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Energy-efficient data collection and fusion in wireless body sensor networks for continuous health monitoring

Carol Habib

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Ph.D. in Computer Science

by

CAROL HABIB

**Energy-efficient Data Collection and Fusion in Wireless Body Sensor
Networks for Continuous Health Monitoring**

Thesis presented and defend in Belfort on Novembre 30, 2018

Composition of the Jury :

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BEYLOT ANDRÉ-LUC	Professor at University of Toulouse	Reviewer
CHRÉTIEN STÉPHANE	Senior Research Scientist at National Physical Laboratory	Examiner
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PRÉPARÉE À L'UNIVERSITÉ DE FRANCHE-COMTÉ

École doctorale n°37

Sciences Pour l'Ingénieur et Microtechniques

Doctorat d'Informatique

par

CAROL HABIB

**Acquisition, traitement et fusion de données issues des réseaux
de capteurs corporels pour une surveillance médicale continue**

Thèse présentée et soutenue à Belfort, le 30 Novembre 2018

Composition du Jury :

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SPIM

école doctorale **sciences pour l'ingénieur et microtechniques**

ABSTRACT

Energy-efficient Data Collection and Data Fusion in Wireless Body Sensor Networks for Continuous Health Monitoring

Carol Habib
University of Bourgogne Franche-Comté, 2018

Supervisors: Abdallah Makhoul, Rony Darazi, Raphaël Couturier

Pervasive and ubiquitous healthcare is currently gaining a growing interest world-wide. This phenomena is mainly supported by the advances in information technology and data science and the need of societies to ensure a good Quality of Life. Wireless Body Sensor Networks play a major role in this paradigm by ensuring a low-cost continuous and remote monitoring of people's health condition. Several challenges exist in Wireless Body Sensor Networks such as the data collection and fusion especially that (1) wireless sensor nodes have limited energy, processing and memory resources, (2) the amount of periodically gathered data is huge, (3) the gathered data are characterized by a heterogeneous nature and (4) the data interpretation to ensure decision-support is influenced by several external factors such as the provided context information of the monitored person.

In this dissertation, firstly an energy-efficient data acquisition and collection technique is proposed. It targets the energy consumed by biosensor nodes for sensing and transmitting vital signs. It consists of a real-time sampling rate adaptation mechanism and a local detection system which are provided at the level of the nodes. The results show that more than 50% of data reduction is achieved at the level of sensing and more than 80% of data reduction is achieved at the level of transmission with a negligible loss of information (Mean Square Error ≈ 0.05) and the energy consumption is 10 times decreased over one hour of continuous monitoring.

Second, a multi-sensor data fusion model for health assessment is proposed. The coordinator of the network performs an assessment of the patient's health condition based on the collected measurements of his/her vital signs. Such data is interpreted in a human-reasoning way and are characterized by ambiguity and imprecision. Thus, we propose to use a Fuzzy Inference System having as an input the aggregate score of vital signs and as an output the health assessment on a scale from 0 to 1. The proposed approach is compared with existing work and validated by healthcare experts.

Then, a context-aware multi-sensor data fusion model for health assessment is proposed. Given that vital signs are highly correlated to the context of the monitored person such as his/her physical activity status, medical record and personal information, their interpretation is highly influenced. Hesitant fuzzy sets are used to subjectively evaluate the intensity of the person's physical activities based on his/her personal information and the activity's characteristics. The results show that the proposed approach evaluates theoretically intensity-classified activities differently based on the people profiles. Furthermore, the results show that fusing vital signs and the available information about the person's current physical activity reduces false alarms and enhances the health assessment.

Finally, a specific monitoring application is targeted. A real-time stress detection and evaluation framework is proposed while taking into consideration the energy consumption constraint. Shimmer 3 GSR+ is used as a wireless sensor node to sense the Photoplethysmogram (PPG) signal and the skin conductance. An android mobile application is developed to extract from the PPG signal stress correlated vital signs such as the heart rate, the respiration rate and the blood pressure. Preliminary results are promising.

KEYWORDS : Health Assessment, Decision-support, Energy Consumption, Context-awareness, Stress monitoring, Fuzzy logic, Fuzzy Inference System, Quadratic Bezier Curve, Hesitant Fuzzy Sets, Early Warning Score, Imprecise and Ambiguous Data, One-way ANOVA, Fisher Test.

RÉSUMÉ

Acquisition, traitement et fusion de données issues des réseaux de capteurs corporels pour une surveillance médicale continue

Carol Habib
University of Bourgogne Franche-Comté, 2018

Superviseurs: Abdallah Makhoul, Rony darazi, Raphaël Couturier

À l'heure actuelle, les soins de santé envahissants et omniprésents suscitent un intérêt de plus en plus croissant dans le monde entier. Ce phénomène est principalement soutenu par les progrès de la technologie de l'information et de la science des données ainsi que le besoin des sociétés d'assurer une bonne qualité de vie. Les réseaux de capteurs corporels sans fil jouent un rôle majeur dans ce paradigme en assurant un suivi de l'état de santé des personnes d'une manière continue, à distance et à faible coût. Plusieurs défis existent dans les réseaux de capteurs corporels sans fil tels que la collecte et la fusion de données physiologiques dans un environnement contraignant. En effet, les nœuds de capteurs sans fil ont des ressources limitées en énergie, traitement et mémoire. En outre, une grande quantité de données est collectée. Ces données sont hétérogènes, ