delà des conséquences traumatisantes, les chutes ont également un impact sur la santé psychosociale et les complications financières sur la famille et la société. L'impact psychosocial se traduit par une perte de confiance en soi, une perte de mobilité et un appauvrissement de la vie sociale jusqu'à l'isolement complet. Être immobilisé au sol sans aide pendant longtemps aggrave les conséquences. Cette situation post-chute se produit si la personne âgée ne peut pas se tenir debout seule et passe plus d'une heure au sol sans soutien. Ainsi, elle correspond à plus de 50% des cas et augmente le risque de décès de 50% dans les 6 mois. Chaque année, les coûts des chutes sont estimés à plus de 25 milliards de dollars en Europe et à plus de 50 milliards de dollars aux USA. Après une chute, la situation réelle des personnes âgées tombées devient plus vulnérable et souvent animées par des sentiments dépressifs. Le développement de systèmes technologiques capables à même d'aider au maintien des personnes âgées à domicile tout en leur offrant des services innovants comme le monitoring temps-réel est devenu une nécessité sociale et économique. D'autant plus que les coûts socio-économiques afférents sont très importants. En effet, les améliorations technologiques ont rendu disponibles des appareils minuscules et très efficaces capables de collecter de nombreuses données liées à la santé des personnes âgées. Ces avancées conduisent à développer des systèmes de santé performants au service des personnes âgées, comprenant plusieurs appareils connectés collectant différents types de données (Vidéos, images, données scalaires, etc.). De plus, les critères de sélection des appareils dans ces systèmes incluent le coût, la zone de travail, la précision, la confidentialité et la conformabilité des personnes âgées. Dans le contexte du vieillissement et de la technologie, nous sommes confrontés à une demande croissante pour la prise en charge des personnes âgées vulnérables. Pour cela, cette thèse est venue consolider scientifiquement le système de surveillance des personnes âgées, nommé *Family Heroes*, qui permet la détection, l'alerte, et la prise en charge de la personne surveillée dans une posture d'inconfort. Ainsi, *Family Heroes* renforce le maintien à domicile des personnes âgées tout en respectant leur souhait le plus cher de conserver leur liberté en vieillissant à la maison. Nous nous sommes concentrés dans cette thèse sur deux aspects fondamentaux : (a) la fiabilité et la sécurité du système *Family Heroes* et (b) la détection automatique des chutes.

Problématique

Les systèmes de santé sont des systèmes critiques en raison de la sensibilité des données qu'ils manipulent mais également ils gagnent en complexité car : (a) ils collectent des données à partir de plusieurs capteurs hétérogènes et (b) le fait que les données capturées restent très sensibles et pourraient être critiques dans une certaine mesure. Pour cela, la mise en œuvre de ce type de système soulève plusieurs problèmes de recherche. Nous nous sommes intéressés dans cette thèse aux 2 problématiques suivantes :

- **Fiabilité et sécurité** : Le développement de systèmes liés à la santé des personnes âgées est un problème complexe et interpersonnel. Il est essentiel de bien définir le problème à résoudre et de le mettre en perspective avec la solution envisagée. Cette approche renforce la relation entre le monde conceptuel et le monde réel. En effet, la fiabilité et la sécurité restent des exigences fondamentales pour le développement de ces systèmes à travers l'analyse, la modélisation et la vérification. L'analyse et la modélisation permettent d'identifier une définition et une caractérisation complète du système, tandis que la vérification formelle assure qu'il est conforme à ses spécifications. Ces 3 étapes fondamentales du processus de développement permettent d'augmenter la qualité du système tout en respectant les exigences du système critique et en évitant toute erreur pouvant impacter la vie des personnes.
- **Détection automatique précise des chutes** : l'étape critique des algorithmes de détection des chutes consiste à mesurer les paramètres pertinents. Différents types de capteurs intelligents permettent l'acquisition de données essentielles. On peut les classer en (1) capteurs corporels (accéléromètres, gyroscopes, magnétomètres, RFID) et (2) capteurs externes (piézoélectrique, microphone, infrarouge passif, caméra). Les performances des capteurs portables sont influencées par la cible, leur emplacement sur le corps de la cible et le fait qu'ils soient ou non portés à tout moment. Ce dernier peut être compliqué à utiliser pendant la nuit. La caméra est le capteur le plus utilisé et le plus attractif par les chercheurs pour détecter les chutes à domicile ou dans les hôpitaux et maisons de retraite pour personnes âgées dépendantes en raison de ses performances. Toutefois, ce capteur est intrusif dans le sens où il ne respecte pas l'intimité des personnes surveillées. Une solution possible à ce problème est l'utilisation de **capteurs de profondeur** où l'information récoltée est sous la forme de données sur la forme (i.e., squelette) de la personne surveillée. Ainsi, son intimité est respectée et par conséquent l'acceptabilité de ce type de dispositif est augmentée. Pour cette raison, nous avons utilisé le capteur Microsoft Kinect, développé dans le contexte de jeux interactifs, où l'information récoltée est sous la forme de données 3D sur le squelette de la personne surveillée. Nous utilisons de tels appareils pour détecter automatiquement les chutes.

Contributions

Pour la problématique de la fiabilité et la sécurité de notre système *Family Heroes*, nous avons proposé une méthodologie combinant la méthode CATWOE et des notions UML pour analyser et modéliser notre système. Tout d'abord, nous avons montré les étapes pour prendre en compte efficacement les exigences et les contraintes du système dans le processus de développement. Ainsi, nous avons utilisé les concepts MARTE pour faire face aux contraintes de temps dans la phase de modélisation. Ensuite, pour assurer la fiabilité de notre système, nous avons proposé une approche de vérification formelle basée sur les modèles UML/MARTE présentés dans l'étape de modélisation. Enfin, nous avons spécifié ces modèles avec des automates temporisés et déployé le model checker

UPPAAL pour spécifier et vérifier les propriétés temporelles.

Pour assurer la sécurité de notre système, nous avons présenté une approche formelle pour traiter les problèmes de cyber-attaques qui peuvent survenir dans le système *Family Heroes*. Ainsi, nous avons défini des scénarios de cyber-attaques liés à ce contexte et proposé de reconfigurer notre système pour faire face aux cyber-attaques. De plus, une vérification formelle a été proposée pour s'assurer de la fiabilité de la reconfiguration proposée du système.

Pour la détection automatique des chutes, nous avons utilisé le capteur multimédia Kinect. Nous avons proposé une nouvelle approche basée sur des seuils qui analyse la variation des angles du haut du corps pendant le cycle de mouvement et d'inactivité de la personne au sol. De plus, nous avons proposé un nouveau modèle léger basé sur Deep Learning LSTM utilisant des caractéristiques géométriques et de pixels. Ce modèle léger est conçu pour fonctionner sur des appareils limités comme ceux de type Raspberry Pi. Les résultats préliminaires sont très prometteurs.

Organisation du manuscrit

Chapitre 2 est dédié aux différents éléments de recherche afférents à ma thèse. Nous exposons les tendances des systèmes qui répondent aux besoins des personnes âgées en matière de sécurité et de santé. Notre état de l'art est plus un panorama technologique, une inspiration et une comparaison destinés à la proposition de notre système *Family Heroes*. Cette analyse nous a permis d'estimer l'importance d'offrir des systèmes de soutien à domicile fiables et à faible coût qui soutiennent la sécurité, la santé et les besoins sociaux.

Puis, nous décrivons les 3 étapes clés (Analyse, modélisation et vérification formelle) et les outils (CATWOE, UML, MARTE et UPPAAL) utilisés pour assurer le bon fonctionnement de notre système critique. Dans la troisième partie, nous décrivons la caractérisation et les facteurs de risque de l'événement de chute. Nous comparons également les différents capteurs utilisés dans les approches de détection de chute. Les inconvénients et avantages de chaque catégorie nous ont conduit à justifier l'intérêt d'utiliser la caméra Kinect dans notre solution. Enfin, nous détaillons les 5 étapes d'une approche basée sur Kinect pour la détection des chutes, ainsi que les mesures de performance pour évaluer une approche.

Dans le **chapitre 3**, nous présentons *Family Heroes* et nos contributions liées à sa fiabilité et sa sécurité. Nous montrons l'application de CAWTOE. Cette démarche d'analyse nous a permis d'identifier les parties prenantes en traitant toutes les nuances, les dimensions et les informations qui composent la situation problématique et les différentes perspectives. Puis, nous détaillons la modélisation de *Family Heroes* en déployant des diagrammes UML (cas d'utilisation, composants et, séquence) et les contraintes temporelles, en exploitant le profile MARTE dans le diagramme de séquence. Ensuite, nous présentons la modélisation du comportement du *Family Heroes* avec un réseau d'automates temporisés. De plus, nous avons vérifiés formellement les propriétés (état de blocage, durée

d'envoi d'alerte au serveur, la gestion d'alerte). La variété des technologies connectées du système Family Heroes l'expose à la zone de risque de cybersécurité. Nous montrons notre approche (modélisation et vérification formelle) qui consiste à concevoir un système à architecture reconfigurable. C'est à dire notre architecture système doit garantir le bon fonctionnement des services (envoi d'alerte, prise en charge) en basculant vers une configuration de secours en cas de cyber-attaque. La vérification formelle des propriétés définies lors de la modélisation démontre le bien-fondé de nos approches.

Chapitre 4 détaillera nos travaux sur la détection automatique de chute à l'aide de la Kinect. Nous commençons par l'approche basée sur des seuils utilisant des caractéristiques géométriques. Nous analysons la variation des angles du haut du corps pendant les phases (pré-chute et critique) et l'inactivité en phase pot-chute. Puis, Nous détaillons notre nouveau modèle léger fondé sur Deep Learning LSTM utilisant des caractéristiques géométriques et de pixels. Ce modèle léger est conçu pour fonctionner sur des appareils limités comme ceux de Raspberry Pi. Les résultats montrent que les caractéristiques géométriques sont pertinentes pour détecter une chute, car elles permettent une identification correcte des mouvements humains dans l'espace 3D.

Dans le **chapitre 5**, nous terminons par une conclusion qui résume nos travaux ainsi que les perspectives envisagées à court et à long terme de notre travail de thèse.

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Chapter 1

Introduction

1.1 Context

The world is facing massive demographic changes on an unprecedented scale. Elder people are the fastest increasing segment of the world's population [60]. The World Health Organization (WHO) estimates that the number of seniors over 60 years old will increase from 605 million to 2 billion, which corresponds to an augmentation of 11% to 22% in the global community [4] (2). Figure 1.1 shows the projected evolution of the population aged 60 and over between 1990 and 2100 in the world. A study suggests that Europe's elderly population is expected to grow rapidly by 58 million between 2004 and 2050 [33]. By 2050, the number of people aged 65 and more in the United States is projected to reach 83.7 million, nearly doubling the population of 43.1 million in 2012 [106]. It is anticipated to be 487 million in China, or nearly 35% of China's total population [83]. In France, the rate of aging continues to increase significantly [45]. According to INSEE, in 2050, 2.5 million elderly people will lose autonomy (15.3% of those aged 60 or more) [80]. These statistics show that aging in Western countries is a given. Thus, the number of frail and dependent older adults would grow. Frailty is characterized by functional limitations and a decline in adjustment skills. Likewise, the dependent corresponds to those who need help to carry out daily activities and require regular monitoring. In France, dependent elderly people represent 8% of the population [6].

According to the WHO, aging is characterized by a gradual deterioration in physical and mental skills. This structural and functional change often leads to a loss of autonomy and chronic diseases (diabetes, Alzheimer's, cardiovascular disease, pathology, etc.) (i.e., Figure 1.1). Over time, they considerably limit the autonomy and increase the risk of home accidents. Among the risks inherent in the elderly, falling remains the most critical and the most problematic [25]. Several factors increase the risk of falls: (a) the person's state of health (i.e., deterioration of the physical condition, etc.), (b) the environment (obstacle, low light, poorly adapted housing, etc.) or (c) behaviors (alcohol abuse, forgets to use an assistive device, etc.). Falls generate serious consequences (fractures, loss of self-confidence, even death). Every year around 28-35% of people over 65 are victims of falls and 32-42% over 70 [105]. According

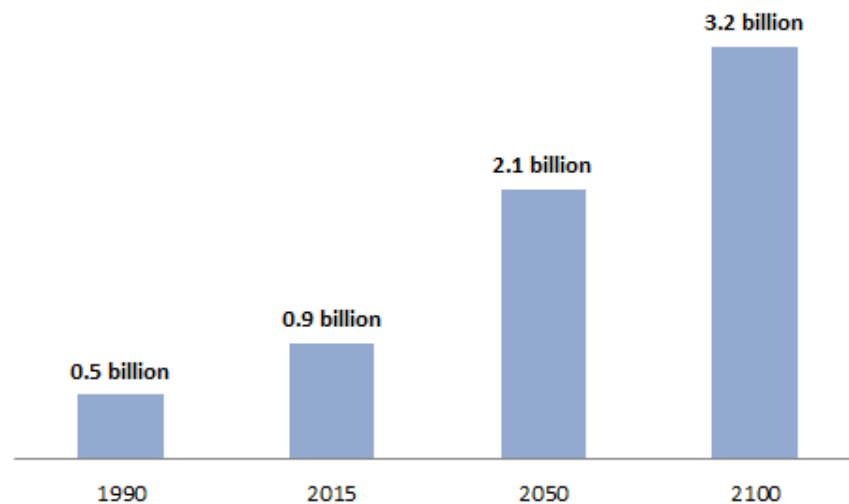


Figure 1.1: Projections of the population aged 60 and over in the world. Source the United Nations site.

to public health in France, every year 1/3 elder adult falls accidentally, of which 2/3 of falls occur at home. Accidental falls cause the death of more than 9,300 seniors each year and the hospitalization of 76,000 people for femoral neck fractures [8]. Therefore, falls dramatically increase mortality and morbidity. However, rapid intervention after a fall reduces the possibility of hospitalization by 26% and death by more than 80% [49].

Beyond the traumatic consequences, falls also impact the psychosocial health and financial situation of family and society. The psychosocial impact results in loss of self-confidence, loss of mobility, and an impoverishment of one's social life to the point of complete isolation. Being immobilized on the ground unaided for a long time worsens the consequences. This post-fall situation occurs if the elder adult cannot stand alone and spends more than an hour on the ground without support [52, 121]. Thus, it corresponds to more than 50% of cases [109, 143] and increases the risk of death by 50% within 6 months [43]. Each year, the costs of falls are estimated at over \$ 25 billion in Europe [141] and over \$ 50 billion in the USA [5]. After a fall, the actual situation of the fallen elderly becomes more vulnerable and often subject to depressive feelings. The development of equilibrated technological systems adapted to the needs of seniors has now become a necessity.

In recent years, socio-economic costs have triggered new research and technologies, both scientific and healthy, to age well and mitigate the severe consequences after a posture of discomfort. Indeed, technological improvements have made available tiny and highly efficient devices capable of remove much data related to the health of the elderly. These advances lead to the development of efficient health systems serving the elderly, comprising several connected devices collecting different data types (Videos, images, scalars, etc.). In addition, the criteria for selecting devices in these systems include cost, working area, accuracy, privacy, and elder conformability.

In the context of aging and technology, we are facing an increasing demand for the care of vulnerable seniors. For this, my thesis falls within the health care system entitled Family Heroes, which allows the detection, alert, and care of the monitored person in a posture of discomfort. Family Heroes strengthens keeping the elderly at home while

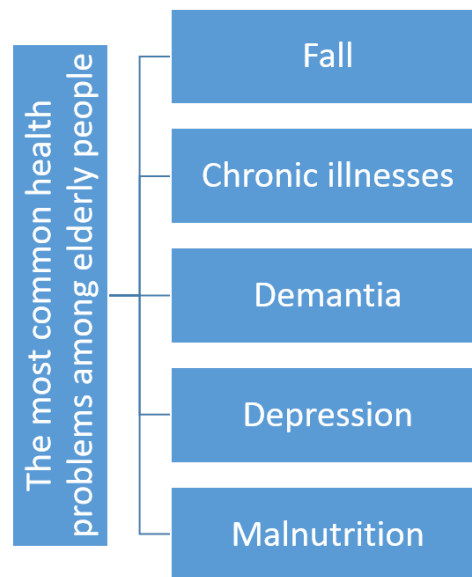


Figure 1.2: The most common health issues in the elderly.

respecting their dearest wish to maintain their freedom as they age at home. We have focused in this thesis on two fundamental aspects: (a) the reliability and safety of the Family Heroes system and (b) the automatic fall detection.

1.2 Problematic

Healthcare systems are critical and gain in complexity because: (a) they collect data from multiple heterogeneous sensors and (b) the fact that the data captured remains very sensitive and could be critical to some extent. For this, the implementation of this type of system raises several research issues. We are interested in the following 2 issues:

- **Reliability and security:** The development of systems related to the health of the elderly is a complex and interpersonal problem. It is essential to clearly define the problem to be solved and to put it in perspective with the envisaged solution. This approach strengthens the relationship between the conceptual world and the real world. Indeed, reliability and security remain fundamental requirements for developing these systems through analysis, modeling, and verification. Analysis and modeling identify a complete definition and characterization of the system, while formal verification ensures that it conforms to its specifications. These 3 fundamental steps in the development process make it possible to increase the system's quality while respecting the requirements of the critical system and avoiding any error that could impact people's lives.
- **Accurate Automatic Fall Detection:** The critical step in fall detection algorithms is to measure relevant parameters. Different types of smart sensors enable the acquisition of essential data. We can classify them into (1) body sensors (accelerometers, gyroscopes, magnetometers, RFID) and (2) external sensors (piezoelec-

tric, microphone, passive infrared, a camera). Wearable sensors' performance is influenced by the target, their location on the target's body, and whether or not they are worn at all times. The latter can be complicated at night. The camera is the most widely used and attractive sensor for researchers to detect falls at home or in hospitals and nursing homes for the dependent elderly. On the other hand, the elderly are willing to use robust and comfortable devices that are non-stigmatizing. These preferences are guaranteed by Microsoft Kinect technology which respects their privacy. The Kinect provides 3D information on its skeleton rather than raw video data. We use such devices to detect falls automatically.

1.3 Contributions

In the previous sections, we have generally mentioned the challenges to be resolved in my thesis. Our first focus was on reliability and safety, highly recommended for our health care system. Secondly, we were interested in automatic fall detection.

More specifically, we have proposed a methodology combining the CATWOE method and UML notions to analyze and model our system. We have shown the steps to take to consider system requirements and constraints in the effective process development. Thus, we used the MARTE concepts to cope with the time constraints in the modeling stage. Then, to ensure the reliability of our system, we proposed a formal verification approach based on UML / MARTE models presented in the modeling step. We specified these models with timed automata and deployed the UPPAAL model checker to specify and verify the temporal properties.

To ensure the security of our system, we have presented a formal approach to deal with the issues of cyber-attacks that may arise in the Family Heroes system. Thus, we have defined cyber-attack scenarios related to this context and proposed to reconfigure our system to face cyber-attacks. In addition, formal verification has been proposed to ensure the reliability of the proposed reconfiguration of the system.

For automatic fall detection, we used Kinect technology multimedia sensor. We have proposed a new threshold-based approach that analyzes the variation in upper body angles during the person's cycle of motion and inactivity on the ground. In addition, we have proposed a new lightweight model based on Deep Learning LSTM using geometric and pixel features. This lightweight model is targeted to run on limited devices like Raspberry Pi ones. The preliminary results are very promising.

1.4 Structure of manuscript

The remainder of this manuscript is organized as follows:

- **Chapter 2** is dedicated to the different research elements related to our thesis. We showcase trends in systems that meet the safety and health needs of older people. Our state of the art is more of a technological

panorama, an inspiration, and a comparison intended for the proposition of our Family Heroes system. This analysis allowed us to estimate the importance of providing reliable and low-cost health care systems that support safety, health, and social needs.

Then, we describe the 3 key steps (Analysis, modeling, and formal verification) and the tools (CATWOE, UML, MARTE, and UPPAAL) used to ensure the proper functioning of our critical system. In the third part, we describe the characterization and risk factors of the fall event. We also compare the different sensors used in fall detection approaches. The disadvantages and advantages of each category led us to justify using the Kinect camera in our solution. Finally, we detail the 5 steps of a Kinect-based approach for the detection of falls and the performance measures to evaluate an approach.

- In **Chapter 3**, we present Family Heroes and our contributions to its reliability and security. First, we show the application of CAWTOE. This analytical approach allowed us to identify the stakeholders by dealing with all the nuances, dimensions, and information that make up the problematic situation and the different perspectives. Then, we detail the modeling of Family Heroes by deploying UML diagrams (use case, components and, sequence) and time constraints by exploiting the MARTE profile in the sequence diagram. Next, we present the modeling of the behavior of Family Heroes with a network of timed automata. In addition, we formally checked the properties (blocking state, duration of the alert to the server, alert management). The variety of connected technologies of the Family Heroes system exposes it to the cybersecurity risk zone. Finally, we show our approach (modeling and formal verification) to design a system with a reconfigurable architecture. Indeed, our system architecture must guarantee the proper functioning of the services (sending the alert, support) by switching to an alternative configuration in the event of a cyber attack. The formal verification of the properties defined during the modeling demonstrates the validity of our approaches.
- **Chapter 4** will detail our work on automatic fall detection using the Kinect. We start with the threshold-based approach using geometric characteristics. We analyze the variation in the upper body angles during the phases (pre-fall and critical) and inactivity in the post-fall phase. Then, we detail our new lightweight model based on Deep Learning LSTM using geometric and pixel features. This lightweight model is designed to work on limited devices like the Raspberry Pi. The results show that geometric features are relevant for detecting a fall, as they allow correct identification of human movements in 3D space.
- In **Chapter 5**, we end with a conclusion that summarizes our work and the perspectives envisaged in the short, medium, and long term of our thesis work.

Chapter 2

Background

In this Chapter, we will expose the trending systems that address the needs of seniors related to security and health. Note that the presentation below of these systems is more of a technological panorama, inspiration, and comparison intended for the proposal of our Family Heroes system.

Then, we describe the 3 key steps and the tools used to ensure the correct operation of the critical system. Next, we describe the characterization of the fall event. We also compare the different sensors used in fall detection approaches. Finally, we will also explain the critical steps of a Kinect-based approach to fall detection. Thus, the performance metrics used to evaluate an approach.

2.1 Health care monitoring system

2.1.1 Introduction

The technological revolution, digital and on-board electronics, has opened up essential perspectives for researchers in the health and safety of vulnerable seniors. These technologies increasingly offer surveillance, alert, prevention, and support services. They promote aging well and staying at home as long as possible. Indeed, health care monitoring systems rely on the interconnection of digital and physical devices to collect and process relevant data remotely. They ensure the rapid intervention of family members and health professionals in critical situations of the elderly. Their fundamental advantage is that seniors are allowed to continue their lives in safety and freedom. Seniors will no longer need to travel to health professionals for specific medical examinations such as heart rate and blood sugar monitoring, etc. In general, these systems provide the functionality of monitoring vital signals such as heart rate, muscle activity, blood pressure, body temperature, respiratory rate, and detecting falls [110].

2.1.2 The two major obstacles

Large high-tech companies were the first to produce wearable systems for the elderly. Samsung was the first to market a connected watch, MobileHelp Smart, which monitors seniors' heart rate and movement. We also mention Apple with their innovative system, Apple Watch 4, which sends text messages to emergency contacts in abnormal situations. In addition, it detects falls with very high precision. Nevertheless, we have to press a button to ask for help. Other companies, such as LG, ASUS, Sony, and Pebble, have invested in applying applications for nursing and chronic disease self-management [72]. Thus, we find companies specializing in the sale of services in the gerontechnology sector. Medical Guardian Freedom is an intelligent device coupled with a mobile application. Family members receive notifications when seniors press a button for help.

There are, however, significant hurdles to overcome:

- **Autonomy:** energy consumption is a major issue for bodily devices both to guarantee the system's sustainability and respect the environment. In the case of healthcare applications, several requirements impact the selection of the energy management method. We have low latency, mobility, and high fidelity [24]. Indeed, there are several energy efficiency methods for systems based on a wireless sensor network, such as energy recovery and transfer, transmission control, topology control, duty cycle, etc. [120]. The permanent protection of the elderly is always of the utmost importance in developing solutions.
- **Cost:** health expenditure remains the priority for senior dependency. The latter is very interested in the devices which contribute to home support. However, the high average cost of these technologies dramatically limits their purchase. Cooperation between the public and private sectors could reduce this burden. Its application allows them to keep up with technological developments and will really help them to age well.

To meet the challenges, the scientific community is interested in solutions based on devices that are at the same time precise, energy-efficient, and inexpensive. A comparative table of interesting research solutions is shown in Table 2.1.

2.1.3 Panorama of Health care monitoring systems

Systems emerging from the research world focus on the two significant issues facing seniors and their families, falls and chronic disease. We believe that it is unfair to compare them with each other in terms of performance because the technologies deployed are different. Dinh et al. [47] presented the design and implementation of an activity and heart rate monitoring system. Their solution distinguishes between movements by collecting data from a 3-axis accelerometer and 2-axis gyroscopes. In a critical situation (fall or fainting), an alert is triggered to the personnel concerned. The gyroscope and heart rate circuit are constantly using energy. In contrast, the accelerometer can be in sleep mode if necessary. Experimental runtime results show it can run for 70 hours when their system is fully

charged.

Bourouis et al. [31] have proposed a system for monitoring seniors in indoor and outdoor environments. Their mobile health system, UMHMSE, analyzes movement and location data to predict risk in real-time. It also processes vital data (blood oxygen levels and heart rate). The authors deployed the logic regression technique in the decision. Thus, the data collected can be viewed by a web application by family members and medical staff. However, the alert is sent directly to the emergency services and family members. In [140], the system assesses the state of health of seniors based on daily activities. It anticipates emergency conditions and automatically sends them to a nearby health center. The reason is that their surveillance system does not need to store and transfer the personal information of the elderly. For them, urination, cooking, and physical cleanliness practices are the 3 activities of maintaining a healthy lifestyle.

Horta et al. have proposed [62] a mobile system for falls and health monitoring. The system is made up of 4 main modules. The fall detection module analyzes the acceleration data transferred in the G-forces to detect falls and recognizes user movements. Thus, the period of inactivity is used to judge the type of movement. Body sensors attached to the user collect essential body parameters and vital signs (ECG, respiration, EDA, BVP, EMG). This data is sent to the receiving node and then to a mobile device (the mobile gateway) via the Bluetooth connection. The tasks of all modules are synchronized so that if a fall is confirmed and the user's vital signals become abnormal, the system generates an alert. Indeed, their solution allows access to data via a browser by the user or medical staff. The Rest Web service is used to send the collected data to a remote database using the HTTP protocol. After receiving an alert notification, the senior can ignore it if there is a false alert or if no help is needed. However, he must press an emergency button to contact the emergency service.

Chuang et al. [39] presented an intelligent system, SilverLink, for remote lifestyle monitoring and care. Their system deploys object and human sensors. Object sensors placed in the user's home are attached to appropriate household objects (pillbox, refrigerator, bathroom, front door, etc.). They make it possible to show the behavior or the state of health according to the elderly's choice and lifestyle. The human sensor is a portable device based on a triaxial accelerometer, and it detects any abnormal movement, including daily activities and falls. In addition, SilverLink provides a web portal to view the data collected by the sensors. However, the alert module forces the person to press a push button to send an alert. Upon receiving an alert, the emergency response team calls the senior to verify their state of emergency and reduce false alarms.

Pinto et al. [113] presented the We-Care system based on IoT technology capable of monitoring, alerting, and recording vital data (body and ambient temperature). Their prototype consists of a We-Watch bracelet, a We-Care card, and a We-Watch gateway. In addition, the data from the accelerometer is processed to detect falls and track the movement activities of seniors. In addition, the body presence detector module triggers an alarm if the bracelet is detached to ensure the continuity of the operation of the process. However, the user has to push a button when he/she needs help. System evaluation showed good battery life, which lasted around 12 days without being replaced

or recharged. In addition, the We-care system is always effective within a radius of 60m.

Saraubon et al. [125] presented a healthcare monitoring system for the elderly based on IoT and mobile technologies. The proposed system consists of a home unit and portable devices. It enables fall detection, remote video monitoring on mobile devices in real-time, voice commands, and vital signals (heart rate) monitoring. The authors use two approaches to detect a fall: (1) the acoustic approach, which uses the sound picked up by the microphone and the sound card. (2) In the accelerometer-based approach, the system deploys the G-force and movement speed, collected from the smartwatch and the accelerometer. However, their solution requires the elderly to press a button or say a keyword or voice command to alert caregivers.

Likewise, the system presented in [13] is based on several e-health body sensors and microphones. A sensor kit, e-health v2, is deployed in the data collection. Then, it sends them to the Microsoft Azure cloud for storage and processing. In addition, the doctor can continuously monitor the medical records of the elderly through the web interface. The gyroscope and the accelerometer are used to detect falls. Voice recognition is used to confirm if the fallen person needs help.

Rachakonda et al. [117] proposed the Good-eye system, which combines computer vision and physiological data (acceleration and heart rate) to predict and detect falls in the elderly. Their solution analyzes the change in acceleration along the y-axis, the sudden change in heart rate variability, and the change in pixels to detect a fall. If the characteristics exceed the predefined thresholds, the system predicts a fall. The alert module is composed of 3 LED indicators intended to warn the user. However, from an operational point of view, this technique is not relevant enough for a critical system considering the lives of the elderly.

2.1.4 Discussion

These different devices grouped under gerontechnology improve the quality of life of people as they age. They fulfill various functions to meet basic needs, such as protecting the environment for seniors, improving their well-being, and reducing mobility problems. We note that the solutions focus on security and health needs. However, fostering social needs is also essential to ensure peace of mind. Among the weaknesses of some systems is the manual process for asking for help and reducing false alarms. Thus, sending the alarm directly to the emergency services. We are convinced that the alert process should be automatic. Family members, neighbors, and volunteers should respond to alerts first to avoid disrupting emergency services in simple cases.

In addition, compared to existing solutions, we can say that the steps of analysis, modeling, and formal verification are absent. Indeed, these 3 stages are fundamental for the development of critical systems, an error of which can have serious consequences on the life of the elderly.

2.2 Analysis, modeling, and formal verification

2.2.1 Introduction

The systems related to the seniors' health are critical and complex whose failure could lead to the loss of human life. Hence, it is essential to start with the analysis step, the modeling, then the formal verification. These steps remain fundamental requirements for the development of critical systems. Analysis and modeling identify a complete characterization of the system, while formal verification ensures that it conforms to its specifications. This approach makes it possible to increase the system's quality while respecting the requirements of the critical system and avoiding any error that could impact the lives of seniors.

- **Analysis:** is the crucial step in a process to come up with a solution. The solution is regularly carried out to solve problems whose complexity depends on the subjects and contexts. The analysis is used to explore the problem's critical factors to avoid confusing the causes and consequences. For this, it is essential to fully understand the issues by maximizing the points of view and hypotheses on the problem. We need to gather more information from the reflection questions. For this, we use the CATOWE analysis method. The mastery of the analysis guarantees the excellent management of all the following steps.
- **Modeling:** This is a fundamental practice for the development of digital systems. We define the views on expressions of needs and a technical solution using abstract models during this step. Several modeling languages provided with semantics make it possible to structure the set of possible behaviors and the properties of the system to be developed. In particular, each model presents the relevant details of the system that allow the reader to understand its behavior fully. A model is only good if it is made to the right level of detail and from the correct perspective. We use UML and its MARTE profile extension for modeling and temporal specification, respectively.
- **Formal verification:** used to verify the properties defined during the modeling step. The properties of a system are specified by logical formulas (temporal, linear) to express its expected behavior. In practice, the behavior is formalized by networks of timed automata, Petri nets, process algebra, etc. Tools named model-checker implement the model and return a positive response if a property is satisfied and a negative if a property is unsatisfied. We have deployed UPPAAL for formal verification.

2.2.2 Overview CATWOE, UML, MARTE, and UPPAAL

CATWOE

Proposing a solution and making a decision in a complex situation requires remarkable analysis. The operation of the latter is based on processes involving the participation of different actors. Indeed, the systems approach

ensured a comprehensive understanding of a problem. It allows us to meet a specific objective. In systems thinking, the Soft System Methodology (SSM) engineering approach is considered the most commonly used application [22]. This approach has been used in healthcare for some healthcare applications [34, 142]. Indeed, SSM focuses on defining elements of deep interest for the model, unlike methods based on a modeling language like UML [26, 144]. Peter Checkland defines CATWOE as part of his SSM problem-solving work [36, 37]. CATWOE gives a good idea of the relationship between the transformation process and global knowledge [26]. This powerful method is an abbreviation for 6 thought control elements below (Customers, Actors, Transformation, Weltanschauung, Owner, Environmental constraints). Indeed, the SSM identifies a rich image in which the problem exists. It deploys the stakeholders of the system from several points of view [22].

- The customers, C, represent the primary targets (beneficiaries or victims) of the system's transformation. In addition, this element concerns the definition of problems and the impact of problems and solutions on them. In other words, it is necessary to distinguish the difficulties they face clearly.
- The actors, A, are the different people who react to the process and ensure that a solution occurs. It thus determines their impacts and their ways of reacting in the process.
- Transformation, T, represents the activity necessary to provide a service to the beneficiaries of the system. This step involves understanding the intermediate steps to be taken before reaching the goal of the process.
- Weltanschauung (world view), W, is the most significant element of the method. This step defines the nature of the problem and explains the real motivations of the process.
- Owner, O, is the proprietor of the system. In the business context, this element comprises the people (investor, entrepreneur, company manager) who have significant authority over the continuity, shutdown, and solution improvement.
- The environmental constraints, E, designate the various constraints which imply the realization and the restriction of the process. It also concerns their influences on the proposed solution.

So, CATWO is a generic and expressive method. It facilitates the understanding of an actual problematic situation in the world. In addition, it provides us with a comprehensive understanding of our system. Figure 2.1 shows the relevant elements to identify all the dimensions of a problem.

UML

In the 1990s, the OMT (Object Modeling Technique) methods of James Rumbaugh, Booch of Grady Booch, and OOSE (Object-Oriented Software Engineering) of Ivar Jacobson influenced object modeling. These three experts merged their methods to develop the unified method, UML (Unified Modeling Language), from version 0.9 [124].

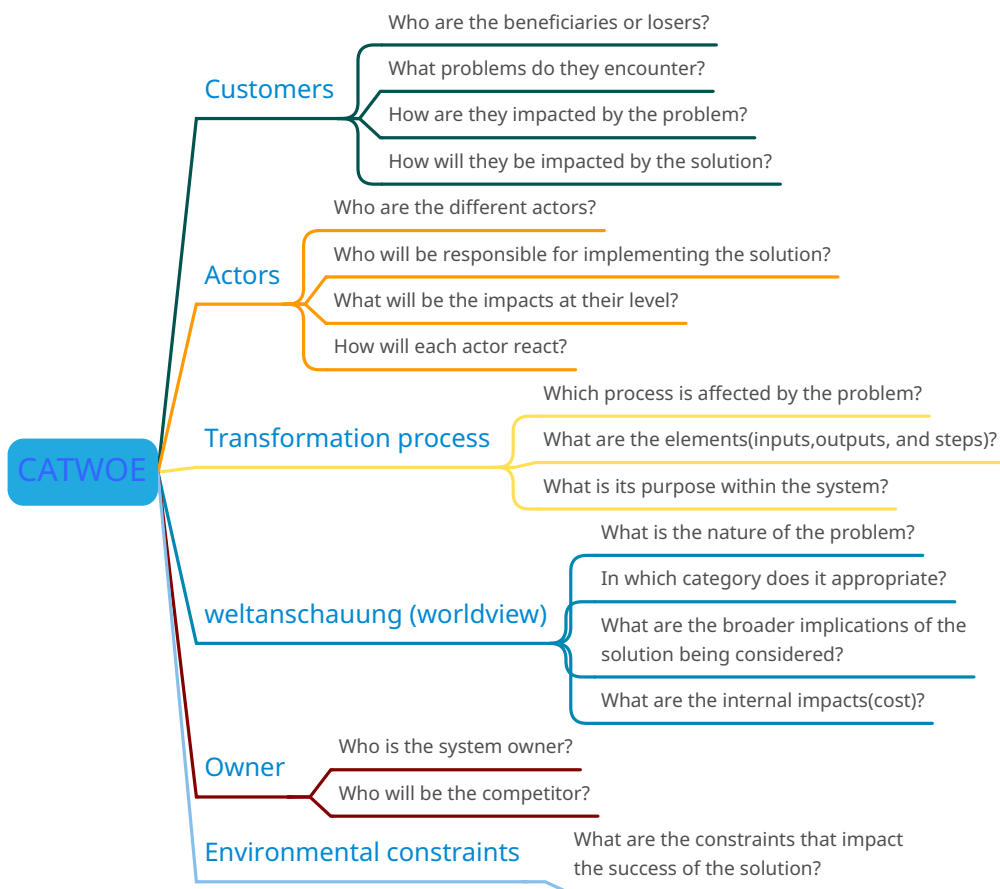


Figure 2.1: CATWOE MindMap.

UML is the reference for object-oriented modeling of real-time systems [53]. Today, it is the industry standard for object modeling [122].

UML consists of diagrams that provide a filtered view of the overall model, allowing a better understanding of the system. It is defined as a metamodel organized into several packages. In general, UML 2 comprises 14 types of diagrams [138], each of them dedicated to the modeling, visualization, and specification of concepts of static or dynamic systems. They are grouped into 2 categories:

1. Static diagrams (structural)

- Class diagram: it allows to express in a precise way the essential static elements of a system, in terms of classes, associations, interfaces, attributes, operations, generalizations, etc.
- Object diagram: it represents the instances of the defined classes and their links at runtime.
- Component diagram: is intended to represent complex structures, with their communication interfaces provided and required.
- Composite structure diagram: expresses the internal organization of a complex static element of a system.
- Package diagram: this diagram reflects the logical organization of the model and the relationships between packages.
- Deployment diagram: it shows the physical configuration of the artifacts on the hardware resources.

2. Dynamic diagrams (behavioral)

- Use case diagram: this diagram describes functional interactions from a user perspective.
- Activity diagram: it is intended to represent the sequence of actions and decisions that participate in the active part of a system.
- State machine diagram: it allows to describe the changes of states and possible transitions of objects of a class or a component according to the interactions in the system.
- Interaction diagram: shows the message flow within a system by generating context for one or more lifelines.
- Interactions overview diagram: it focuses on the overview of the control flow.
- Sequence diagram: presents the sequence of messages passed between objects within an interaction according to the chronological order of the messages sent between them.
- Communication diagram: used to show communication between objects within an interaction.

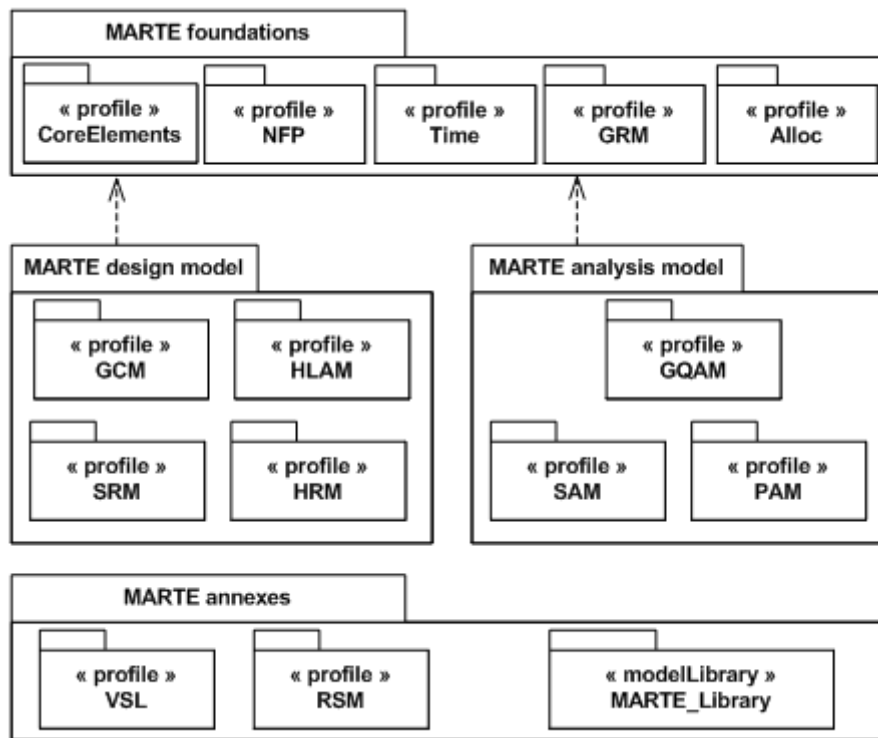


Figure 2.2: Architecture of the UML MARTE profile [57]

- Timing diagram: merges state and sequence diagrams to illustrate the evolution of the state of an object according to time constraints.

UML modeling, graphical and textual, uses simplified and unambiguous notions that facilitate understanding a system. It also generates a precise formalization of concepts and significant coverage of modeling needs. Thus, we have the possibility of translating UML models into formal models for formal verification. On the other hand, modeling some properties is difficult to accomplish using UML. Therefore, the UML extension mechanism, named UML profile, has been proposed to solve this problem.

MARTE

The OMG group has standardized UML profiles, which are sets of approaches and mechanisms for creating extensions to UML. This appropriation to a particular domain is possible on all the UML models without questioning the UML metamodel. Indeed, UML profiles allow taking into consideration extra-functional specifications which vary from one sector to another.

The OMG group introduced MARTE in order to model real-time and on-board systems. This UML profile is used to specify the time constraints intrinsic to real-time systems [57, 19]. Indeed, MARTE defines an expressive temporal model to provide a generic temporal interpretation for UML models. It does not impose any particular execution model, analytical technique, or implementation technology. Figure 2.2 shows the MARTE architecture, which in-

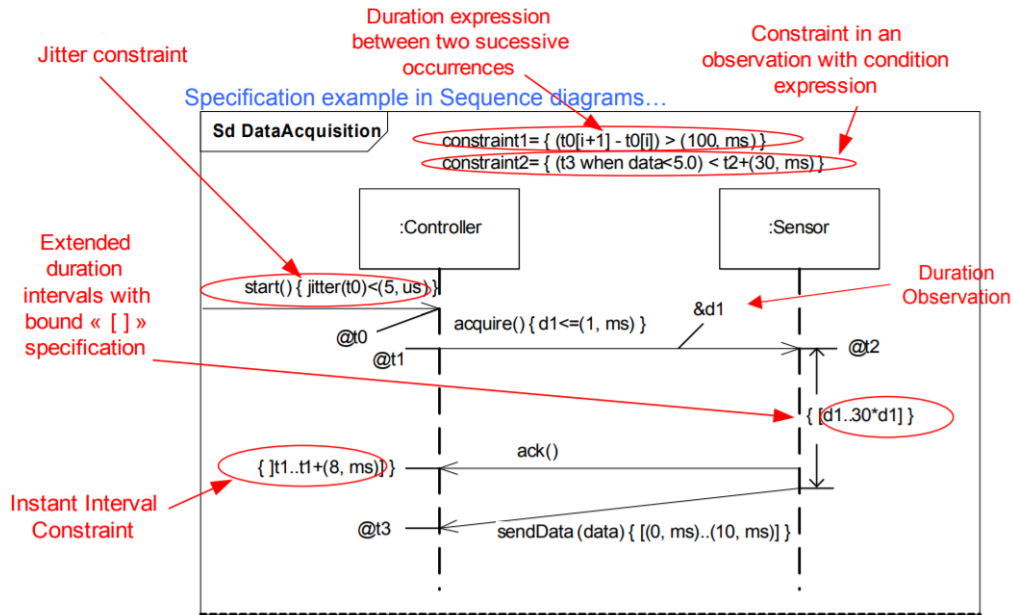


Figure 2.3: MARTE example in sequence diagram [2]

cludes four packages: the MARTE foundation, the design model, the analysis model, and the appendices. The basic package sees itself as the core of the MARTE profile. Notions related to time are found in the Time subpackage. It is made up of 4 subdomains [127]. (1) The TimeStructure consists of a set of times that can be discrete or dense. (2) TimeAccess defines the concept of a clock, which provides access to the logical/physical time structure. (3) TimeValueSpecification allows the indication of instants and durations, and (4) TimeUsage brings together the most used modeling concepts: time events, time behaviors, and time constraints. Figure 2.3 shows an example of using a UML sequence diagram with observations of times and durations. It is based on the Value Specification Language (VSL), which facilitates the MARTE profile. Time observation is a time reference at a given moment during the execution of actions. It is used to express temporal constraints in the MARTE model. In addition, the intervals of the time constraints are expressed between a pair of braces.

@t0 is associated with the invocation of the start method, which activates the sequence. This instant is constrained in two ways by constraint1 (which shows that the start receptions are periodic with 100ms with jitter less than 5ms) and the jitter constraint. @t1 and @t2 are used as variables to define the duration of observation (&d1). We have the possibility of adding conditions as in constraint2 on the data variable leaving the sensor.

UPPAAL

UPPAAL is a general tool environment developed in collaboration between Uppsala University in Sweden and Aalborg University in Denmark [1, 23]. It is used to model, validate and verify critical real-time systems. In UPPAAL, a system is modeled as a network of timed automata. These constitute one of the models of continuous-time reactive systems proposed by Alur and Dill [15]. UPPAAL has demonstrated its effectiveness for systems modeled as

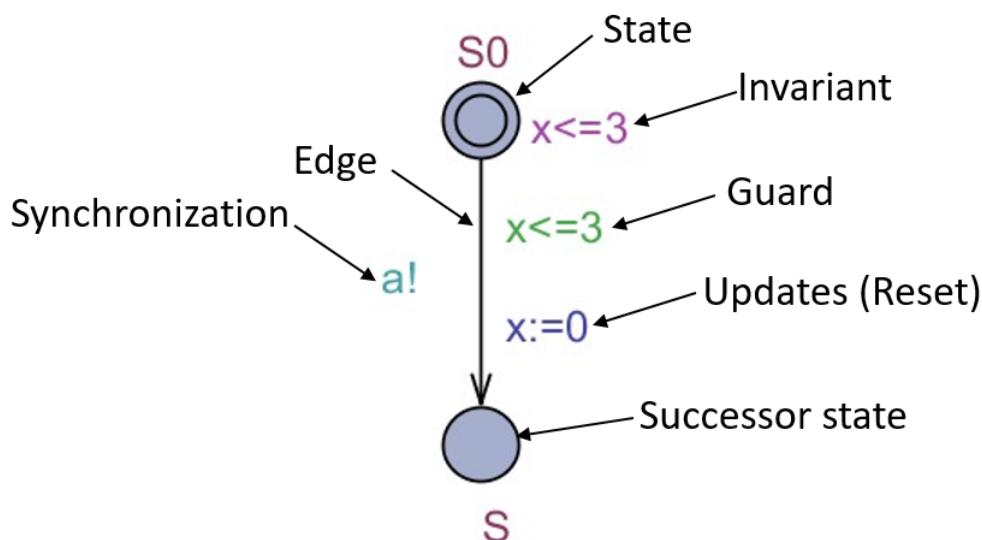


Figure 2.4: A simple timed automaton in UPPAAL

networks of timed automata coupled with time constraints, integer variables, functions, data structures, or synchronization signals. This model checker also generates a diagnostic trace to explain the state of a property and the visualization of traces using queries.

In fact, the networks of timed automata communicate with each other via the synchronization of the channels using the transmitter/receiver principle or shared data. Indeed, on a synchronization channel s , the transmitter model sends the $s!$ signal, and the receiver synchronizes with it via the $s?$ signal. A timed automaton is an extended finite state machine with clock variables used to specify time constraints. Figure 2.4 shows a simple timed automaton in UPPAAL, consisting of two states, a clock variable x , and a transition. States are generally characterized by invariants, which specify conditions on clocks. Thus, all the time spent in a state must satisfy the defined invariant. The model moves from one state to another through the transition(edge). The edges are annotated with:

- Guard: which is the condition to be fulfilled to enable the transition between states. This condition on the values of the variables must be compatible with the invariant of the original state.
- Synchronization: the processes of the different automata are synchronized on common synchronization channels. The absence of this element indicates that the actions are internal to the model.
- Updates: they represent the evaluation of variables or the resetting of certain clocks after a enabling a transition.

Formally a timed automaton is defined as a n -tuple structure (L, L_0, X, A, I, T) [15] such as:

- L a finite set of states (locations);
- $L_0 \subseteq L$ an initial state;

- \mathbf{X} a finite set of clocks (variables) with non-negative real values;
- \mathbf{A} a finite set of transition labels;
- $\mathbf{I} : \mathbf{L} \rightarrow \mathcal{C}(\mathbf{X})$ associates an invariant to each state (\mathcal{C} is a set of conjunctions over simple conditions on \mathbf{X});
- $\mathbf{T} \subseteq \mathbf{L} \times \mathbf{A} \times \mathcal{C}(\mathbf{X}) \times 2^{\mathbf{X}} \times \mathbf{L}$ a set of action transitions.

Each $e = \langle l, a, \Phi, \lambda, l' \rangle \in T$ corresponds to a transition between the states l and l' , guarded by the constraint Φ , labeled by a , and which resets the variables λ in X to zero.

The UPPAAL tool integrates three fundamental parts: a graphical interface for the system's visual design, a simulator to examine its dynamic behavior, and a command-line verification server to verify its properties.

This tool allows to verify temporal properties : reachability, safety, liveness, and absence of deadlocks. UPPAAL exploit an extended subset of Timed Computation Tree Logic (TCTL) to specify and verify temporal properties. To explain the semantics and formal expression of these properties, we admit p and q as two-state formulas. The letter A and E in TCTL means for all paths and one path, respectively.

1. The absence of deadlock: the formula $A[]$ **not deadlock**, is used to check that there is no deadlock in the system behavior.
2. Reachability: it allows to check consistency in the system. It is expressed by $E \langle \rangle p$ to verify the existence of a path starting from the initial state such that p is satisfied along this path.
3. Safety: it shows that the system will never reach a critical state; in other words, something bad will never happen in the system. It is expressed by $A[]p$ (p must be satisfied in all the accessible states), or by $E[]p$ (there is at least one path in which all states satisfy the property p).
4. Liveness: which expresses that something will eventually happen, it is expressed by $A \langle \rangle p$ (all the execution paths eventually lead to a state satisfying the property p) or by $p - - \rangle q$ (p always leads to q : any path beginning with a state where p is satisfied, eventually reaches a state which necessarily satisfy q).

2.2.3 Discussion

In order to develop a health care system for seniors, one should not go headlong into coding. Therefore, it was agreed first to organize the ideas to solve a complex problem through analysis, define the requirements and properties, and verify the satisfaction of the properties. In this context, taking into account real-time constraints is also essential for modeling the system's behavior and verifying its properties. The complementarity of the CATWOE technique of SSM with UML allows an excellent clear definition of the system used for efficient modeling. In addition,

UPPAAL is a very efficient tool that allows the verification of properties of systems, previously modeled in networks of timed automata, expressed as a function of TCTL.

Paper	Elderly needs			Analysis	Modeling	Formal verification
	Health	Security	Social			
[47]	-Monitoring heart rate	-Fall detection -Automatically alert the concerned personnel	-	-	-	-
[31]	-Monitoring blood oxygen level and heart rate	-Fall detection -Automatically alert the emergency service and family members	-	-	-	-
[140]	-Monitoring health status based on ADL	-Automatically alert a nursing center	-	-	-	-
[62]	-Monitoring vital signs (ECG, respiration, EDA, BVP, EMG)	-Fall detection -Manually request help	-	-	-	-
[39]	-Management health tasks like taking medications	-Fall detection -Manually request help	-Favorite communication between seniors and family members via video and photo sharing interface	-	-	-
[113]	-Monitoring body and ambient temperature	-Fall detection -Manually request help	-	-	-	-
[125]	-Monitoring heart rate	-Fall detection -Alert manually or by voice for help	-	-	-	-
[13]	-Monitoring vital signs	-Fall detection -Ask for help vocally	-	-	-	-
[117]	-Monitoring heart rate	-Fall detection	-	-	-	-
Ours	-Monitoring heart rate, blood pressure and body temperature	-Fall detection -Automatically alert family members then emergency services in some cases	-Planning social tasks to do with the entourage of seniors -Call the fallen senior to reduce the risk of panic	-CATWOE	-UML -MARTE	-UPPAAL

Table 2.1: State of the art on research solutions for health care monitoring system, and adapted and non-exhaustive comparison.

2.3 Automatic fall detection

2.3.1 Introduction

Two things are certain: anyone is susceptible to falling to the ground, and the elderly favor the use of comfortable technologies. The rate of falls increases with age and loss of autonomy. It often imposes catastrophic consequences (injury, depression, death, social isolation, etc.) among seniors. Consequently, socio-economic costs have triggered the development of approaches to meet the security need of seniors. In the literature, the scientific community's solutions are based on sensors that are both reliable and low-cost. However, computer vision remains the most suitable solution to monitor seniors and automatically detect falls. Because the camera is a crucial source of information for identifying human activities; It also avoids the dependence problem of body sensors. In other words, the user is always secure without the need to attach the sensor to their body. In addition, approaches based on the RGBD camera, Microsoft Kinect, guarantee the preferences of seniors by meeting the requirements related to comfort, safety, and privacy.

2.3.2 Fall characterization

The fall is a complicated movement with a wide range of characteristics depending on the situation. In order to provide a practical fall detection approach, it is essential to understand its types and cycle of movement. There are possibly 3 types of the fall event:

- Heavy fall: rapid and unintentional loss of balance that ends in a violent collision with the ground.
- Soft fall: the senior absorbs the shock with the ground by hanging to a support or a wall to control his fall.
- Syncopal fall: is due to a loss of consciousness or an elderly person's discomfort.

In the literature, we find the characterization of fall proposed by Noury et al. [104]. The authors divided the action of falling involuntarily into 4 phases (pre-fall, critical, post-fall, and recovery). The mechanism of a fall is illustrated in Figure 2.5.

- Pre-fall phase: corresponds to the practice of daily activities. This period precedes the fall and includes sudden actions, sitting or squatting, without causing detection of a false fall.
- Critical phase: corresponds to the sudden movement towards the ground. It lasts between 300-500 ms.
- Post-fall phase: describes lying on the ground. It does not have to last long so as not to have significant consequences.
- Recovery phase: describes lifting the person off the ground on their own or with the help of someone.

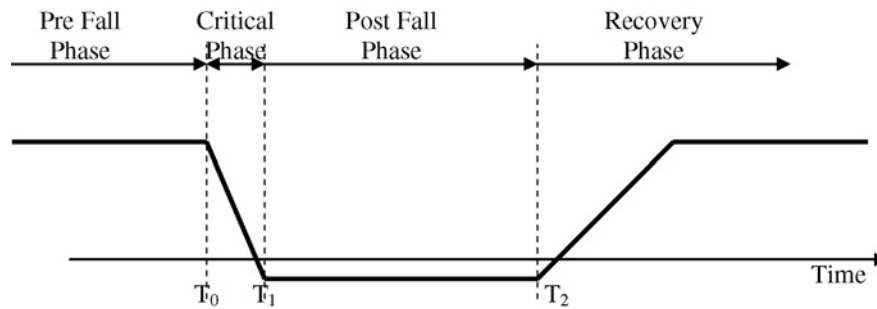


Figure 2.5: The fall characterization [104]

2.3.3 Risk factors for falls

The risks of falling result from multiple factors related to the senior himself and his environment [18, 137]. WHO has classified the risks into 3 categories:

1. Intrinsic factors are directly linked to aging, more precisely to the results of the alteration of the body's molecular functions. They include chronic and cognitive diseases, mobility loss problems, visual disturbances, high medication use, malnutrition, etc.
2. Extrinsic factors: correspond to environmental risks. We have 3 main factors: poor adaptation of the habitat, the use of walkers and footwear, unsuitable for the ground, and low light in the presence of an obstacle.
3. Risk exposure: corresponds to the situational factors describing the practice of certain tiring activities that increase the risk of falling.

However, it should be noted that intrinsic parameters become more and more dangerous with age. The complex relationship between factors makes the fall a multifactorial event. Indeed, the factors make it possible to cross a threshold causing the fall.

2.3.4 Classification of sensors deployed in fall detection

The key step in the fall detection approach is the precise and reliable measurement of relevant characteristics of human activity. Different types of sensors are used to achieve this goal. These sensors are classified into 2 categories: (1) sensors worn by the elderly (accelerometers [30], gyroscopes [84], magnetometer [63], RFID [38]), and (2) external sensors (piezoelectric [16], microphone [87], passive infrared [115], one camera [99], several cameras [42]). The different sensors have advantages and disadvantages depending on the selection criteria (price, working area, confidentiality, comfort, and accuracy). Figure 2.6 shows the comparison of each category of sensors.

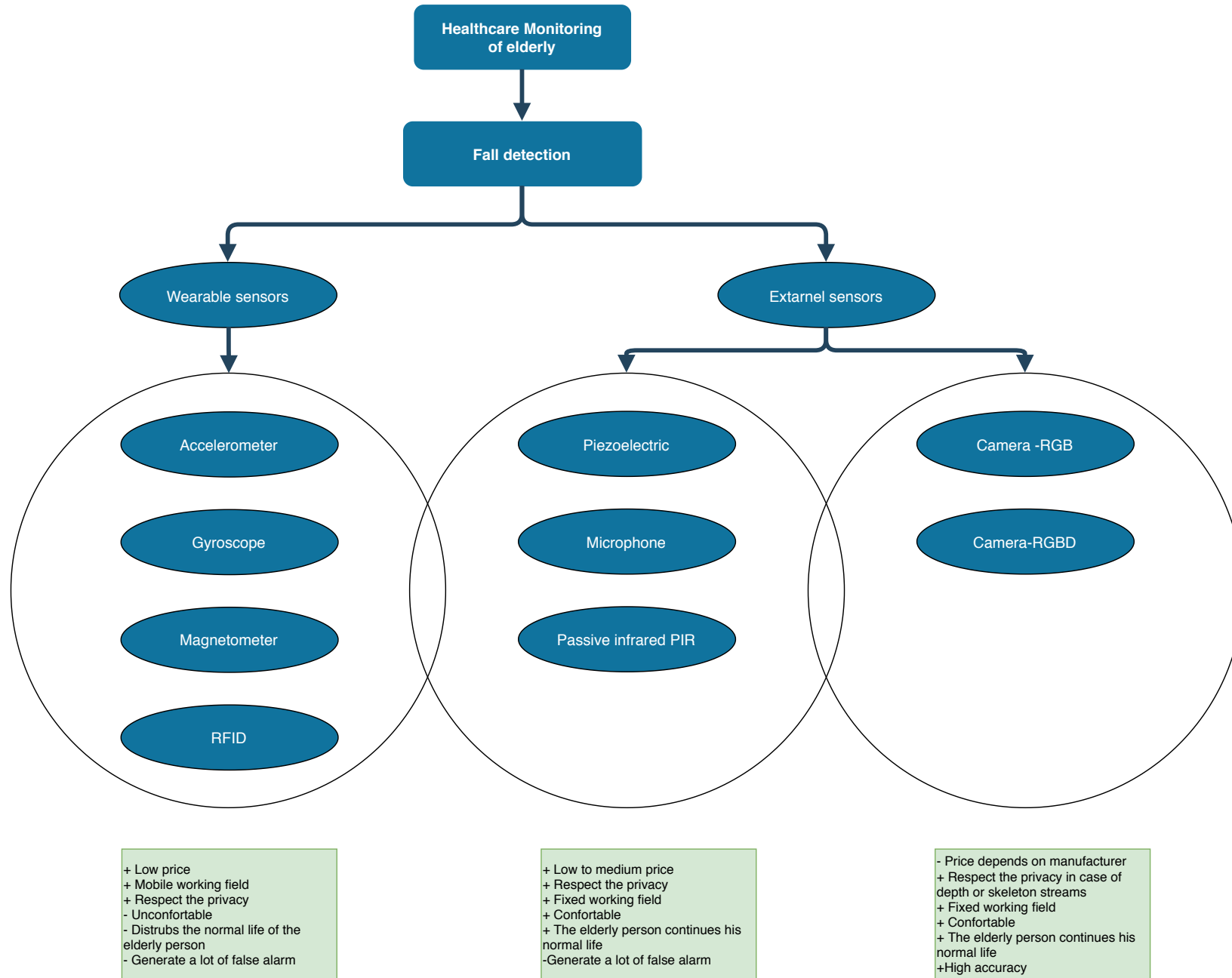


Figure 2.6: Comparison of sensors (+ : advantages, - : disadvantages)

The activation of portable sensors strongly depends on the subject, his position on the body, and the choice to wear them permanently. Most of these sensors are generally refused by the elderly due to the high rate of false alarms and the difficulty of continuously having them attached to their bodies. On the other hand, the elderly favor solutions based on the RGBD sensor. The significant advantage of this technology is the respect of privacy by generating depth data instead of traditional color data. Indeed, the Kinect camera is the most attractive and the most used by scientific researchers to track falls.

2.3.5 Kinect-based fall detection approaches

A fall detection system can be described as a closed-loop system, consisting of five main modules: (1) Data acquisition, (2) Preprocessing, (3) Features extraction, (4) Actuation algorithm, and (5) Interpretation in control (i.e. Figure 2.7. We will describe precisely these different stages.

Data acquisition

Data acquisition is the most critical step for all fall detection methods. In the case of a vision-based system, it consists of tracking the target continuously in the scene. First, the camera acquires the predefined data flows. Then, the processing unit analyzes them. Kinect greatly facilitates the proper surveillance of older adults in controlled environments. This technology with different types of intelligent sensors encourages the differentiation of a human from another object in the scene. The three generations of Kinect record and hear in real-time, day and night. They provide four types of vision streams (color, depth, infrared, and skeleton¹) and sound signals.

Fall detection techniques based on RGB or depth fluxes do not monitor the parameters of the subjects' joints. Instead, they are based on image processing techniques on the frames around the region of interest. On the other side, some models use the 3d positions of the body's joints estimated by the Kinect. They monitor the change in posture position before, during, and after the fall. In most approaches, volunteers perform scenarios of falls and activities of daily life to make data sets. They operate in experimental configurations that guarantee the safety of the participants. The evaluations of the approaches in offline mode are carried out with data already prepared. The integration of data collected by older people is a challenge for researchers; Because the real data helps to enhance the realism of fall detection techniques. The researchers adapt the data acquisition conditions, the types of scenarios, and the characteristics to perform their algorithms successfully.

Preprocessing

The data acquisition module, in turn, sends the data to the preprocessing unit. This stage favors the algorithms to make the correct decisions. First of all, we consider this step as essential to refine and prepare the parameters.

¹The skeleton class in V1 has been replaced by the Body class after.

It is not straightforward to be separated from the subsequent stages of treatment. Different types of filters and techniques are used to clean up the signals and accentuate pertinent information. We Found that filtering has been used extensively in depth data. We are not interested in going into much detail. Although we aim to identify the main lines applied. We judge that the preprocessing designates the set of tasks that give the scientists a data-independent as much as possible of the defects specific to Kinect and experimental configurations.

- In image preprocessing, Different algorithms often detect the target person when they appear and reappear in the Kinect's field of vision. They extract the silhouette in a video sequence and follow different parts of the body. The segmentation processes used are grouped into adaptive and non-adaptive methods for detecting the background and foreground of the image. Filters are primarily designed to reduce noise while preserving the definition and structure of the data. Its objective is to obtain a set of connected pixels having a form that can be analyzed facially. (a) The morphological methods (erosion, dilation, opening, and closing) are applied after the binarization of images. They are used to modify the structure and shape of regions of interest in frames. These non-linear operators also apply to remove or fill pixels as needed. (b) the normalization process is also used to modify the input data into a more informal pixel intensity range. (c) Some researchers apply the change of the Cartesian image coordinate system to the polar coordinate system. The main advantage of this change is that it solves the non-linear deformation of the pattern. (d) the median, averaging, particle, and Kalman filters are also deployed to homogenize and smooth areas. The median filter retains proper contours compared to the others. (e) Framing objects by encompassing geometric shapes is used in particular works. The authors relied on the coordinates in a predefined coordinate system to delimit the external surface of the objects of interest in the scene and identify their locations. (f) To measure specific geometrical features compared to the ground, they used techniques like the v-disparity, Hough transformation, and least squares. They used them as an alternative to the parameters of the floor plane equation delivered by the SDK.
- The large quantity and diversity of the dataset require the Split step. Indeed, the authors divide the data into two minimum parts according to predefined objectives. (a) The training data is the largest. They are used to train the algorithms in addition to calculating parameters in the case of thresholding algorithms. (b) The test data verify the performance of the approaches deployed. It must be made up of new data not used when designing and adjusting the model. Usually, the best performance is obtained with 70-80% for training and 20-30% for testing.

Features extraction

Measuring human activity leads to the collection of a large amount of essential data. To obtain the best performance, it is advisable to work with the smallest number of values, which will describe the relevant properties of human movement. These values are called (characteristics, features, or judging criteria). Scientific researchers always

select relevant descriptors. The characteristics are defined during the construction of the objectives to be achieved. They aim to reduce the error rate. They also try to minimize the risk of over-fitting the model. Thus, to control the reaction time of the approach. The fall is manifested by biomechanical changes that lead to a loss of dynamic balance in the elderly [91].

During the fall, a cycle of movements is repeated until the body reaches the ground. In particular works, the fall is considered a Spatio-temporal study. They define a reference frame, such as space and time landmark, to describe the overall characteristics of the fall. (a) They analyze events over time, characterized by trajectory, speed, and acceleration. Indeed, using a single parameter type does not lead to a reliable system that distinguishes the different types of actions. For example, according to the variation of the speed alone, fall detection leads to an incorrect classification of the fast lying on the ground. In other words, the approach detects daily activity, such as a fall. (b) Fall detection can be reduced to a simple study of the distance between precise joints on the ground. Among the drawbacks of the evolution of the joint's position, we cite the stop receiving relevant data, especially occlusion. It explains the increase in the rate of false alarms. Besides, the body during the fall cycle is sometimes represented by its center of mass. The mass's center is estimated as much the geometric center of the silhouette, or an articulation like (hip center) plays its role. (c) The fall aspect is sometimes explored by kinematic parameters, such as the inclination angle, which makes it possible to analyze the direction and the flexion of the body relative to the ground or its initial posture. (d) In other cases, mathematical calculations are applied to the pixels of a frame to derive local visual characteristics. Among these characteristics, we cite the Histogram of oriented gradients (HOG), Motion History Image (MHI), curvature scale space (CSS), wavelet moment and depth range difference, etc. These features facilitate the interpretation of the older adult's movement in the field of vision. On the other hand, the main drawback is the processing time of the image data. (e) The fusion of kinematic and visual data with variations in displacement or velocity over time has shown its effectiveness in having a global description of all the issues involved. (f) time is also used as an additional characteristic to reinforce the approach's decision.

Actuation algorithm

After modeling the specific characteristics from large sets of learned data, the judgment unit intervenes in the method for arbitrating events. (a) Threshold-based approaches are established on a value judgment. Generally, a comparison of the acquired data with predefined values [123, 27, 149, 102, 69, 114, 94, 98, 73, 51, 67, 82, 54, 112, 97, 55, 150, 108, 86, 65], adaptive threshold [136, 28, 126, 148, 103, 152], or both [101, 131] is carried out. The authors define the thresholds based on a configuration installed on logical hypotheses very close to real-life or based on experimental trials. Setting a threshold is a real challenge for researchers. They are always trying to find the most generalized values possible. These values correctly detect the events despite the physical variations of the subjects monitored (size, sex, and age) and the experimental configurations (the type of scenario, Target-Kinect distance, Kinect positioning).

(b) Machine learning is more compatible with variations in the operational constraints of fall detection. Their generalization capabilities can distinguish approaches based on this type of algorithm. They often achieve remarkable results. These algorithms are characterized by their ability to receive many data and learn from it. However, real-time implementation and execution in the embedded system remain a scientific challenge. Machine learning techniques commonly used for fall detection include (SVM [75, 128, 46, 44, 10, 48, 100, 151, 81, 134, 17, 111, 21, 95, 108, 14, 86], K-Means [74], BoW-VPSO-ELM [92], BoW-naive Bayes [12], RBF [134], Fuzzy-logic [70, 68, 78], MLP [134, 111], NCA [17], Decision tree [93, 133], C4.5 [17], Random forest [71, 17], Fisher vector [21], LMNN [154], Bayesian framework [153], Hidden Markov model [50], NBC [95], and sparse representation [65]). Deep Learning, machine learning with neural networks, is also used to detect falls in the elderly. Deep Learning models are attracting much attention from scientists. They reach a level of performance previously unachievable, sometimes higher than human performance. The algorithms used are (DNN MyNet 1D-D [139], DNN [134], ANN [17, 95], ResNet [155], BPNN [147], and LSTM [11]).

Interpretation in control

Falls, unfortunately, lead to severe fatal and morbid consequences. These issues worsen with the presence of long-lie after a fall. This aspect occurs when the older adult cannot stand up alone and spends more than an hour on the ground before someone comes to help [121, 52]. A static study has shown that staying immobilized on the ground for more than an hour is a 50% risk of death within 6 months [43]. More than 50% cannot get up alone from the floor by themselves [109, 143]. Hence the necessity for effective and rapid automatic alerting in each approach to anticipate the consequences of prolonged immobilization on the ground. Long-lie leads to muscle weakness complications, pressure area development, pneumonia, dehydration, missing medication, and hypothermia [35]. The automatic notification, SMS-Mail-Call, to the emergency services, family members, and neighbors must occur immediately after the accident. In the literature, we find that there are several strategies for warning. Researchers have used as a condition the period of inactivity of the fallen person [28]. Several durations have been implemented 0.7s [10], 5s [101], 10s [147, 112], and 60s [75, 74, 73]. Voice exchange is also used via the Kinect's voice recognition system [67]. This solution without a timer is not recommended, especially in case the elderly lose consciousness. In some works, the authors have indicated the alert system's presence in their methods but without details on the triggering process [70, 68, 69, 134, 131, 111, 82, 54, 11, 93, 78, 150]. Sometimes, the older person lives in the anxiety of falling again. This behavior impoverishes his social life and increases his isolation. The integration of neighbors, family members, and volunteers in the intervention after the fall minimizes the psychological and social consequences [51].

This functionality also appears in the form of audio, message [128], or visual exchange [51] of information between the target and the caregivers (family, neighbors, professional). We can name this task through feedback. One of its objectives is to reduce the approach's error rate.

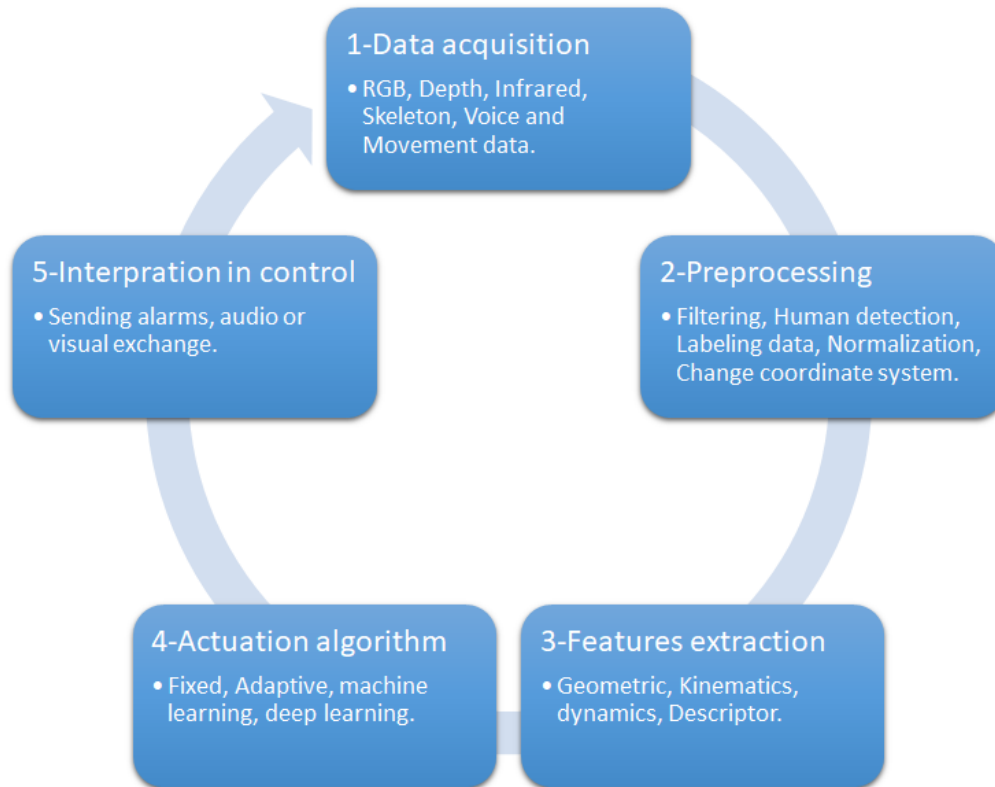


Figure 2.7: The general flowchart of Kinect-based fall detection approaches.

2.3.6 Performance measurement metrics

The performance of a fall detection approach is measured using standard terms. These terms verify, in particular, how often the judgments of the system are correct to the actual events. Fall detection is seen as binary detection/classification. The confusion matrix and its derivations are the most used measurement tools to assess the quality of a fall detector [116, 59]. We will explain the metrics used. We give the general definition of each measurement and its application in the fall detection algorithm. Before going into details, we found that these terms are used in threshold and machine learning/deep learning approaches.

To measure the total performance, we must have the four components of the confusion matrix (True Positive TP, True Negative TN, False Positive FP and, False Negative FN). A TP is a result where the algorithm correctly predicts the positive observation. Similarly, a TN is a result where the algorithm correctly predicts the negative observation. Likewise, an FP and FN are an outcome where the model incorrectly predicts the positive and negative class, respectively. The true and false observations are known in almost all fall detection papers for the real-life events of falls and ADLs, respectively. Therefore, the TP and FP count the number of falls and ADLs detected as falls, respectively. The same counting principle applies to the TN and FN. Table 2.2 explains the distribution of terms for each situation. The table's columns correspond to the real situation of actions, and every row is linked to the algorithm's result.

The confusion matrix exposes how the approach is confused when it judges scenarios detected by the tiny

		Real situation	
		Fall	No-fall/ADLs
predicted situation	Fall	TP	FP
	No-fall/ADLs	FN	TN

Table 2.2: Confusion matrix

devices. It gives us an explication not only of the errors made by the system but also the types of errors that are made. Several evaluation measures based on the confusion matrix's elements are defined. They are also used to quantify the performance from different perspectives [130].

Accuracy is the proportion of the total number of observations correctly detected. It proves the success rate of fall detection approaches. It only reflects the reality of the system when we work on symmetric datasets, where we do not notice a disproportion between the number of real situations (Falls and ADLs).

$$Ac = \frac{TP + TN}{TP + TN + FP + FN} \quad (2.1)$$

Error rate (misclassification rate) represents the ratio of incorrectly detected observations to the total number of data, or simply one minus the accuracy. It explains how often the fall detection algorithm is wrong.

$$ERR = \frac{FP + FN}{TP + TN + FP + FN} \quad (2.2)$$

Precision is the ratio of correctly positive prediction to the total number of predicted positives observations. It determines the percentage of actions, identified as fall, that has been detected correctly. This performance expression allows judging the stability of a fall detection algorithm.

$$Pr = \frac{TP}{TP + FP} \quad (2.3)$$

Sensitivity (Recall or recognition rate or true positive rate) can be defined as the proportion of actual positives result in that has been correctly detected. In other words, this metric measures how useful the algorithm is in identifying the falls states.

$$Se = \frac{TP}{TP + FN} \quad (2.4)$$

Specificity (selectivity or true negative rate) is the proportion of actual negatives outcomes that have been correctly identified. It shows the ability of algorithms to recognize ADLs and avoid false alarms correctly.

$$Sp = \frac{TN}{TN + FP} \quad (2.5)$$

False alarm rate (false positive rate or fall-out) is equivalent to one minus the specificity. It is calculated by dividing the number of ADLs, which were incorrectly detected as fall, by the total number of ADLs instances.

$$FAR = \frac{FP}{FP + TN} \quad (2.6)$$

Three elements determine the validity of a fall detection algorithm, which are sensitivity, false alarm rate, and miss rate [89]. In order to fully determine a fall detection approaches' efficacy, both precision and sensitivity should be calculated. Nevertheless, the improvement of one of both elements is generally made at the expense of the other. For high sensitivity and low precision, we have most of the falls that are correctly identified (low FN), but we have a lot of false positives and vice versa. Thus, the estimation of performance tends towards the calculation of specificity and F-score.

Three terms used in the performance evaluation also deserve to be mentioned: F-score (F1 score) combines the precision and sensitivity by calculating the harmonic mean. It provides the algorithm's capacity to detect all judicious situations.

$$F - \text{score} = 2 \left(\frac{\text{Precision} \times \text{sensitivity}}{\text{Precision} + \text{Sensitivity}} \right) \quad (2.7)$$

Kappa value is mainly a measure of the system's compared to how it would have worked merely by chance; It judges the inter-rater reliability of fall detectors [96, 99]. The best value of kappa is when it approaches 1.

$$k = \frac{\text{Accuracy} - \text{Expected Accuracy}}{1 - \text{Expected Accuracy}} \quad (2.8)$$

$$\text{Expected Accuracy} = \frac{\frac{(TP+FN) \times (TP+FP)}{TP+FP+TN+FN} + \frac{(TN+FN) \times (TN+FP)}{TP+FP+TN+FN}}{TP + FP + TN + FN} \quad (2.9)$$

The area under the ROC curve (AUROC) is obtained from the ROC curve, which shows the variation in sensitivity and specificity as a function of the decision threshold. It measures the excellence of the approaches' precision for all possible decision thresholds. The fall detection approach is perfectly discriminating if the AUROC achieved 1. Also, the principle of evaluation by cross-validation has been used in some approaches based on machine and deep learning.

A fall detection system is considered perfect if the above performance terms have a value close to 1 (100%), and the fall-out with the error rate must be very close to zero.

2.3.7 Discussion

The field of fall detection aims to improve seniors' security and prevent loss of independence. It is made up of approaches aimed at quantitatively analyzing activities. Today, these approaches are entirely dedicated to data analysis and processing, which describe the human movement captured by sensors. Microsoft Kinect hardware and software development has attenuated many computer vision problems. It has dramatically changed the way you communicate with a machine through a single device. The researchers took advantage of this technology to develop different fall detection applications. Seniors are supportive of Kinect camera. They find that using this technology can give them a greater sense of security by respecting their privacy and ensuring the continuity of their lifestyles.

In the literature, the precision of specific approaches is impacted by constraints related to the angle of view, the occlusion, the use of insufficient characteristics to distinguish between true fall and like-fall events. We are convinced that combining the Kinect with other sensors helps us avoid occlusions, lack of data, and local limitations of the work area. Furthermore, the deployment of upper body skeletal data also enables the effective identification of activities. In addition, the use of algorithms based on deep learning and adaptive threshold makes the approach more dynamic to changing experimental setups.

2.4 Conclusion

In this second chapter, we have seen the monitoring systems of the health care of the elderly and its 2 major obstacles. This analysis enabled us to estimate the importance of offering reliable and low-cost home support systems that support security, health, and social needs.

Secondly, we presented in detail the tools used in our approaches to reassure the reliability and the security of our critical system named Family Heroes. Then we described the characterization and the risk factors of a fall. We have also classified the different sensors used in the detection of elderly falls. The disadvantages and advantages of each category led us to justify the interest in using the Kinect camera in our solution. Finally, we have detailed the different modules used in Kinect-based approaches and performance evaluation metrics. Moreover, we have discussed the limitations of some approaches and the solutions to work around several limitations.

In the next chapter, we will present our system and our contribution to the analysis, modeling, and formal verification of the Family Heroes system.

Chapter 3

The reliability and security of the Family

Heroes system

This chapter details our model-oriented methodology for designing a secure and reliable cyber-physical health care system for the elderly. First, we start with the representation of our Family Heroes system. Then, the analysis and modeling of Family Heroes are covered in this chapter. Later, we detail the implementation and the procedures of the models obtained in timed automata in the UPPAAL model-Checker. We also explain the results obtained on the formal verification of the properties.

3.1 Introduction

Currently, keeping the elderly at home without technological assistance is very difficult, especially in physical weakness and health problems. The increase in the number of seniors citizens has directed several research studies to health care systems design. This area offers many benefits to the elderly and their families. Indeed, families prefer to keep their seniors at home rather than sending them to specialized institutes. As for the needs of seniors, the solution must constantly monitor the elderly, be non-intrusive, comfortable, trigger rapid alerts in an emergency, and not costly.

With the increasing complexity of these critical systems and for them to be reliable and secure, it is necessary to invest much time in the theoretical part before coding and evaluating. This implies analyzing the problem to be solved, modeling the system's behaviors, and formal verification of its functional properties (safety, reliability, temporal constraints, etc.).

Based on this background, a model-driven methodology was implemented to design a secure and reliable cyber-physical health care system for the elderly.

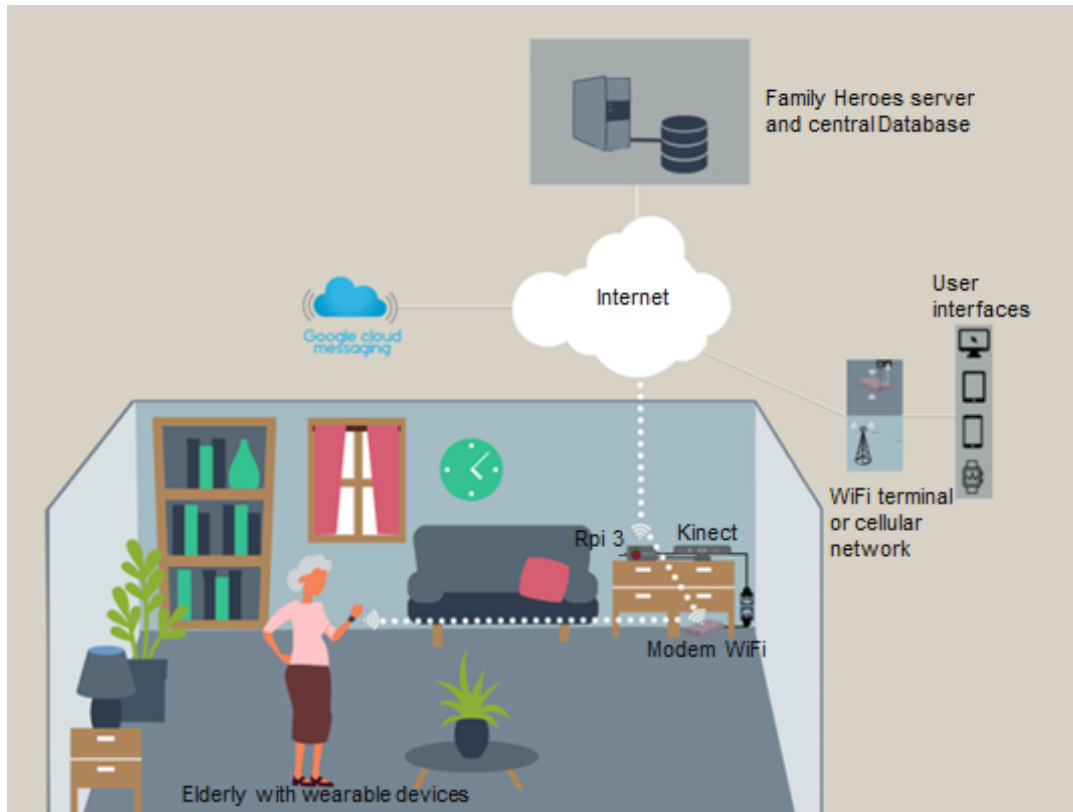


Figure 3.1: overview of Family Heroes system.

3.2 Family Heroes system

Our Family Heroes system objectives are based on the concept that mental and social health are equally as important as physical health in aging as they are at any other time in life. Our system responds to the scientific, social, and economic challenges of technologies for the elderly. It promotes autonomy, home support and can also be deployed in establishments that would like to strengthen the supervision of seniors

Family Heroes is based on new technologies allowing the collection of data on posture and vital signals. It ensures rapid intervention to reduce the consequences of accidents (fall or unstable health) and to break social isolation. Figure 3.1 shows the overall architecture of our solution. Family Heroes system is characterized by its multi-sources, open modular architecture, the composition of reliable and inexpensive devices, and its maintenance of family and social relations.

- The multi-source system allows users who wish to age at home to prevent and detect health risks (monitoring vital signals and automatic detection of falls) while maintaining their freedoms.
- Modular open architecture: allows the integration of different types of sensors for future applications related to the behavior analysis of seniors. It also enables communication technologies for data sharing combining multi-source data and threshold-based or deep learning-based analysis techniques.

- The availability of tiny devices encourages developing a comprehensive health care monitoring system, accessible to all social classes with performance and flexibility accepted for elderly home or institutional applications.
- Maintaining family relationships is manifested because family members and neighbors are the leading actors in Family Heroes. They react to alerts before emergency services intervene in some cases. Social isolation is also broken by allowing each member to plan social activities with the seniors.

The Kinect and the smartwatch form the heart of the Family Heroes system.

- The Kinect generates 3D data of the skeletal joints of people within its field of view. It respects the privacy and privacy of elderly people.
- The category of smartwatches equipped with 4G and LTE does not need to be paired with a mobile device to connect to the network. In addition, they are equipped with a speaker and a built-in microphone. The ability to make calls and receive notifications directly on the watch is one of the most appealing features. Indeed, we can directly access the data collected thanks to the possibility of integrating an e-Sim [20]. Therefore, the Huawei 2 4G is the best candidate for heart rate monitoring in our system.

3.3 Analysis using CATWOE

We apply the CATWOE method in the development of technology for the elderly. Therefore, we want to have a generative understanding of our system. To do this, we have identified the stakeholders and the elements dedicated to its proper functioning. Indeed, we deal with all the nuances, dimensions, and information that make up the problematic situation and the different perspectives.

Our approach explained in Table 3.1 allowed us to have the definition below adapted to thought by design. Thus, from the identification of the beneficiaries, the actors involved in the transformation of the Family Heroes, the actions to be undertaken, the vision of the world justifying its reason for being, the owners, and finally, the consideration of the constraints and the shared challenges we had a global picture of our system. Furthermore, by enriching the relational logic between the conceptual and real worlds, we began the modeling stage.

So, The Family Heroes system is part of the remote healthcare monitoring system used primarily by those around the elderly to take care of people with a physical problem (fall and irregular health situation) or social isolation as quickly as possible. The process is applied through a sequence of acts, considering health recommendations and caregivers' and resources' availability.

Table 3.1: CATWOE method

Elements	Main reflection questions	
Customers	Who are the beneficiaries of Family Heroes? What problems do they face? How are they affected by the problems? How will they be impacted by the Family Heroes system	The beneficiaries of the Family Heroes system are the Dependent and Fragile Elderly. At this age, the problems often encountered are: falls, discomfort and social isolation. These problems lead to physical and psychological injuries. Our system guarantees rapid support in the event of a problem and the strengthening of social ties.
Actors	Who are the actors involved in the process? Which actors will be responsible for intervening? How will the actors react? How will the solution process go?	The main actors are the entourage of the elderly person (neighbor, family member) who form a network of Heroes. The emergency department and employees of Family Heroes systems are also involved. A hero will be responsible for applying the solution on the front line. If necessary, the emergency service intervenes. They manage the situation by providing rehabilitation actions. Each connected actor is authorized to receive an alert, consult vital data and schedule tasks. If there is no response from the Heroes or the situation is dangerous, the emergency service intervenes/Family Heroes employees take care of the administrative and technical part.
Transformation	What are the goals of the Family Heroes system? How will the solution process go? What is the purpose of the Family Heroes system?	Avoid serious consequences and break social isolation. The system devices collect vital data, positioning and tasks (social activities or medical appointments). Then, it synchronizes and processes the data to generate alerts and calls. The purpose of our system is to have well aged elderly people at home and to integrate better socially.
Worldview	What is the overall source of the problem? What are the solutions envisaged to deal with aging? What are the criteria for solutions? What is the impact of the Family Heroes system?	Demographic aging in the world is very visible on the age pyramid. Faced with the challenges linked to aging, the creation of intelligent environments adapted to the needs and expectations of the elderly is a necessity. These systems must be reliable and at low cost to promote aging in good moral and physical health. Our system makes a positive contribution to society.
Owners	Who will own the proposed system?	Family Heroes system is owned by the Family Heroes services business in the future.
Environmental constraints	What are the constraints that impact the success of our solution?	Our system is not a remote assistance system since the main players are committed to provide real help when available. It respects the privacy and anonymity of the user. The constraints related to data security, the timing of the alert and the minimum false alarm are taken into account in the development.

3.4 Process Alarm Scenarios

In this section, the different scenarios related to our solution are analyzed to decide which is more appropriate to develop our system.

The secondary consequences of prolonged immobilization on the ground after an accident, a fall, or health problems are as severe as the direct physical and psychological consequences. Hence, we will study several alarm scenarios to provide the fastest possible rescue and minimize the time older people remain on the ground.

Indeed, immobilization on the ground for a long time leads to poor blood circulation in the veins and increases the risk of metabolic disorders [29]. The disturbance of normal blood flow is manifested by the appearance of blood clots in the veins. This phenomenon is known as phlebitis, which in some cases can cause a fatal complication of fatal pulmonary embolism. Therefore, hard flooring gradually produces poor tissue oxygenation due to the pressure of a person's weight in one place. As a result, the skin will begin to deteriorate more or less quickly to form skin lesions the eschar.

Similarly, the older adult's muscular crushing causes rhabdomyolysis, leading to heart dysfunction and significant kidney problems due to the sudden increase of potassium in the blood. Falling into an uncomfortable, unheated place will cause a gradual drop in body temperature. The person will lose consciousness if he or she stays in the cold for a long time. Also, seniors often take treatments regularly (anticoagulants, antiarrhythmics, etc.). The involuntary difficulty of taking their medication risks severe consequences on their lives.

For this, an older adult's immediate care avoids serious consequences and reduces the risk of mortality. The key criterion for selecting the alert scenario is the expected time spent lying on the ground. The older person's entourages are the main actors who will react after receiving an alarm in our solution. Moreover, in some cases, the emergency service intervenes to help. In table 3.2, we describe each scenario's weakness below and the level of immobilization on the ground. We have excluded the manual process of sending an alarm (pressing a button or voice communication). The alarm triggering in our system is entirely automatic.

1. Scenario A: The alert is sent to members in order of preference defined during registration in the Family Heroes system. The system must wait for each member's response and then resend the alert to the next member in case of refusal or no response within a certain time frame.
2. Scenario B: The system calculates the distance between the senior's home and each member in real-time. Then, it sends the alarm to the nearest member.
3. Scenario C: The system simultaneously sends the alert to all connected members and the emergency service. The older adult disrupts the emergency service if the situation does not require hospitalization.
4. Scenario D: The system sends the alarm simultaneously to the members registered to the profiles, then in 5 minutes, if it does not receive a validation response. A message is sent to the emergency service with the

Table 3.2: Comparison of alert process scenarios

Scenario	Weakness	Time of staying on the ground
A	Waiting time for response from each member	High
B	The system must wait for the distance calculation. If a member refuses, it repeats this intermediate step.	High
C	Obstruct the emergency service if there is no danger to the senior's life.	Medium
D	-	Low

necessary elderly's personal information.

In our system, we adopt scenario D because we guarantee that the time to stay on the ground after an accident is low. Besides, the volunteer has the complete freedom to notify the emergency service as needed. We will detail this scenario in the system's behavior in fall detection with the UML sequence diagram.

3.5 Modeling of Family Heroes system

The concepts described by CATWOE in the previous part are used to initiate UML models. The objective of the first step is to define the high-level needs and characteristics of the Family Heroes System.

3.5.1 The vision of our system

The fundamental objective of the future health care monitoring system, Family Heroes, is to minimize the dramatic consequences of domestic accidents (falls and health problems) among seniors. Beneficiaries will no longer need to carry out actions to seek help. The process is carried out automatically thanks to the technologies used. Our solution will allow networks of heroes, the entourage of seniors, to receive alerts, consult vital data, and break social isolation. We detail the description of needs in the use case specifications.

3.5.2 Functional requirements

The Family Heroes GUIs should combine functionality about alerting, entourage, first aid, and availability with planning (see Figure 3.2).

- **Alert:** The first need of the elderly is to send an alert as quickly as possible in a critical situation. For this, the victim no longer needs to press a button to trigger the alert. All communications between system modules are automated.
- **Community:** people around seniors (family members, neighbors, volunteers) can become active members. Their sincere commitment allows them to connect to the profile of the elderly. This approach greatly alleviates the psychological state of seniors. Moreover, it also avoids hampering the emergency services for each alert.

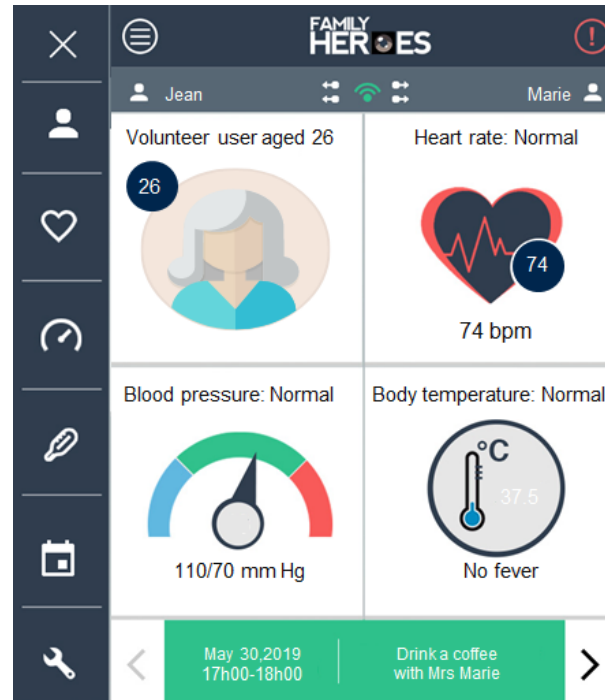


Figure 3.2: Screen presenting the system's mobile application.

- **First aid:** for each alert, a connected member must validate the notification. If no one reacts within the predefined time, the system sends a message to the emergency services. Indeed, the member, who agrees to intervene, adapts according to the accident to provide appropriate care or request an ambulance.
- **Planning:** At any time, it is possible to define tasks to be carried out together (drinking coffee, shopping, medical examination, etc.). Only one action is possible per time slot in the application. A reminder notification is sent before the time specified in the calendar. Members can create a communication channel between themselves to express their unavailability on such a day.

3.5.3 Identification of actors

Actors are one of the initial UML concepts in the model composition process. From CATWOE and the initial expression of needs, we identify them. Indeed, an actor can be a person or a hardware/software which plays a specific role. The human actors in Family Heroes are those who directly interact with the system. They are authorized to view or modify the system's state by sending or receiving communications in the form of data. During our analysis, we identified the following actors:

- **The elderly:** It should be noted that this user is responsible for the existence of the Family Heroes system.
- **Members:** they interact directly by playing specific roles. They only access the senior profile if they have the right to do so via a secret code.

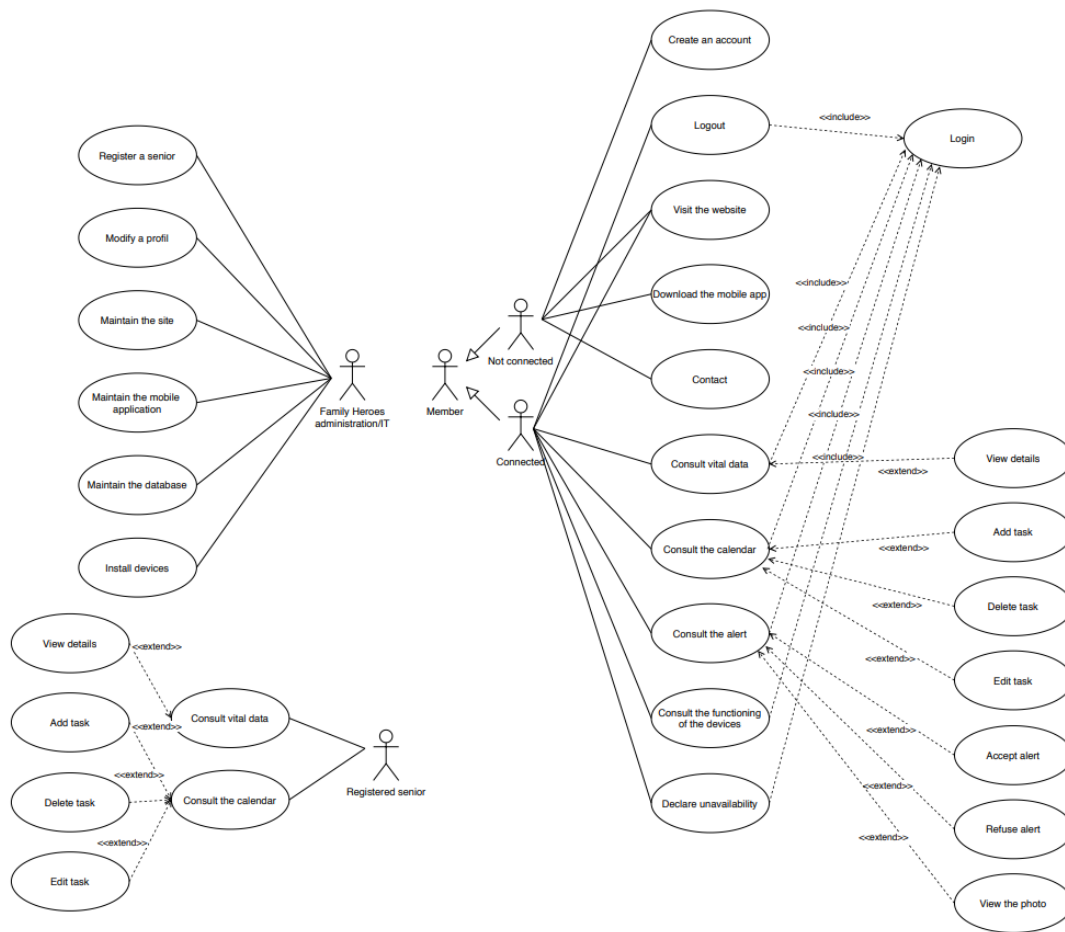


Figure 3.3: UML use case diagram in Family Heroes system.

- **Webmaster:** employees are responsible for the proper functioning and maintenance of technical elements.
- **Family Heroes Service:** Employees take care of registration and administration.

3.5.4 Identification of use cases

For each actor identified above, we represent all the actions accomplished and generate a favorable result for such an actor.

We show the different ways each user can interact with our system (see Figure 3.3). Each use case brings added value to the actor concerned. It has a purpose in itself and can be achieved independently of others. For example, the administrative service can register an older person by providing a secret code to transmit to his entourage who wishes to monitor a senior. The IT department takes care of the maintenance of IT equipment and the management of databases. The employees also install the equipment at the beneficiary of the system. In addition, they modify a profile based on a medical certificate.

Connected and authorized members have the right to consult vital data, receive alerts, declare their unavailability,

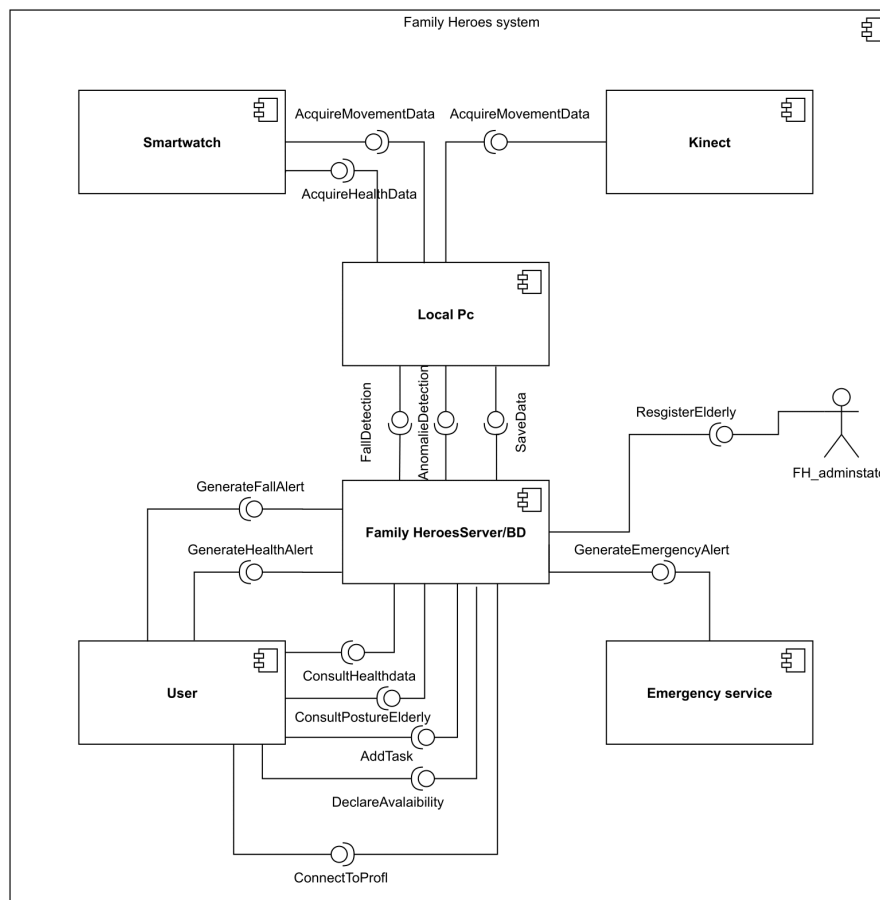


Figure 3.4: UML components diagram of Family Heroes system.

consult schedules, and equipment operation. Visitors can also contact the Family Heroes service for information, visit the site and download the app. Finally, we mention that the elderly can view their vital data and request tasks at any time.

3.5.5 UML component diagram

We represent the architecture of our system via the UML component diagram. This architecture includes a set of functionalities to be respected during construction but does not describe the components' dynamic behavior. Figure 3.4 details the UML component diagram of our system. The different components fill each other to provide the services required for other components. The local PC uses the kinematic and health data acquisition services provided by the two technologies, smartwatch and Kinect. The Family Heroes server and database also deploy the PC's health and fall detection services and data storage. It also carries out the registration of the older adult and the user's connection to the Family Heroes system. The user connector fills the server interface to use the different services (alert, real-time data consultation, task planning, and availability declaration). The emergency service uses the alert generation service to take care of seniors in critical situations.

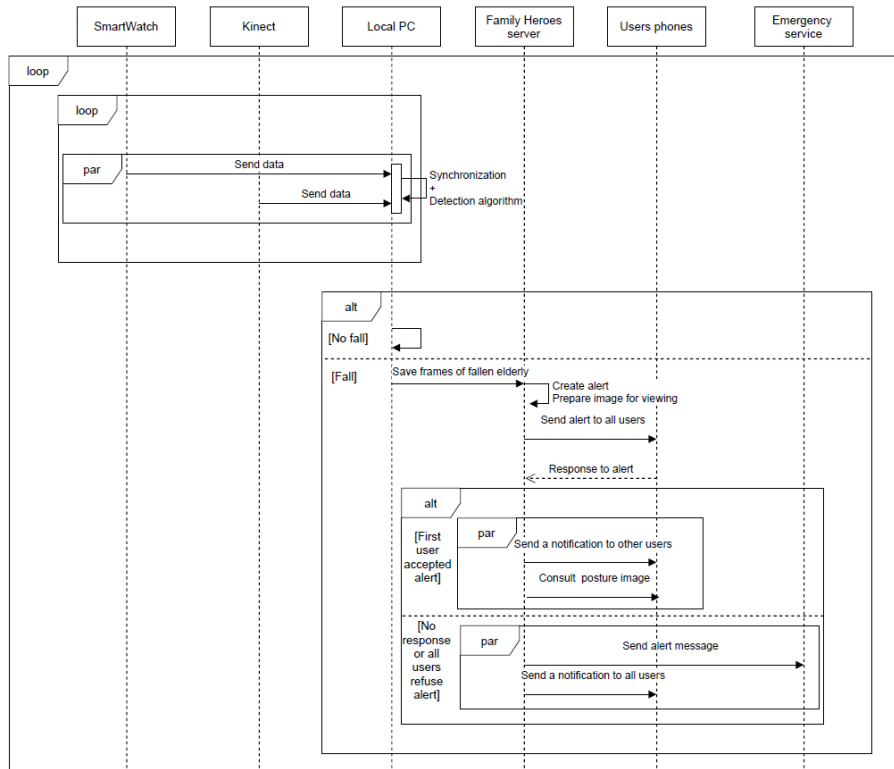


Figure 3.5: UML sequence diagram of fall detection in Family Heroes system.

3.5.6 UML Sequence Diagram Modeling of Fall Detection Subsystem

To describe the interactions between different devices and actors in our Family Heroes system, we propose to use the UML sequence diagram. Figure 3.5 represents the behavior of our system in the scenario of monitoring the elderly's activities to detect a fall in chronological order. The arrows show the flow of data and messages circulating between the different elements of our system.

1. The Kinect and the smartwatch continuously acquire the positioning data of the elderly person. The data collected is sent to the local PC processing unit.
2. On receiving the data, the pc performs the preprocessing step, the synchronization. Then it analyzes them by calculating the characteristics to judge the type of movement.
3. The detection algorithm records posture frames in the case of a fall. The server then triggers an alert and prepares the images for viewing in the Family Heroes mobile application.
4. The system informs all members connected to the older person's profile by simultaneously sending him a fall alert.
5. Members can accept or refuse the alert. After receiving an acceptance, the system sends a new notification to the other members to indicate that the situation will be treated; And allows him to view the image after

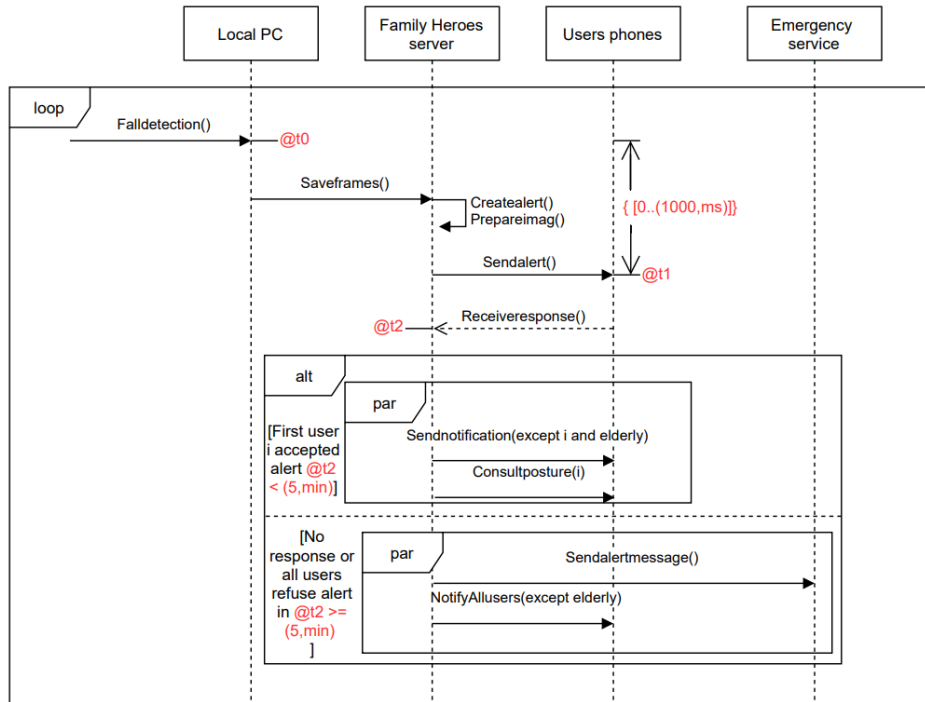


Figure 3.6: UML sequence diagram with time constraints of the Family Heroes system.

adequate security because it is about the dignity of the elderly.

6. The refusal of an alert or the absence of response allows the system to send an alert message to the emergency department with the necessary information (personal, medical, geolocation, and family members' contact). It also sends a notification to all members.

3.5.7 Modeling of real-time constraints using MARTE

We model the real-time constraints in the fall detection scenario. So, we enrich the UML sequence diagram described in Figure 3.5 by time constraints thanks to exploiting the MARTE profile. Indeed, MARTE allows the VSL to define and specify constraints on dates and durations.

We consider that the alert must be sent 1 s (one second) after the detection of the fall event, and the users' answers must be received no later than 5 min after. Figure 3.6 shows the interaction after a detected fall with observations of time constraints. The time observation @t0 denotes the instant of detection of a fall. The time constraint specified between braces specifies that the set of processes executed by the action initiated at @t0 must be performed in 1 s @t1. @t2 marks the instant of reception of the responses to the alert. Thus, the user has a duration of 5 min to respond to the alert. The system sends an alert to the emergency service in other cases (refusal or time exceeds 5 min without response).

We point out that technically the time constraints considered in our scenario are acceptable, but we will validate

them with medical professionals before system development.

3.6 Formal verification

In this section, we propose to model the behavior of the Family Heroes system with the network of timed automata. To guarantee the safety of our system (its correct functioning), we propose to formally verify its temporal properties using the UPPAAL model-checker.

3.6.1 Timed automata description

According to the UML component diagram presented in Figure 3.4, our system comprises 6 interacting devices (Smartwatch, Kinect, local Pc, server, mobile applications for users, and emergency service). We specify each system device with one timed automaton to describe its behavior. Our timed automata model is consistent with the modeling diagrams and time constraints defined previously in Sections 3.5. Indeed, these automata are defined by considering the sequence diagrams defined previously.

The set of timed automata specifying our system are described in Figure 3.7. We point out that by default, in the UPPAAL tool, the display color allows us to understand the different elements in an automaton. In a transition, light green corresponds to the guard, light blue for the synchronization chain, and dark blue for updates. The color of a state with its invariant is purple. The state of transitions with the letter U is called a state of urgency, and it forces the process to make an instant transition from one state to another.

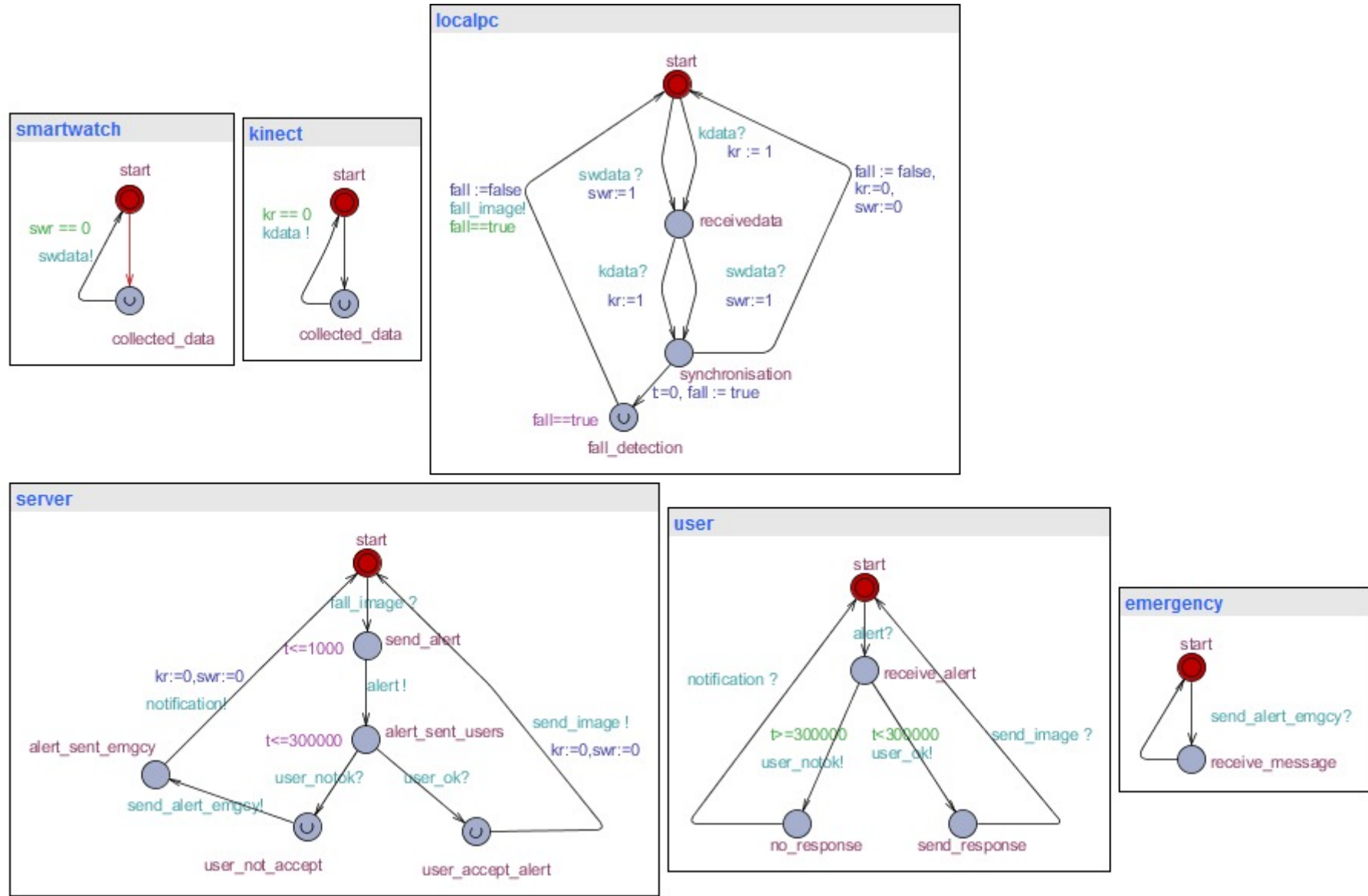


Figure 3.7: Timed automata specifying Family Heroes components.

To understand the specification with UPPAAL timed automata of our system, we propose, in the following, to describe the automata that specify the behaviors of two main system components: the server and the users' phones. For example, the formal definition of server automaton template is :

- $\mathbf{L} = \{\mathbf{L}_0 = \text{start}, \text{send_alert}, \text{alert_sent_users}, \text{user_accept_alert}, \text{user_not_accept}, \text{alert_sent_emergency}\}$.
- $\mathbf{T} = \{\text{fall_image}, \text{alert}, \text{user_ok}, \text{send_image}, \text{user_notok}, \text{send_alert_emgcy}, \text{notification}\}$.
- $\mathbf{Variables} = \{t, kr, swr\}$.

Moreover, the user automaton that models the user's phone process is characterized by 4 states ($\text{start}, \text{receive_alert}, \text{send_response}, \text{no_response}$). The user phone process is enabled when the user's phone receives an alert (alert?). This reception switches it to the send response state (send_response) by sending the accept signal (user_ok!) if the clock is strictly less than 5 min ($t < 300000$). Then it returns to the initial state after receiving the image of the fall (send_image?). In the other case, the process goes to the no response state (no_response) if the time exceeds 5 min ($t \geq 300000$), by sending the signal (user_notok!). After that, the server alerts the emergency service. Subsequently, the system returns to the initial state by receiving a notification (that the emergency service handles the alert) from the server (notification?).

3.6.2 Temporal properties verification

We specify ten temporal safety and liveness properties (formalized with UPPAAL syntax) described in Table 3.3, divided into two groups: those which should be satisfied by the system and those which should not. The results of this verification allow us to decide on the operational safety of the system.

The formal verification shows, for example, that:

- our system never reaches any deadlock state (R1),
- our system does not satisfy the property stating that after the fall detection event, the server sends the alarm after 1 second (R4).
- after a fall detection, the system will behave with one of these two possibilities: the users will respond to the alert within a maximum period of 5 minutes, or the server will immediately inform the emergency service to handle the alert (R2).
- users should not respond after 5 minutes of sending the alert(R8).

Table 3.3: Formal verification of temporal properties

Name	Property	Meaning	Satisfied
R1	A [] not deadlock	The system never reach any deadlock state	Yes
R2	(localpc.fall_detection && fall == true) - -> ((server.user_accept_alert && t <300000) or (server.alert_sent_emgcy && t >= 300000))	Always after a fall detection event, the system will behave with one of these two possibilities: the users will respond to the alert within a maximum period of 5 minutes, or the server will immediately inform the emergency service to handle the alert	Yes
R3	localpc.fall_detection - ->server.send_alert && t <= 1000	Always when local pc detects a fall, the server will eventually send the alert within a maximum period of 1 second	Yes
R4	localpc.fall_detection - ->server.send_alert && t >1000	Always when local pc detects a fall, the server will eventually send the alert within a period exceeding 1 second	No
R5	A [] (server.alert_sent_emgcy imply t <300000)	Always when the server reaches the alert_sent_emgcy state implies that t is strictly less than 5 minutes	No
R6	A [] (server.alert_sent_emgcy imply t >= 300000)	Always when the server reaches the alert_sent_emgcy location implies that t is greater than or equal to 5 minutes	Yes
R7	A [] (server.user_accept_alert imply t <300000)	Always when the server reaches the user_accept_alert location implies that t is strictly less than 5 minutes	Yes
R8	A [] (server.user_accept_alert imply t >= 300000)	Always when the server reaches the location user_accept_alert implies that t greater than or equal to 5 minutes	No
R9	A [] (server.send_alert imply server.t <= 1000)	Always when the server send_alert implies that process server respects t is less than or equal to 1 second	Yes
R10	A [] (localpc.fall_detection imply localpc.fall == true)	Always when the local pc reaches the fall_detection location implies that the fall is detected (true)	Yes

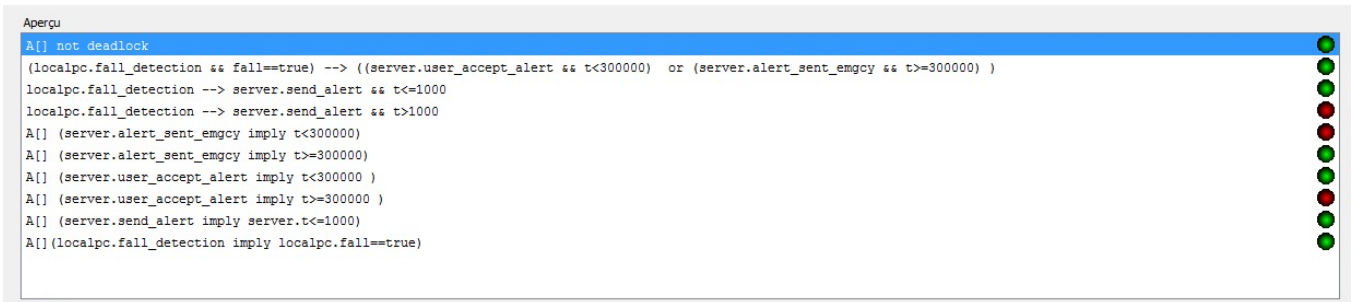


Figure 3.8: Results of properties verification.

In Table 3.3, we explain the meaning of the properties considered in the verification. The results show that our system satisfies and violates the properties that are expected to be satisfied and those to be violated. Figure 3.8 shows a part of the UPPAAL verifier interfaces with the verification result. The green circular marker indicates that the property is satisfied, and the red marker indicates that the property is not satisfied. According to these results, we guarantee the reliability of Family Heroes CPS.

Table 3.4: 2 techniques used to deal with a cyber-attack

Techniques	Cyber-attack manifested by
Identification of unusual behavior in the system	Receiving a large number of password reset requests, the unusual flow of mail (spam and phishing) comes out of the system.
Analyze system network traffic	A slowdown in network speed due to spikes in network traffic.

3.7 Cybersecurity of Family Heroes System

3.7.1 Overview

Cyber-attacks on critical systems constitute a significant threat [64, 40]. Moreover, they are a major threat that could produce dangerous consequences on people's lives. Indeed, the consequences could impact the health system's reliability in terms of its operation and protect sensitive personal data. The attack scenarios are multiple, and those that are common in our context are:

- Paralyze a system by disabling the webserver: this type of attack crashes software and hosted data to block users' access to services by abruptly taking control of the webserver.
- Putting data at risk to corrupt, steal or destroy it: Data are particularly sensitive and confidential in the health-care sector. Cybercriminals often infiltrate to get their hands on various computerized data to exploit them maliciously.
- Control devices: Numerous loopholes in the control protocol favor the hackers' motive to manipulate devices for criminal interests remotely.

Therefore, the cyber-attack constraint must be considered at the design level to prevent the consequences mentioned above.

To deal with cyber-attacks in the Family Heroes system, we propose focusing on system architecture. In other words, we propose an approach that consists of designing systems with reconfigurable architecture. The system architecture must guarantee the smooth running of services by switching to a rescue configuration in the event of a cyber-attack. Moreover, it should be noted that the variety of connected technologies in the Family Heroes system exposes it to the cybersecurity risk zone. We will not detail the security techniques to be deployed in our system (authentication security, encryption of sensitive data, network protection) but rather the alternative solution. This solution will guarantee the continuity of sending alerts when a cyber-attack occurs.

Indeed, it is essential to detect a computer intrusion to reduce the cyber-attack consequences quickly. In Table 3.4 we cite two categories of techniques used to fight against a cyber-attack [119].

Therefore, we propose an approach that allows reconfiguring the system when a cyber-attack occurs while en-

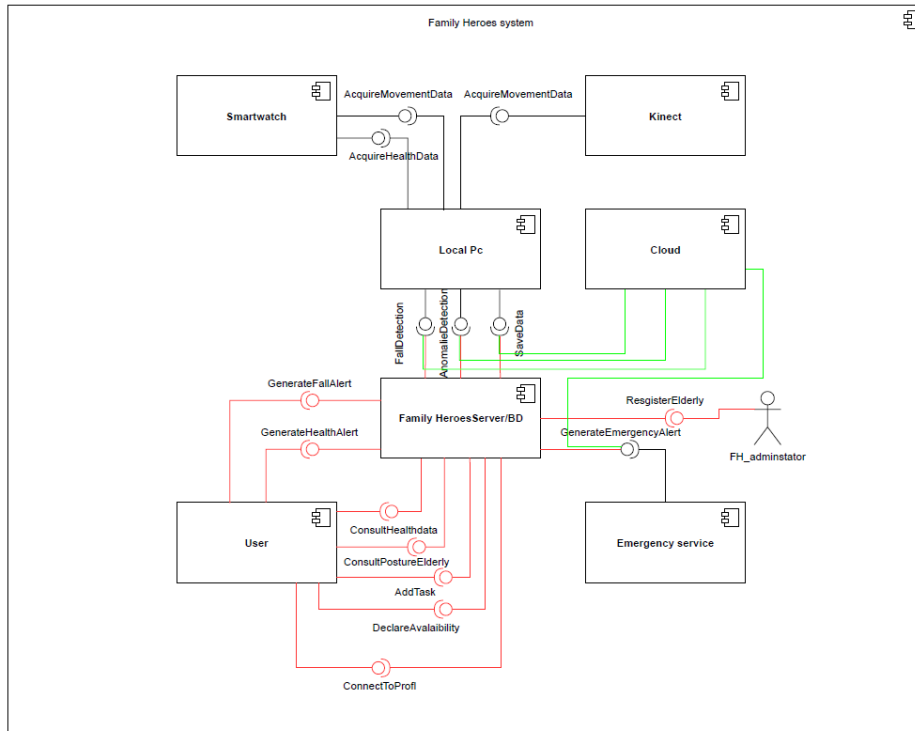


Figure 3.9: UML components diagram of the alternative solution.

ensuring the availability of system services. To achieve this, we adopt the approach related to slow network traffic to switch to the alternative solution by reassuring the operation of sending emergency alerts. That is, the system must:

1. Disconnect all members because the cyber-attack could come from the users.
2. Connect the processing unit to the cloud.
3. Isolate the server/database.

3.7.2 Architecture of a reconfigurable system

We represent the architecture of our system and the organization of its components after a cyber-attack using the UML component diagram in Figure 3.9. We show in detail the new connections between the different components during the execution of the alternative solution. The connections in red correspond to the temporal interruption of the functionalities and the bright green to the new communication. Indeed, the new organization of the components (connected watch, Kinect, local PC, Cloud, and emergency service) still satisfies the requirement to send alarms in case of fall or unwellness. The cloud replaces the server of Family Heroes to use the services of critical situation detection and data storage provided by the local PC. The emergency service then uses the alarm generation service hosted in the cloud.

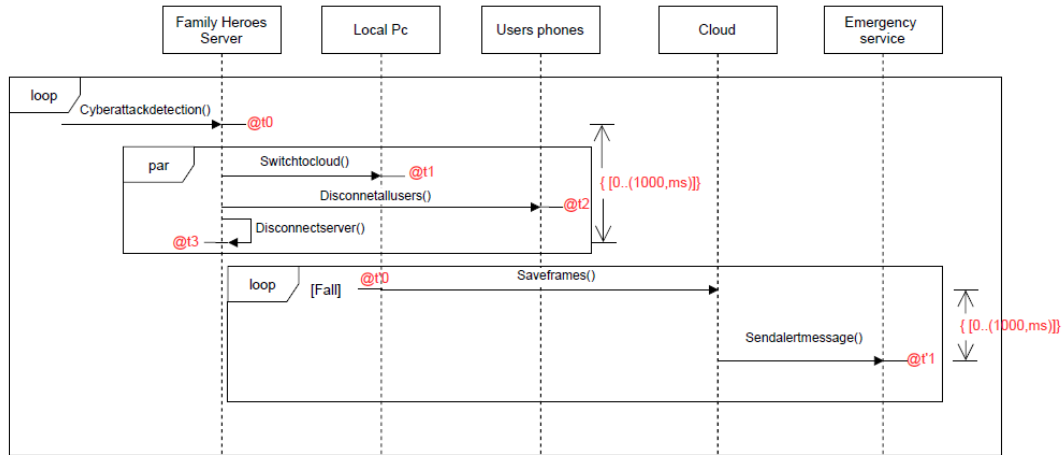


Figure 3.10: UML sequence diagram in fall and cyber-attack scenario.

3.7.3 System behavior modeling

We model the system behaviors with the sequence diagram with the time constraints of the MARTE profile, as detailed in Figure 3.10. This model used the elderly activity monitoring scenario for fall detection.

The temporal observation @t0 represents the instant when the server detects a cyber-attack. Then, all processes executed by the initialized action @t0 must be executed in 1s @t1, @t2, and @t3. These processes include: (1) switching communication to the cloud, (2) disconnecting users, and (3) disconnecting the server from the network. @t'0 marks the timed observation of the detection of a fall. Then, within 1s (one second) after receiving the image of the fallen person from the local PC, the cloud sends the alarm to the emergency services.

3.7.4 Timed automata description

Compared to the automata in Section 3.6.1, we have added the states corresponding to the alternative solution as detailed in Figure 3.11.

- Local PC model: the local PC is modeled by a timed automaton synchronized with the smartwatch (*swdata?*), the Kinect (*kdata?*), and the server (*requestcyberemergency?*). In case of a cyber-attack, it sends synchronization messages to the cloud (*cloud_ready!*) when it reaches the position (*Switchcommunication_tocloud*). It also has 2 possibilities of communication in case of a fall (*fall == true*), either with the cloud (*fall_image_cloud! &&cyberattack == true*) in the alternative solution, or with the server (*fall_image! &&cyberattack == false*) if there is no cyber danger. The automaton thus modifies the values of the corresponding variables (*kr*, *swr*, *fall*, *t*) according to its planned execution to avoid deadlock.
- Cloud model: the cloud automaton describes its communication with the local PC and the emergency service in case of a critical situation in a second. Initially, its model starts from the state (*start*). Then, when

the local PC establishes its communication with the cloud (*cloud_ready?*), the cloud reaches the next state (*cloud_ready_communication*). The detection of a fall activates its transition to the *send_alert* state after receiving the image of the older adult lying on the ground (*fall_image_cloud?*). In the last transition, the cloud sends the alarm to the emergency service (*send_alertcloudEmergency!*) respecting the defined time property.

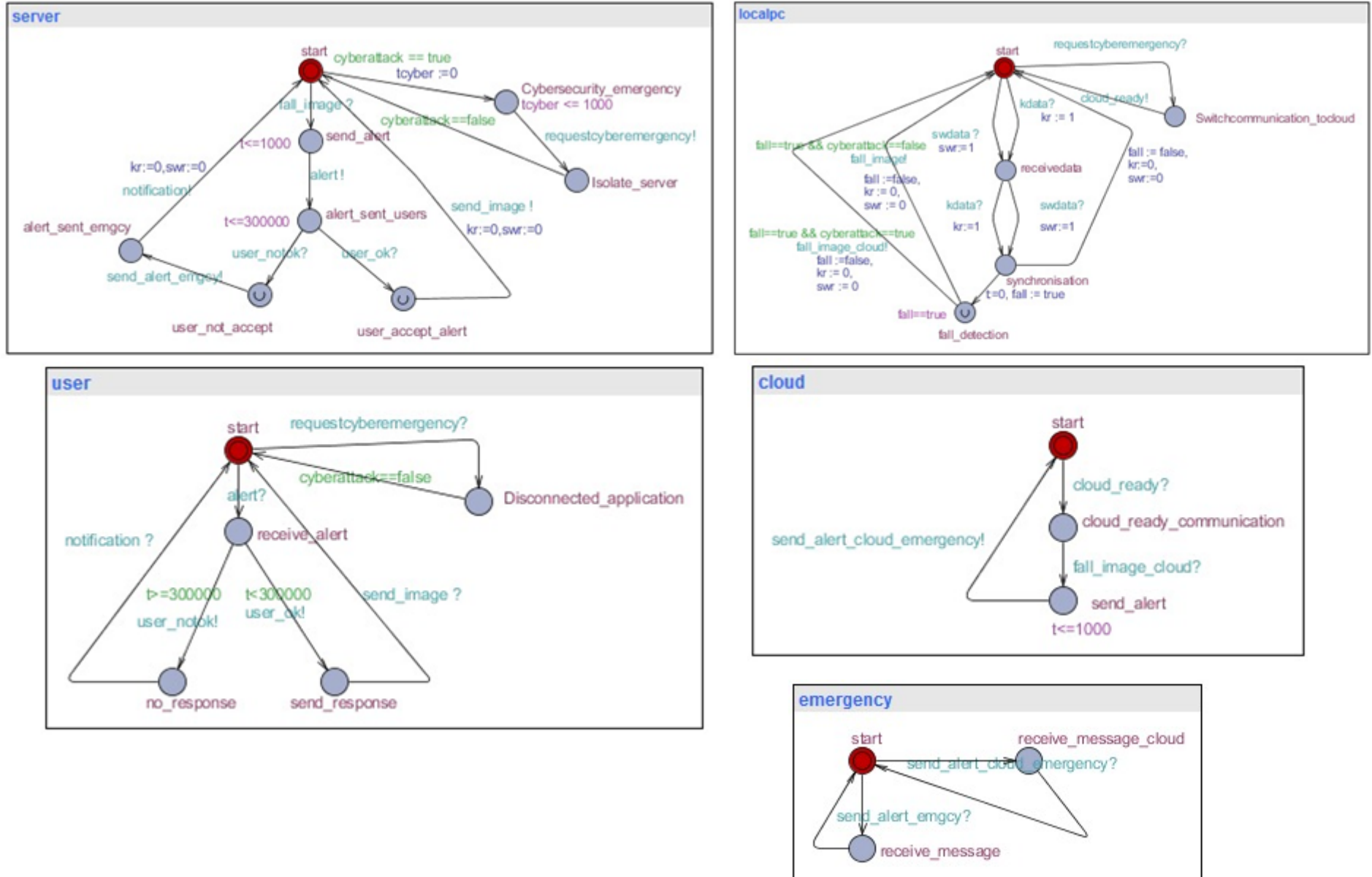


Figure 3.11: Timed automata specifying the cyber-attack scenario.

Table 3.5: Formal verification of properties

Name	Property	Satisfied
R1	A[] not deadlock	Yes
R2	server.Cybersecurity_emergency - ->((localpc.Switchcommunication_tocloud && tcyber <= 1000) and (user.Disconnected_application && tcyber <= 1000) and (server.Isolate_server && tcyber <= 1000))	Yes
R3	A[]user.receive_alert imply cyberattack==true	No
R4	A[]user.receive_alert imply cyberattack==false	Yes
R5	localpc.fall_detection && cyberattack==true - ->cloud.send_alert && t <= 1000	Yes
R6	localpc.fall_detection && cyberattack==false - ->cloud.send_alert && t <= 1000	No

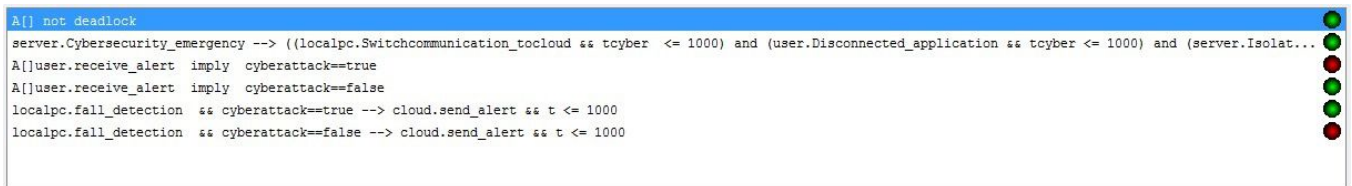


Figure 3.12: Formal verification of properties.

3.7.5 Formal verification of properties

To guarantee the proposed system reconfiguration ensures the availability of critical system services during a cyber-attack, we propose to verify formally, with the model-checker UPPAAL, the following temporal properties that concern system security:

1. The absence of deadlocks for all possible executions of our model (R1);
2. The detection of a cyber-attack by the server causes the switching of communication to the cloud, the disconnection of all users, and the disconnection of the server from the network in 1s (R2);
3. Users cannot receive alerts during the cyber-attack (R3);
4. Users receive alerts whether there is no cyber-attack (R4);
5. After a fall, the cloud sends the alert to the emergency services in 1 second (R5);
6. The cloud does not communicate with emergency services in the absence of a cyber attack (R6).

As shown in Table 3.5 and 3.12, the properties that are expected to be satisfied (R1, R2, R4, R5) are satisfied, and those that are expected to be violated (R3, R6) are violated. Consequently, the security of our system is guaranteed when a cyber-attack occurs, which shows the soundness of our approach.

3.8 Conclusion

The development of a critical health care CPS for the elderly is a real challenge that can only be met by ensuring their reliability and high performance. We presented a three-step approach for analysis, modeling, and verifying a

system for the elderly, Family Heroes. The originality is the precise application of these three steps in our system development cycle to ensure its correctness. First, we used the CATWOE method to analyze and understand the general context of our system. UML and MARTE to model the behaviors and interactions of Family Heroes components and their temporal constraints. We also checked our model against the time requirements and properties defined in the modeling steps using the UPPAAL tool, which allows us to ensure its reliability. We have also studied the security aspect of our system in the event of a cyber-attack.

Chapter 4

Fall detection in the Family Heroes System

This chapter is devoted to our 2 methods of automatic fall detection using the Kinect camera. First, we start with the representation of Kinect technology. Then, we explain our approach based on thresholds by deploying geometric characteristics (the variation in height and angles of the upper body) and inactivity on the ground. Next, we detail our new lightweight model based on LSTM Deep Learning using geometric and pixel features. This model is designed to work on limited devices like the Raspberry Pi ones.

4.1 Introduction

Each person is susceptible to falling at least once in their life. The frequency of falls is increasing, and the consequences worsen in the elderly who have physical weakness and are alone at home. Indeed, the monitoring of human activities in 3D using artificial vision has attracted much attention from researchers in recent years. Microsoft's RGB-D sensor films a high-frequency 3D scene and provides several types of information for each pixel. Its advantages include automatic calibration and the fact that lighting conditions do not affect the fidelity of the 3D reconstruction. However, detecting a fall of an older person from a video scene raises several questions.

- What type of data should be used to respect the privacy of seniors?
- From which characteristics do we obtain a correct characterization of the fall?
- What approach is suitable for the correct detection of a fall over time?

Therefore, it is essential to comprehend the problem's concept to develop reliable solutions that can be applied in real-time. The choice of features is crucial in proposing a method. Also, the different types of data acquired from the Kinect help us estimate geometric, kinematic, and pixel characteristics in 2D and 3D space. We are convinced that the skeletal data (3D coordinates of human joints) determine relevant characteristics to analyze the whole

movement in 3D space. Consequently, they make it possible to propose very effective approaches for detecting falls in the elderly.

4.2 Microsoft's Kinect technology

4.2.1 Brief history

The Microsoft Kinect (formerly known as the natal project) made its first public appearance during the Electronic Entertainment Expo in June 2009 [3]. Initially, this optional accessory was intended for the video game console, Xbox 360, for digital leisure. It allowed us to interact directly with a video game's content without any controller; The player is simply the controller. The Kinect can be controlled by motion recognition and voice commands.

Over 8 million copies are sold 60 days after its release in November 2010. The Xbox 360 keeps the Guinness World Record as the fastest-growing consumer electronics device sold [135]. Then in February 2012, Microsoft unveiled the official use of this depth sensor on PC. After the great success of Version 1, Microsoft continued its development project and it released the Kinect V2 in 2014. This giant company resuscitated its Kinect after the announcement of the production halt in 2015. They presented a new connected camera, the Microsoft Azure Kinect, at the 2019 MWC in Barcelona [7]. Through innovation on different versions of Kinect, scientific researchers have shown Kinect's potential as a platform for science and industries to create innovative new applications; Kinect has opened enormous opportunities for the scientific community to tackle societal issues such as health, education, aging well.

4.2.2 Technical specifications

The Kinect includes different sensors that consolidate and analyze the visual and sound data collected within its operating range. It can capture three kinds of images, RGB image, depth image, and an infrared image. We present a comparison of common technical elements. The following technical information is collected from official Microsoft documents [9], such as books [145, 107, 118]. The comparison of technical characteristics is presented, for each model, in Table 4.1.

Features	Kinect V1	Kinect V2	Azure kinect
Sensors	RGB 3D Depth 4-mic progressif linear array Accelerometer 3 axis	RGB 3D Depth 4-mic progressif linear array Accelerometer 3 axis	RGB 3D Depth 7-mic circular array Accelerometer 3 axis Gyroscope 3 axis
Color stream	640 x 480 @ 30fps	1920 x 1080 @ 30fps 1920 x 1080 @15fps	3840 x 2160 @30fps
Depth stream	320 x 240 @ 30fps	512 x 424 @ 30fps	640 x 576 @ 30fps 512 x 512 @30fps 1024 x 1024 @ 15fps
Operating range	0.8 ~4.5m	0.5 ~4.5m	0.5 ~3.86m
View angles (H x V)	57° x 43°	70° x 60°	75° x 65°
Joints per person	20	25	31
Depth method	Structured light	Time of flight	Time of flight
Tilt motor	Motorized (up down 27°)	Manual	Manual
Hardware Requirements	Dual-core 2.66GHz 2GB RAM	Dual-core 3.1GHz DX11 graphics processor 4GB RAM	Dual-core 2.4GHz HD620 graphics processor 4GB RAM
Supported OS	Win 7, Win 8 Win embedded standard 7	Win 8 Win embedded 8	Win 10 Ubuntu 18.04
Connectivity	USB 2.0	USB 3.0	USB 3.0

Table 4.1: The comparison between the 3 generations of kinect technology

The Kinect V1 includes an RGB camera, a 3D depth sensor (infrared camera and CMOS detector), a 3-axis accelerometer, a 4-microphone network, and a tilt motor. Its 3D vision technology was developed by the company PrimeSense. The information is interpreted from the structured infrared light projected continuously. It maps the infrared lightroom and creates a thermal map that identifies the distance between the lens and the scene for each pixel. The RGB camera allows recording the video stream in 640 x 480 at 30fps. The depth sensor generates depth data in 320 x 240 format in 30fps. Microphones allow the spatial location of a sound source as well as the elimination of background noise. They collect sound data in 16Khz. The motorized foot makes it possible to move the change of vision up and down by a value of 27°. A USB 2.0 port and a USB power adapter are required to interface with a PC. Microsoft's minimum recommendations are x32 and x64 processor, at least dual 2.66GHz type, 2GB RAM, and a Direct X9.0c compatible graphics card. Version 7 is required on the Windows side.

The Kinect V2 first contains an RGB camera with high definition in 1920 x 1080 and a wide-angle capture. It collects data in 30fps and 15fps under high light and low light conditions, respectively. The 3D information is obtained by the depth sensor and the infrared emitter. The fusion of these two technologies has made it possible to obtain accurate data in 3D space even under dark lighting conditions. The V2 uses the Time of Flight method to generate a complete 3D image of the measured object. This principle makes it possible to measure the distance of a scene from the time taken by light to reach the objective and return. The depth sensor operates at a resolution of 512 x 424 in 30fps. The IR Stream can be used at the same time as the color.

The Kinect V2 also includes a high-quality 4-mic linear progressive array. The latter allows capturing useful informa-

tion in noisy conditions in 48Khz. The orientation of these sensors enables the detection of the sound's origin area over a 180° range. The V2 also includes a 3-axis accelerometer. The Kinect V2 communicates with a PC via a USB 3.0 controller. Thus, Microsoft has provided minimum recommendations regarding PC's performance to run the V2: 64-bit processor required, a Dual-Core 3.1GHz, 4GB of RAM, and a Direct X11 compatible graphics adapter. This version works on the pc that has at least a Windows 8 or Embedded 8 operating system.

Kinect's innovation will come from the capacity to miniaturize and improve sensor performance in each edition. The integration of the cloud, artificial intelligence, and Kinect motion-sensing technologies distinguish Microsoft Azure Kinect. It can be deployed with or without cloud services, and It is half the size of V2. This box contains, first of all, a 12MP RGB camera, a 1MP TOF depth camera, a circular array of 7 microphones, an inertial motion unit (a 3-axis accelerometer and a 3-axis gyroscope). The RGB camera captures images with a high resolution of 3840 x 2160 at 30fps. The depth sensor captures information in space at different resolutions 640 x 576 and 512 x 512 in 30fps, and 1024 x 1024 in 15fps. IMU allows sensor orientation and spatial tracking. It only works if the color and/or depth sensors work. It allows the external synchronization of sensor flows from several Kinects. Microsoft's minimum recommendations: Processor must be 64, at least dual Core 2.4GHz, 4GB RAM, and a graphics processor HD620 or higher, USB 3.0 port. This version is supported by Windows 10 or Ubuntu 18.04 LTS.

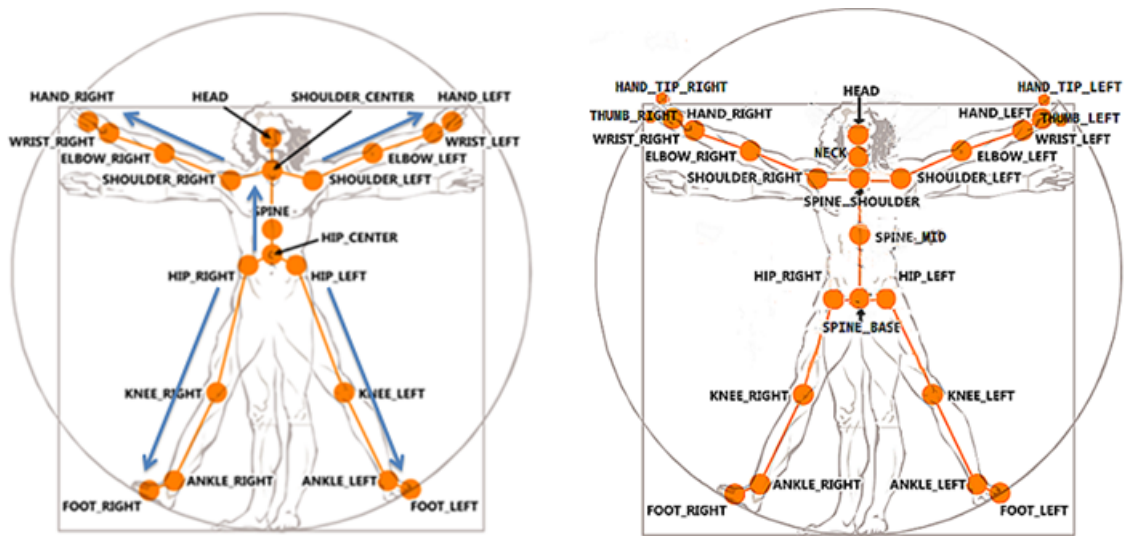
In reality, each new generation of Kinect is more powerful and is presented in a new style. In addition, the innovation of the sensors, the evolution of the shape, and motion recognition algorithms embedded in them allow having more reliable data of the filmed objects. Thus, this versatile technology is far from being outdated.

4.2.3 Kinect software tools

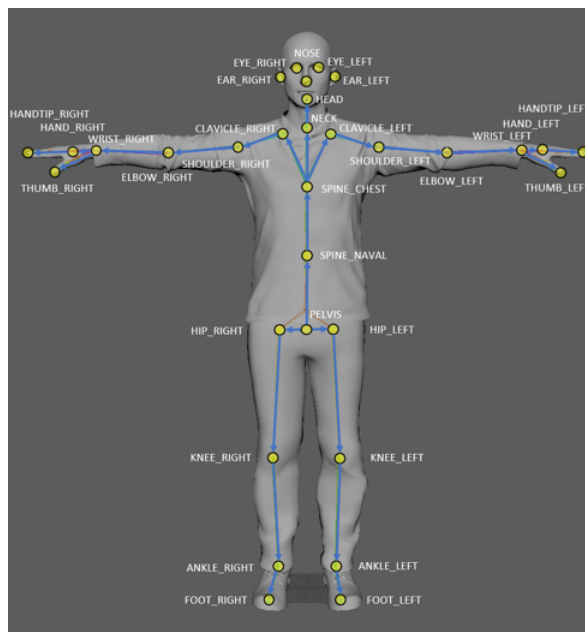
Microsoft has planned to use Kinect only for video games during the day of publication. However, Adafruit has launched a hacking contest to make Kinect functional on Windows with an increased bonus of up to 3K\$ [41]. Hackers groups have successfully exploited Kinect data on PC. They have provided free libraries and unofficial SDKs (CL NUI platform, Libfreenect, OpenNi, PCL). To act against hack initiatives and open source libraries, Microsoft launched the first official SDK in July 2011 [32]. The official SDK allows users to develop applications that encourage gesture and voice recognition. It provides direct access to Kinect data. This SDK includes drivers for deploying the Kinect on a computer running with the required operating system. Thus, application programming interfaces (APIs), device interfaces, and samples codes are available in the development kit delivered by Microsoft. It is interesting to note that the research laboratories were the first users of Kinect outside consoles. Most of the previous libraries offer basic functionalities such as (camera calibration, automatic body calibration, skeleton tracking, face tracking, scanning). Each library has advantages and disadvantages.

OpenNi and Microsoft SDK are the most used libraries in the development community [58]. OpenNI's most compelling benefit is its flexibility for multiple operating platforms. Also, it is most beneficial to use OpenNi to provides

the best results on finding colored points clouds. However, Kinect SDK is more stable in terms of the accuracy of the original image and the preprocessing technology. Moreover, it is more convenient to use when it requires skeletal monitoring and audio processing. Each version of Kinect can detect and interpret the movements of a specific number of individuals in the scene. It exploits a person's skeleton by generating 3D data (position and orientation) for particular joints [79] (i.e. 4.1 4.2). The depth data and the Random Forest classifier establish the skeleton in each frame acquired [129]. The random forest categorized each pixel into the background or part of the body. The pixels allocate to each body part are clustered to create the skeletal model. The ease of obtaining the skeleton has made the Kinect one of the most suitable technologies in fall detection.



(a) The hierarchy of joints provided by V1 and V2 [66]



(b) The hierarchy of joints provided by Azure Kinect [9]

Figure 4.1: Joint positions relative to the tracked human body

4.3 Threshold based approach

4.3.1 Related work

This section is interested in models based on thresholds from 3D skeletal data acquired from the Kinect, without placing markers on the target's body and without preprocessing steps. Fall detection is a study that is based on the simplified representation of a movement or posture. In the literature, this type of approach consists of using mathematical equations to describe properties of movements, then comparing them to predefined values. If the values exceed the thresholds, the system detects a drop and sends alerts in some cases. These features are more complex because they involve several constraints related, on the one hand, to the physics of the person and, on the other hand, to the experimental configuration of the study. Therefore, the authors try to find the most relevant characteristics to achieve both general and deterministic algorithms in separating all types of movements.

Yajai et al. [148] proposed an analytical approach based on surrounding the human silhouette by an Adaptive Directional Bounding Box. The 3D coordinates of the 20 joints of the human body are used as input data to calculate the characteristics. Indeed, the variation of 4 characteristics (the ratios: (1) of the height-width of the bounding box, (2) of the center of gravity, (3) of the diagonal, and (4) of the height between the maximum bounding box and current) in time represents the movement of the person. Furthermore, their method tackled the difficulty of detecting falls, forward and backward, by virtually rotating the camera in a direction perpendicular to that of the fall. To increase the active area, Mundher et al. [101] hooked the Kinect to a mobile robot. The authors used the distance from the ground of 5 joints (head, shoulder center, hip center, ankle right, and ankle left) in this work. They also used the period of inactivity (5s) to validate a fall and decrease the false alarm rate. Their approach integrates modules for voice control and robot tracking.

Lee et al. [82] proposed a fall detection system based on the distance between the center of mass and the ground and its velocity (horizontal and vertical). In effect, they deployed the hip center joint as a center of mass of the person. In addition, the performance analysis agrees that the velocity in both directions can detect the fall in all directions. The authors also showed a complimentary postural recognition algorithm. Their objective is to distinguish between a fall and like-fall to increase the specificity of their approach. In the same context, Kawatsu et al. [67] uses dynamic characteristics of the 21 joints. They estimate the distance between the ground and each joint, the average vertical velocity over N frames. Their method recalculates the average value over the number of joints detected if a joint is not detected due to an occlusion.

The authors in [55] introduced the principle of data fusion to detect falls. Their approach is based on the skeletal characteristics from Kinect and the joint acceleration from a 3-axis accelerometer. One of their challenges was synchronizing two sources. For this, they have developed an ad hoc synchronization algorithm. Indeed, they deployed the variation of spine-base position along the y axis, the magnitude of the acceleration (placed once on the wrist then the waist), and the orientation angle between the x -axis and the vector g . In addition, they evaluated the spine's

	Kinect V1	Kinect V2	Azure Kinect
Number of body tracked simultaneously	2	6	N/A ^a
Number of joint per person	20	25	32
Enumerates of Joints in SDK	0-Hip_Center 1-Spine 2-Shoulder_Center 3-Head 4-Shoulder_Left 5-Elbow_Left 6-Wrist_Left 7-Hand_Left 8-Shoulder_Right 9-Elbow_Right 10-Wrist_Right 11-Hand_Right 12-Hip_Left 13-Knee_Left 14-Ankle_Left 15-Foot_Left 16-Hip_Right 17-Knee_Right 18-Ankle_Right 19-Foot_Right	0-Spine_Base 1-Spine_Mid 2-Neck 3-Head 4-Shoulder_Left 5-Elbow_Left 6-Wrist_Left 7-Hand_Left 8-Shoulder_Right 9-Elbow_Right 10-Wrist_Right 11-Hand_Right 12-Hip_Left 13-Knee_Left 14-Ankle_Left 15-Foot_Left 16-Hip_Right 17-Knee_Right 18-Ankle_Right 19-Foot_Right 20-Spine_Shoulder 21-HandTip_Left 22-Thumb_Left 23-HandTip_Right 24-Thumb_Right	0-Pelvis 1-Spine_Naval 2-Spine_Chest 3-Neck 4-Clavicle_Left 5-Shoulder_Left 6-Elbow_Left 7-Wrist_Left 8-Hand_Left 9-Handtip_Left 10-Thumb_Left 11-Clavicle_Right 12-Shoulder_right 13-Elbow_Right 14-Wrist_Right 15-Hand_Right 16-Handtip_Right 17-Thumb_Right 18-Hip_Left 19-Knee_Left 20-Ankle_Left 21-Foot_Left 22-Hip_Right 23-Knee_Right 24-Ankle_Right 25-Foot_Right 26-Head 27-Nose 28-Eye_Left 29-Ear_Left 30-Eye_Right 31-Ear_Right
Development language	C++, C#, VB	C++, C#, VB	C, C++

^a The official documentation did not specify the exact number "Azure kinect body tracking can track multiple human bodies at the same time".

Table 4.2: Comparaison between the kinect SDK version for Body

position, its distance from the ground, and the acceleration when the accelerometer was placed on the waist. We found that the evaluation of the approaches was carried out in environments simulated by volunteers. In some cases, the threshold values are calculated from experimental trials, or the authors use already published values. Thus, the types of simulated and evaluated activities are not identical in all research works. Therefore, the comparison between the performance of the approaches is unfair due to the lack of common experimental elements.

4.3.2 Our approach

Our method of detecting falls using the Kinect V2 is inspired by vector observation. Indeed, a person can be represented by a point p in 3D Cartesian space. Its displacement causes a variation of the coordinates of $P(x_t, y_t, z_t)$ at each instant t . In our study, the Kinect camera is the center of the coordinate system. So, \vec{OP} is the vector connecting the center with the exact location of the person. In addition, the combination of 2 vectors also allows us to find the angle formed by them. A fall is a sudden tilt of the body towards the ground caused by a loss of balance and the law of gravity. As the person approaches the ground, the value of the angle between a standing-tilt position and lying down on the ground increases. We use this variation as a relevant characteristic in the detection of falls in the elderly.

Our approach is made up of several modules:

- Extraction of the 3D coordinates of the upper body (head, neck, shoulder right, shoulder left, and spine shoulder);
- Analyze the variation along the y axis;
- Examine the variation of the angle over time;
- Observe the period of inactivity.

Figure 4.2 illustrates our fall detection approach. Acquiring the 3D coordinates of the joints is a crucial step. We did that by using the official Kinect SDK. In the Kinect coordinate system, the X-axis is the horizontal axis, Y is the vertical axis, and Z is depth. Once the data is acquired, we monitor the variation between the maximum height y_{max} and y_t of the joints. The Ymax value corresponds to the highest Y coordinate of each joint at $[t_0; t_1]$. Thus, a 20% decrease in y_{max} between $[t_1; t_2]$ lets us know if there is a change in posture. On the other hand, the fall and certain daily activities are characterized by a common significant variation in the person's height. As a result, we apply the conditions of angle variation ($> 30^\circ$ during $[t_2; t_3]$) and inactivity ($y_t < 80\%$ of y_{max} during $[t_3; t_4] = 5s$) to determine if a fall has occurred. The angle is calculated using the formula 4.1. $\vec{OP}_t \cdot \vec{OP}_{t+1}$ is the dot product of the two vectors, and $\|\vec{OP}\|$ is the norm of the vector.

$$\cos \alpha = \frac{\vec{OP}_t \cdot \vec{OP}_{t+1}}{\|\vec{OP}_t\| \cdot \|\vec{OP}_{t+1}\|} \quad (4.1)$$

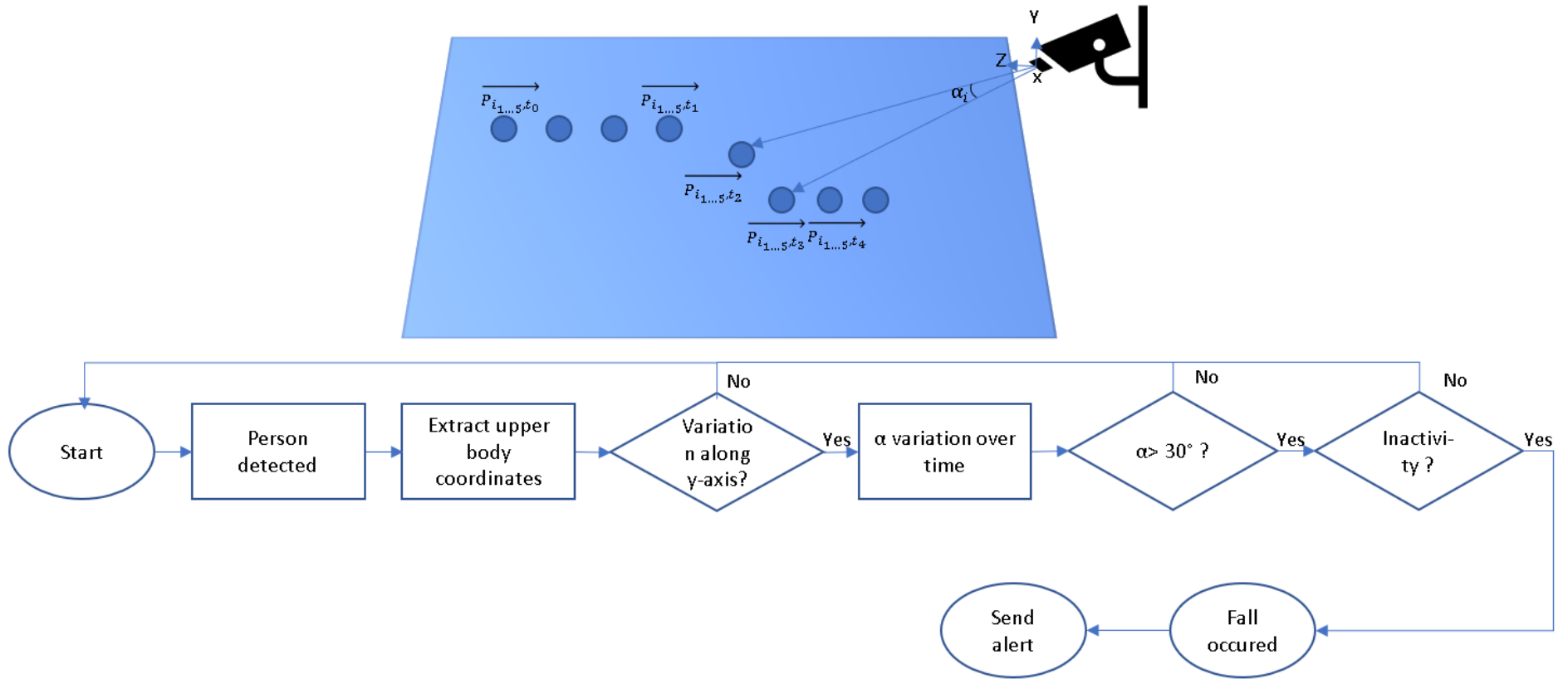


Figure 4.2: Overview of our threshold based approach.

		True action	
		Fall	ADL
Predict action	Fall	133	5
	ADL	57	15
		SE=70%	SP=75%

Table 4.3: Experimental data analysis.

4.3.3 Experimental evaluation and discussion

2 young volunteers aged over 24 took part in the experience. They simulated scenarios such as daily activities (sitting on a chair, lying on a bed, crouching on the floor, tilting to pick up an object from the floor) and falls (fast lateral, slow lateral, backward, and forward). A total of 210 intentional actions, acquired at a rate of 30fps, were used to evaluate our approach.

As part of the experiment, we placed the Kinect at the height of 70-80cm, then at a height greater than 1.6m. The volunteers carried out the activities in the camera area at several distances (2.5m, 3m, and 3.5m) and in a secure environment. We used the sensitivity and specificity metrics to evaluate the performance of our approach. The results are shown in Table 4.3. Performance is measured as a percentage. As indicated by Table 4.1, our approach can correctly detect 70% of falls and correctly filter 75% of daily activities.

The main advantage of our approach over the existing methods below is that there is no need first to recognize the floor plane equation or perform image processing steps. In addition, it is directly applicable to the skeletal data of the Kinect. It also works without limitations with light and without violating the privacy of the elderly.

The first experimental evaluation allows us to structure new perspectives. In particular, various avenues for improvement are possible for our approach. First, the number of joints used can be replaced by just one (the head). On the other hand, adding more features can be a solution with accuracy very close to 100%. This ad is composed of characteristics from the Kinect or a second data source such as a 3-axis accelerometer. Indeed, we adapt the use of an external source which is one of the essential requirements of the Family Heroes system. In the literature, the deployment of an accelerometer makes it possible to distinguish between a fall and a daily activity "lying on the ground" due to the enormous difference between the magnitude of the acceleration vector for each activity. The characteristics of the Kinect are crucial in distinguishing between a fall and everyday activities such as sitting in a chair, giving birth [55]. In addition, more experimentation must be set up. Finally, we need to have more volunteers to simulate more scenarios as well.

4.4 Deep Learning approach

4.4.1 Related work

In this part, we present research works on fall detection using deep learning and the Kinect camera.

Li et al. [85] proposed a CNN-based model that analyzes the deformation characteristics of the human form in each image to detect falls. In their approach, they modified the architecture of the AlexNet model by changing the number of neurons in the last two fully connected layers and removing all the response normalization layers. Indeed, they labeled the video sequences of the URFD dataset for experimental evaluation in 4 phases (3 for the activity of daily living (ADL) and 1 for the fall where the target is on the ground). In total, they evaluated their approach with 8500 images (7733 for ADL and 767 for the fall) after a pre-processing of the data (rescaling, deletion of the average image, and normalization). Their method executed in real-time reaches an average accuracy of 99.98% for 10-fold cross-validation.

Biomechanical equilibrium characteristics with LSTM are introduced by Xu et al. [146] to detect falls in the elderly. The authors estimated the variables of changes in human equilibrium (center of mass, line of gravity, and base support region) from 3D skeletal data acquired by Kinect. Then, they used the LSTM structure on the data sequences to classify human activities. They deployed 244 activities from the TST V2 dataset in the training and validation of their method. The experimental results showed that the fall detection accuracy is 95%.

The fall detection approach proposed by Abobakr et al. [11] is based on Convolutional Neural Network (CNN) (ResNet), Recurrent Neural Network (RNN) (LSTM), and logistic regression. Their ConvLSTM combination analyzes visual descriptors and temporal dynamics from input depth videos. They proposed a model characterized by the extractor of Spatio-temporal features and end-to-end training using back-propagation. The depth videos, captured by the Kinect V1, are preprocessed using four techniques (depth normalization, resizing, image cropping, and RGB colorization) before being implemented in the deep learning models. They evaluated their method using the public URFD dataset such that each video is segmented in a sequence of 80 frames. In total, they deployed 80% (1750 sequences) of data for training and 20% (725 sequences) for the validation step. The experimental performance of the system is high with 98% average precision, 97% accuracy, 100% sensitivity, and 97% specificity. Their approach can detect falls in real-time with a processing rate of 15 sequences per second on NVIDIA TITAN-X GPU.

Ge et al. [56] proposed a solution to detect human falls based on a deep recurrent convolutional network architecture (CNN and LSTM) and the co-saliency method. In their system, each frame of the input RGB video is processed by the co-saliency technique to enhance and extract dynamic regions of human movement. Then, the RCN architecture learns the enhanced video sequence, by co-saliency, to judge whether human activity is falling or not. Their deep learning architecture comprises 16 CNNs, each consisting of 5 layers and an LSTM with 256 hidden units. The ACT4² dataset was deployed to assess the performance of their method. It includes 768 video clips. They split the

data into 50% for training and 50% for testing. Experimental results showed that the combination of the co-saliency enhancement and CNN/LSTM increased the model's performance with an accuracy of 98.96%.

Lie et al. [88] proposed a fall detection based on 2D skeletons estimated from RGB frames sequence based on the same principle of combining models. Their approach is treated in 2 stages. In the first stage, they deployed Deepercut, a pre-trained CNN model, to estimate the 2D skeleton pose (x and y coordinates of 14 joints) from each input image. Then, the spatial features of the joints are converted from image coordinates to skeleton centroid coordinates. Then, they used RNN with LSTM to predict actions into 5 classes (standing, walking, falling, lying, and rising). Indeed, the RNN model processes as input a sequence of 8 frames, i.e., 8 2D-skeletons. The experimental evaluation in their dataset was carried out with 60% of the samples for training and 40% for testing. The results show that the system has an average accuracy of around 90%. Real-time implementation can be executed on GTX 1060 6G GPU with a processing rate of 8 frames per second. The system triggers an alert based on the history of the last 20 predictions (safety or danger situation).

Tsai et al. [139] proposed a video-based fall detection system composed of traditional algorithms and 1D-CNN named MyNet1D-D. The traditional preprocessing techniques (foreground segmentation, labeling, thinning, and searching) are deployed to extract the features (x, y, z) of the seven main joints appropriate to their approach. They transformed the depth information captured by the Kinect V2 into skeleton information. To evaluate their method, they used 2722 sample videos (70% for training and 30% for testing) from NTU RGB+D datasets. The experimental results on an NVIDIA Jeston TX2 showed good accuracy of 99.2%. In addition, the MyNet1D-D can provide real-time detection with a processing rate of 15 frames per second.

4.4.2 Background

LSTM

LSTM is an extension of the concept of RNNs well adapted to sequence classification. These networks make time explicit and process information from relatively long sequences by considering past situations. They do not suffer from the vanishing/exploding of gradients during learning [61]. Indeed, its internal cell memory allows keeping a state over several time steps. Fig. 4.3 shows the architecture of an LSTM unit.

An LSTM cell is controlled by three interactive gates (input gate, forget gate, and output gate). These control gates represent calculation areas to manage the flow of information by carrying out determined actions. In other words, they manage memory reading and writing. They also generate two categories of outputs (hidden state h_t and cell state c_t).

The forget gate judges which information should be stored or neglected by applying a sigmoid to the information of the previous hidden state h_{t-1} and the current input data x_t . When the value f_t is close to zero, the unit only

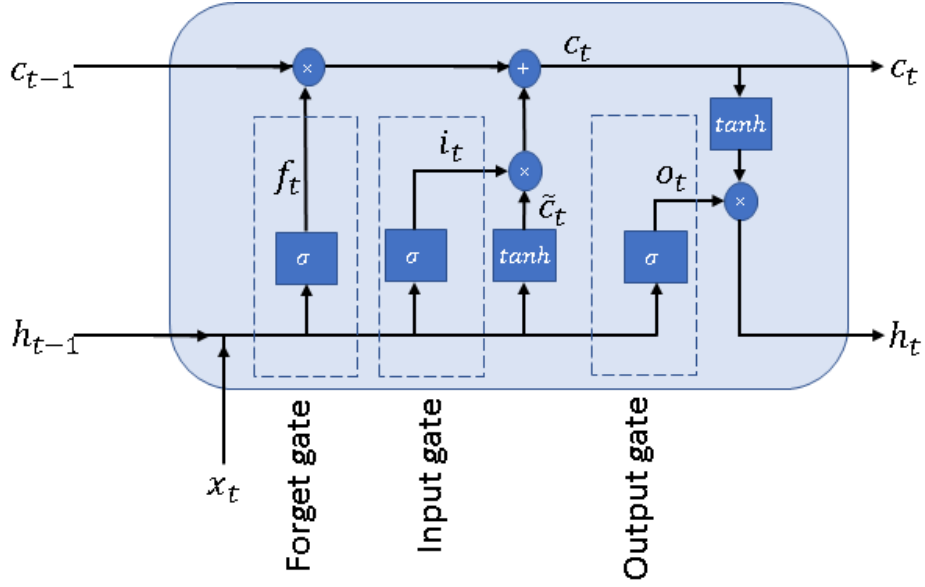


Figure 4.3: LSTM unit architecture.

considers the current information.

With the same processing principle, the input gate lets the relevant information be stored in the cell state. If the value i_t is close to 1, it lets the external information pass. i_t is manipulated with the output of the cell state candidate layer \tilde{c}_t . They will be important in the decision-making at times t and $t + 1$.

The information of the forget gate and the manipulated input gate are used to calculate the cell state c_t . The output gate's value o_t and the new cell state c_t will decide the value of the hidden state h_t . If the value is close to 1, the unit sends the information to the other units by providing output.

The behavior of an LSTM unit can be summarized in the following equations:

$$f_t = \sigma(U_{xf}x_t + U_{hf}h_{t-1} + b_f) \quad (4.2)$$

$$i_t = \sigma(U_{xi}x_t + U_{hi}h_{t-1} + b_i) \quad (4.3)$$

$$\tilde{c}_t = \tanh(U_{xc}x_t + U_{hc}h_{t-1} + b_c) \quad (4.4)$$

$$c_t = (f_t \otimes c_{t-1} + i_t \otimes \tilde{c}_t) \quad (4.5)$$

$$o_t = \sigma(U_{xo}x_t + U_{ho}h_{t-1} + b_o) \quad (4.6)$$

$$h_t = (o_t \otimes \tanh c_t) \quad (4.7)$$

Such that U are the matrices of the weights, and b are constant terms.

URFD Dataset Description

The University of Rzeszow fall detection dataset (URFD) [76] is a very rich dataset of vision and motion data. It consists of 70 event sequences where measurements are acquired using 2 Kinect cameras and an accelerometer. For falls, they used both cameras and the corresponding accelerometer. While the ADLs are only recorded by the camera, parallel to the ground, with the accelerometer. All RGB and depth images are synchronized with the motion data based on the timestamp value. The video sequences are measured by cam-0, parallel to the ground, at the height of about 1m. They also used cam-1 in-ceiling configuration at 2.5m from the ground. In addition, the accelerometers were mounted on the waist or near the pectoral muscles. In total, 30 falls, 40 activities of daily living, 10 of which were fall-like, were performed by 5 people in traditional spaces such as offices, classrooms, etc. [77]. In our study, we deployed the features extracted from the depth sequences captured by the cam-0. In total, 11544 samples are used. These features are grouped into two categories:

- Geometric
 - Ratio between the height and the width of the detected person's bounding box (HeightWidthRatio);
 - Ratio between maximum and minimum axes of the segmented person (MajorMinorRatio);
 - Ratio between the size of the person in the bounding box and his height in the standing position (HH-maxRatio);
 - The actual height of the person (H);
 - Distance between the person's center of gravity and the ground (D);
 - Ratio of the number of point clouds attached to the 40 cm high cuboid to the person's size cuboid (P40).
- Pixels
 - Person's pixel occupancy report in the bounding box (BoundingBoxOccupancy);
 - Standard deviation of pixels from the center of gravity for the x and z axes (MaxStdXZ).

In our experiment, we give importance to the set of selected features, and we ignore the order of the combination of features.

4.4.3 Our approach

To detect older people's falls with great precision by exploiting Kinect material and LSTM techniques, we propose a three-step organized approach, as shown in Fig 4.4: Data processing, choosing the model architecture and evaluating the model.

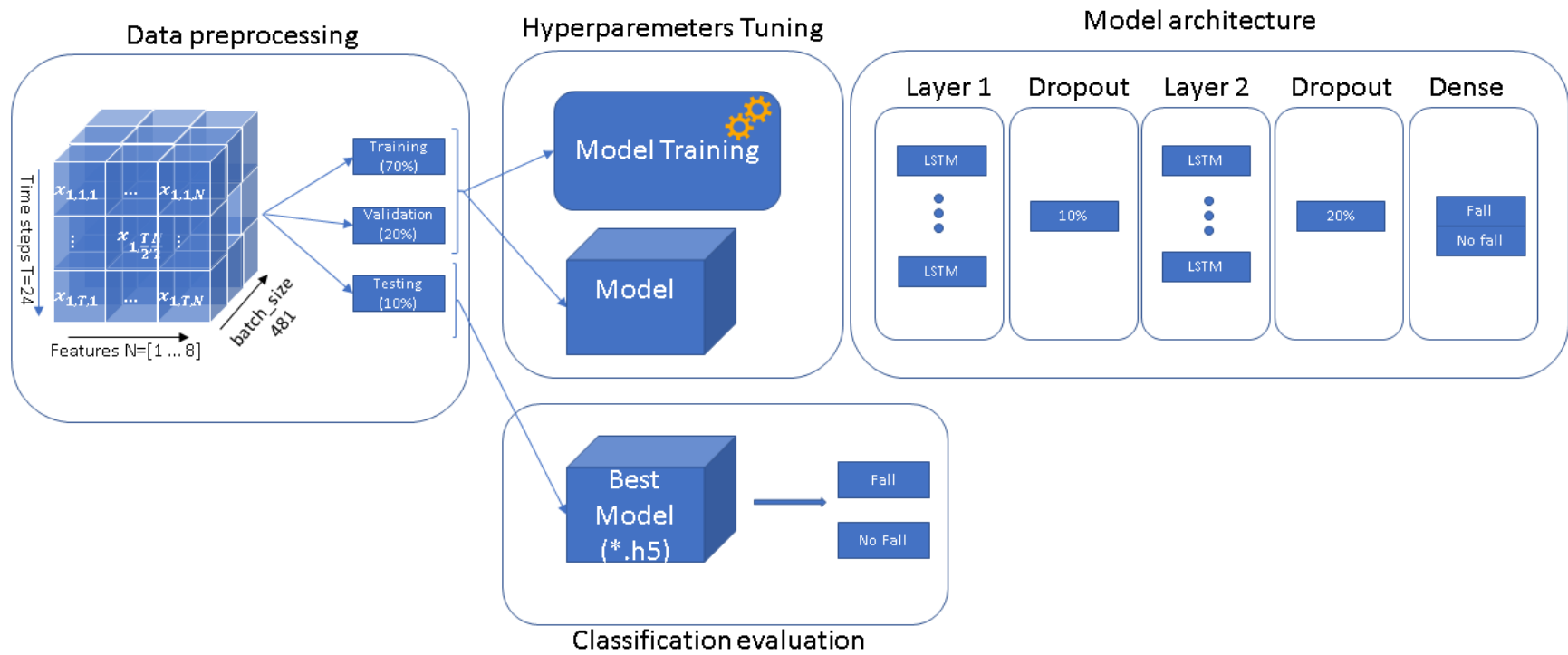


Figure 4.4: Our global LSTM model.

Data preprocessing

Noury et al. [104] defined a person's fall into 4 phases: Pre-fall, Critical, Post-fall, and Recovery. The prefall phase corresponds to some of the day-to-day human activities. Also, the abrupt movement of a person's body towards the ground describes the critical phase. Then, the inactivity of the person on the ground corresponds to the post-fall phase. Finally, the last phase characterizes his or her recovery from the ground. The URFD authors labeled the volunteers' posture in each measure according to 3 categories : (-1) if the person is not lying on the ground, (0) when the person is falling, intermediate pose, and (1) means that the person is lying. After analyzing the samples, we found that the values -1,0,1 correspond to the pre-fall, critical, and post-fall phases, respectively.

In our approach, we replaced the output (-1) with (0) and (0,1) with (1). In other words, the new output 0 corresponds to the pre-fall phase (ADL and fall-like) and 1 for the critical and post-fall phase together. In this case, each fall-like sequence contains values belonging to the 2 classes (non-fall '0' then fall '1'), while the ADL one belongs only to the class (non-fall '1').

The second step of data preparation corresponds to the resizing of the numerical values of the features by applying the MinMax normalization method [90]. This technique allows having comparable values on a standard scale while keeping the information and the interval distribution between the values. We apply it to restrict our architecture's complexity and training stability while equalizing the weights of descriptors. As a result, we avoid having the larger-scale feature dominate the other so that each feature is equally essential. We resize the values of the original samples x_t from (x_{min}, x_{max}) to $[0,1]$ using the following formula:

$$x_{scaled} = \left(\frac{x_t - x_{min}}{x_{max} - x_{min}} \right) \quad (4.8)$$

Proposed LSTM architecture

In general, the number and type of layers and the number of units in each layer express the LSTM architecture. Our study applied the empirical method that engages a quantitative analysis of several configurations to discover the best one.

Therefore, our model consists of 2 LSTM layers of 24 units each, 2 dropout layers, and a dense layer. The 10% dropout layer is between the 2 LSTM layers and the 20% between the second and the fully connected dense layers. We deployed the dropout in order to avoid overfitting during the training of our model [132]. As a result, we also confirm the absence of the overlearning problem in all our cases. Furthermore, this regularization technique randomly disables 10% and 20% of the connections to the LSTM units at each iteration. Indeed, the choice of a low percentage did not allow avoiding overfitting, and a high percentage impacted the model's accuracy. In addition, the output layer uses a sigmoid as an activation function in order to perform binary classification.

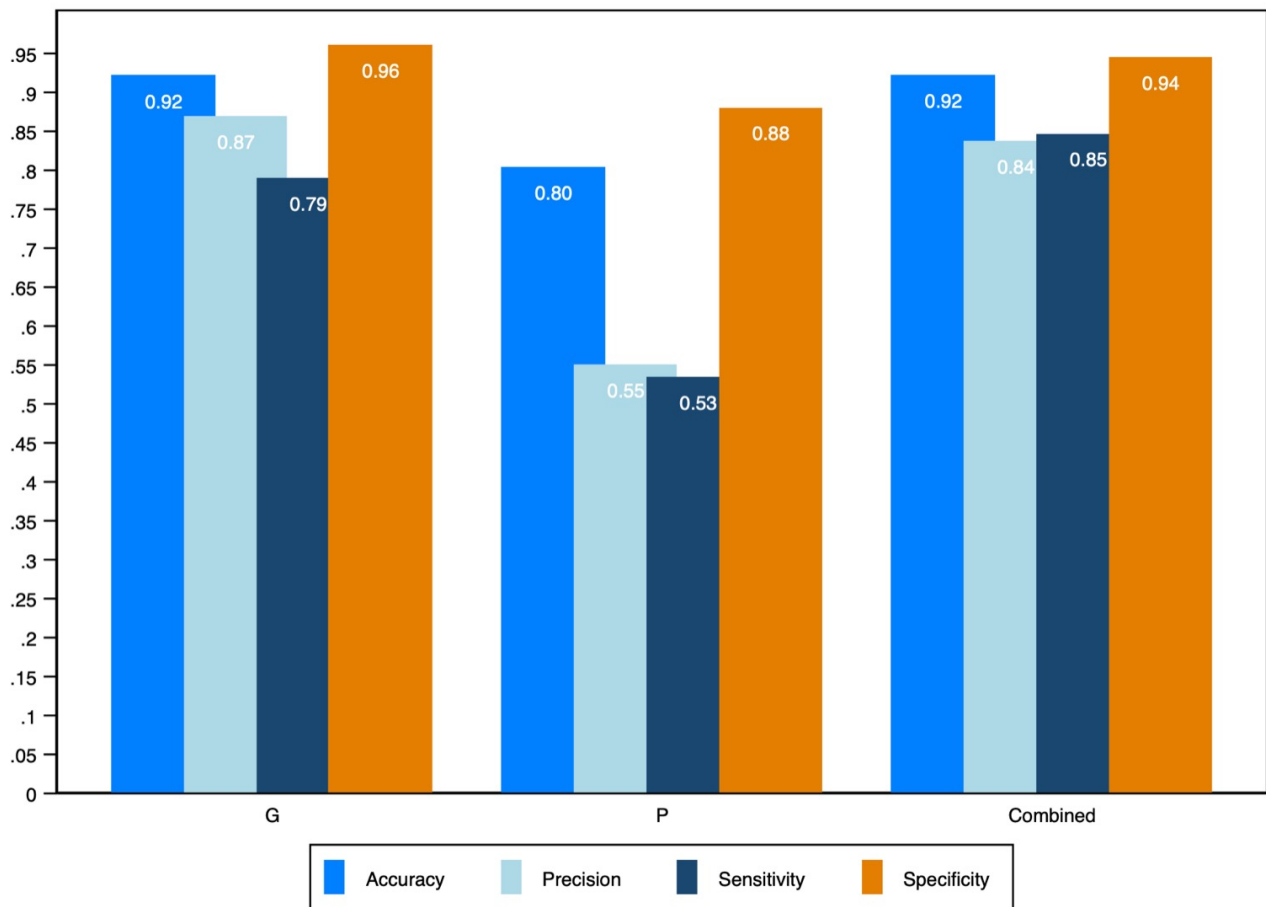


Figure 4.5: Average Values of metrics performances.

Experiments and discussion

The experimental implementation was performed on a Raspberry Pi 3 Model B V1.2. We split the sequential data into 70% for training, 20% for validation, and 10% for testing. The results were obtained from the registered models with the highest performance for each combination of features. Indeed, we trained each model with the training of 200 epochs and a learning rate of 0.001. In total, we evaluated a total of 255 feature combinations with our lightweight LSTM model.

To evaluate the performance of our model in each combination, we used the following 4 metrics (accuracy, precision, sensitivity, and specificity). A fall detection model is considered perfect if the values of FP and FN are zero, and the above performance terms have a value close to 1 (100%).

In general, we find that among the 255 different combinations, those including at least one geometric feature (G) always give the best performance compared to those composed only of pixel features (P). As seen in Fig. 4.5, the average values of Acc, Pr, Se, and SP for G and Combined (G+P) are higher compared to those for P.

We also noticed that the geometric descriptor P40 is quite discriminating, at the final decision level, compared to

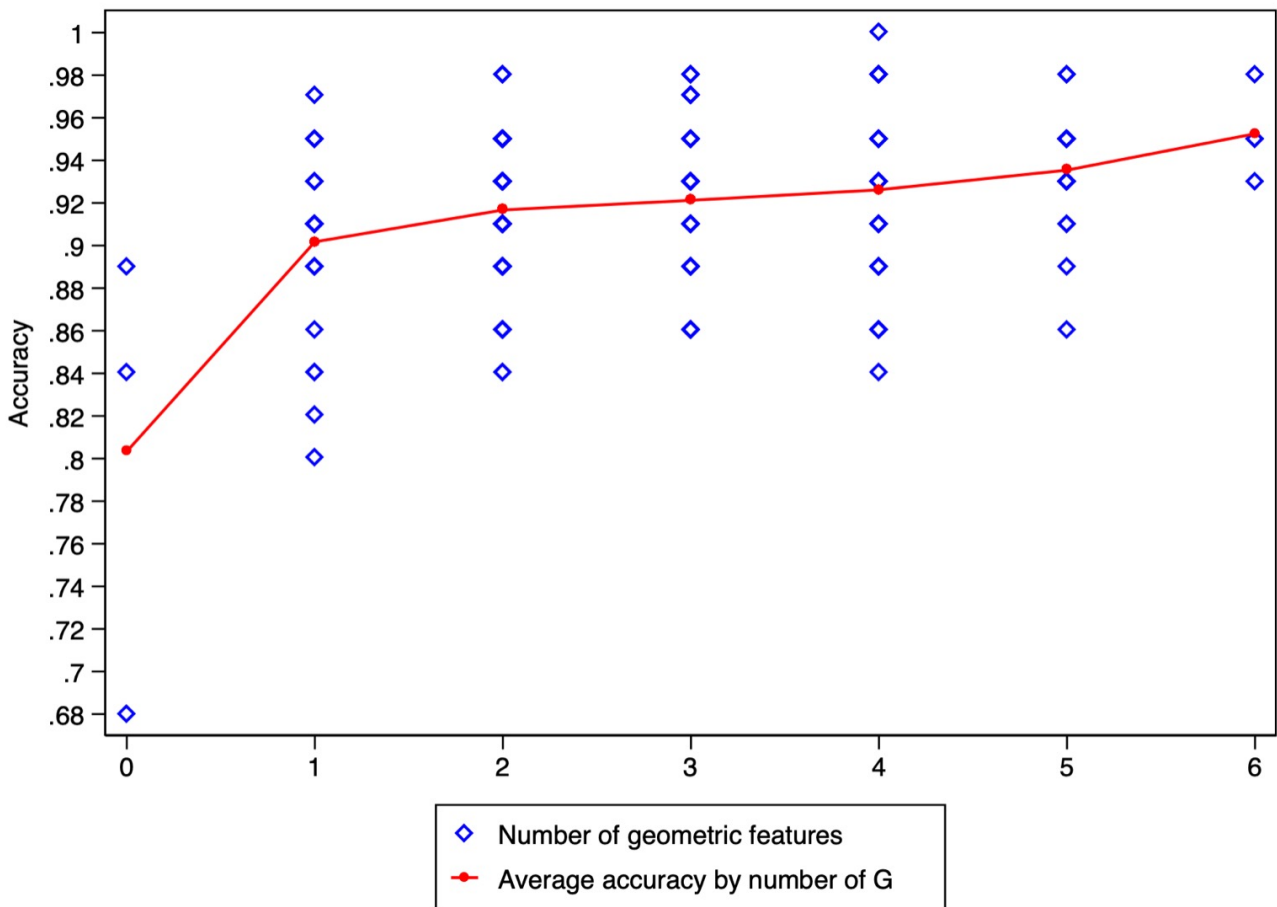


Figure 4.6: Variation of the accuracy according to the number of geometric features.

the other five geometric descriptors. This confirms one of the results deduced by the authors of the URFD dataset that P40 is relevant for fall event detection [77].

Method	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Li's [85]	99.98*	-	100*	99.98*
Xu's [146]	95	-	-	-
Abobakr's [11]	98*	97	100	97
Ge's [56]	98.96	-	-	-
Lie's [88]	90	-	-	-
Tsai's [139]	99.2	99.1	98.9	-
Ours	100	100	100	100

*Average Value.

Table 4.4: Comparison with different fall detection approach based on deep learning and Kinect

We note that the performance of our lightweight LSTM-based fall detection model with the four geometric features (HeightWidthRatio, HHmaxRatio, H, and D) is better than those in the literature. Fig. 4.6 and Table 4.4 show the significantly improved results.

In the literature, the authors do not explicitly argue for selecting features to judge the motions either from the image data or from the sequential data input to the model. Also, the existing deep learning models are mainly designed to be implemented on machines characterized by their enormous computing power. Therefore, the originality of our solution is based on the 2 challenges mentioned. Indeed, we have evaluated the relevant set of features to detect a fall as correctly as possible. We have also provided a lightweight and accurate LSTM architecture that can be implemented in real-time on devices at a low cost.

4.5 Conclusion

In this fourth chapter, we have shown 2 precise and practical solutions for detecting falls in the elderly. First, we have shown the Kinect technology in terms of its history, technical characteristics, and development tools. We analyzed the performance of the 2 proposed approaches; this analysis shows their good functioning. Thus, the first method needs to be improved by adding a complementary data source such as the accelerometer of a connected watch. This complementarity allows us to have more essential features. From the second method, we also succeeded in showing the importance of geometric properties in detecting falls. In addition, our lightweight LSTM model is designed to work on limited devices like the Raspberry pi ones.

Chapter 5

Conclusion

5.1 General conclusion

The phenomenon of aging has become a significant public health problem in all countries. It is often characterized by a degradation of physical and biological capacities, which allows chronic diseases and the loss of autonomy. More specifically, it leads to a severe limitation of autonomy among vulnerable seniors and an increased risk of domestic accidents. The different consequences of aging (health, economic and social) have also triggered new technologies to deal with this problem.

The vast majority of senior citizens desire to remain at home as long as possible in total safety. Indeed, home support has several advantages (better quality of life in a family and neighborhood environment, and a significant reduction in expenses in care management). Consequently, the Scientific's solutions meet aging requirements but with immense precedence linked to comfort, security, respect for privacy, and social ties.

The various studies in our thesis provide theoretical and practical answers in the context of technologies that promote the maintenance of seniors at home. Our results have shown that our health care system, Family Heroes, can maximize the safety of seniors by providing detection, alerting, and supported for dangerous situations.

Family Heroes is characterized by a wealth of information generated by different digital devices. This diversity increases the complexity of our critical system. Due to this complexity, we validated its specification, related to reliability and security, by analysis, modeling, and formal verification by model-checking. First, we showed the complementarity between the analysis method (CATWOE) and UML concepts, which allowed us to clearly define and identify the requirements and constraints of Family Heroes. In addition, its behavior is strongly linked to time (of communication, triggering of the alert process, and care). For that, we used the MARTE concepts to model the temporal constraints. Then, we proposed modeling Family Heroes' behavior in the form of timed automata under UPPAAL. This step was followed by formal verification of the properties in the syntax corresponding to the UPPAAL temporal model-checking. As a result, we validated the properties (the absence of deadlock, accessibility, safety,

and liveliness of its operation).

The variety of connected technologies in our system exposes it to the cybersecurity risk area. To ensure its security, we have proposed a formal modeling and verification approach to design a system with a reconfigurable architecture. In other words, the solution is to switch to an alternative architecture while keeping the alerting services and the support by the emergency services. The results of the property verification show the validity of our solution. Also, we detailed the second axis of our thesis, which concerns the automatic detection of falls. Indeed, the precise detection of falls is challenging to study and implement; Because it is not only a question of detecting positions and orientations but also analyzing the whole movement in 3D space. In order to achieve this goal, we have proposed 2 methods: (1) detection based on thresholds and (2) detection based on deep learning. The first is the classic approach, using 3D data from the upper body, which determines whether the values of the characteristics of the movement conform to specific predefined values. The second is the trend approach in classifying human activities, which, using fictitious neural connections, classifies movements (a fall or a daily activity). The first solution involves (1) monitoring the target's height, (2) the angular variation between 2 positions when moving, such that the Kinect is the origin of the coordinate system. Also, (3) inactivity on the ground to validate the fall. In the second solution, we defined a lightweight LSTM architecture capable of processing sequential features on a single board computer such as the Raspberry pi used in our evaluation. We studied the 255 combinations of the 8 characteristics extracted in a public data set (URFD). The results showed that the geometric characteristics are relevant for the detection of falls. We were also able to show the efficiency and high performance of our architecture.

5.2 Perspectives

The perspectives of the studies presented in this manuscript revolve around several lines of thought and are found in various research contexts.

- In the short term, we mainly need to focus on the continuity of the V-cycle to have a complete experimental prototype. The various UML modeling diagrams and the validated properties must be reflected in the coding of a conceptual model. In addition, the security of communicated data must be considered during development to avoid any malicious act. We also propose to evaluate the prototype in real situations. A real evaluation of the prototype will be used for a valuation and transfer of our system to a pre-industrialization. The work of this thesis opens up horizons towards scientific collaboration projects with retirement homes. Much of this collaboration should be based on the acquisition of real data to evaluate future approaches within the framework of the health care system for the elderly. It would also be essential to respect the privacy and safety of seniors volunteers.
- In the medium term, version 3 of the Kinect is available on the market. We plan to move towards the Azure

Kinect DK. This new technology makes it possible to track more joints compared to versions 1 and 2. The joints being tracked are much anatomically stable in the broader capture field. The new features give a better 3D visualization of the skeleton followed without any influence of light conditions. We also aimed to create a database using the Azure Kinect. It will be accessible to the entire scientific community to develop new approaches while optimizing the experimental setup time.

- In the long term, the treatment of several types of characteristics at different scales requires standardization at the same scale to avoid the dominance of large-scale ones. The importance of the data normalization step directs us to study the impact of different normalization methods on the performance of our fall detection model. Among the techniques to be tested, we cite (Z score, standard deviation, Decimal scaling, and Median). Finally, other classification models adapted to sequential data processing (Vanilla LSTM, Bidirectional LSTM, and convLSTM) remain little explored in the context of detecting falls of vulnerable seniors by the Kinect. We will explore them in a study that will be refined so that we adopt the most reliable algorithm and with the fewest features.

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Titre: Développement d'une plateforme de maintien à domicile des personnes âgées fondée sur les capteurs multimédias

Mots clés: Système de Soins de Santé, personnes âgées, Analyse, Modélisation, Vérification Formelle, Détection des Chutes, Kinect.

Résumé: Tous les pays sont confrontés à des changements démographiques importants à une échelle sans précédents. Les seniors constituent le segment de la population mondiale qui augmente le plus rapidement. Ceci entraîne une augmentation des personnes âgées dépendantes et vulnérables marquées par une perte d'autonomie et maladie chronique. Ces complications augmentent les taux de mortalité et morbidité dans nos sociétés. Ces dernières années, les conséquences socio-économiques sur les seniors et sa famille, et le fait des tarifs élevées dans les établissements spécialisés d'hébergement ont attiré l'attention sur le maintien à domicile en servant des nouvelles technologies fiables et pas cher. Mais développer un système de soins de santé critique pour les personnes âgées est un véritable défi qui ne peut être relevé qu'en garantissant la fiabilité et la haute performance. Dans le cadre du futur système de soins de santé nommée Family Heroes, nous sommes intéressées dans cette thèse à sa fiabilité et sa sécurité. Ainsi, Nous avons étudié la détection automatique des chutes à l'aide de la caméra Kinect.

Plus précisément, nous avons proposé une méthodologie combinant la méthode CATWOE et des notions UML pour analyser et modéliser notre système. Nous avons montré les étapes à suivre pour prendre en compte efficacement les exigences et les contraintes du système dans le processus de développement. Ainsi, nous avons utilisé les concepts MARTE pour faire face aux contraintes de temps dans la phase de modélisation. Ensuite, pour

assurer la fiabilité de notre système, nous avons proposé une approche de vérification formelle basée sur les modèles UML/MARTE présentés dans l'étape de modélisation. Nous les avons modélisés avec des automates temporisés et déployé le vérificateur de modèles UPPAAL pour spécifier et vérifier les propriétés.

Pour assurer la sécurité de notre système, nous avons présenté une approche formelle pour traiter les problèmes de cyber-attaques qui peuvent survenir dans le système Family Heroes. Ainsi, nous avons adopté un scénario de cyberattaques liés à ce contexte et proposé de reconfigurer notre système pour faire face aux cyberattaques. De plus, une vérification formelle a été proposée pour s'assurer de la fiabilité de la reconfiguration proposée du système. Les résultats ont montré le respect des propriétés (L'absence de deadlock, l'accessibilité, la sécurité et la vivacité) dans Family Heroes.

Pour la détection automatique des chutes, nous avons utilisé le capteur multimédia de la technologie Kinect. Nous avons proposé une nouvelle approche basée sur des seuils qui analyse la variation de hauteur, les angles du haut du corps au cours du cycle de mouvement, et l'inactivité de la personne au sol. De plus, nous avons proposé un nouveau modèle léger basé sur Deep Learning LSTM utilisant des caractéristiques géométriques. Ce modèle léger est conçu pour fonctionner sur des appareils limités comme ceux de Raspberry Pi. Les résultats sont très prometteurs.

Title: Health care platform development based on multimedia sensors

Keywords: Health care System, Elderly, Analyze, Modeling, Formal Verification, Fall Detection, Kinect.

Abstract: All countries are facing significant demographic changes on an unprecedented scale. Seniors are the fastest-growing segment of the world's population. It increases dependent and vulnerable older adults marked by loss of autonomy and chronic illness. These complications increase mortality and morbidity rates in our societies. In recent years, the socio-economic consequences on seniors and their families and the high prices in specialized accommodation establishments have drawn attention to home support by using new reliable and inexpensive technologies. However, developing a critical healthcare system for the elderly is a real challenge that can only be met by ensuring reliability and high performance. Within the framework of the future health care system named Family Heroes, we are interested in this thesis in its reliability and safety. Thus, we studied the automatic detection of falls using the Kinect camera. More precisely, we have proposed a methodology combining the CATWOE method and UML notions to analyze and model our system. We have shown the steps to take to consider system requirements and constraints in the development process effectively. Thus, we used the MARTE concepts to face the time constraints in the modeling phase. Then, to ensure the reliability of our system, we proposed

a formal verification approach based on the UML / MARTE models presented in the modeling stage. We modeled them with timed automata and deployed the UPPAAL model checker to specify and verify properties.

To ensure the security of our system, we have presented a formal approach to deal with cyber-attack issues that may arise in the Family Heroes system. Thus, we adopted a scenario of cyberattacks linked to this context and proposed reconfiguring our system to face cyberattacks. In addition, formal verification has been proposed to ensure the reliability of the proposed solution. The results showed the respect of the properties (No deadlock, accessibility, security, and liveness) in Family Heroes.

For automatic fall detection, we used the multimedia sensor of Kinect technology. We have proposed a new approach based on thresholds that analyzes the variation in height, the angles of the upper body during the cycle of movement, and the person's inactivity on the ground. In addition, we have proposed a new lightweight model based on Deep Learning LSTM using geometric features. This lightweight model is designed to work on limited devices like the Raspberry Pi. The results are very promising.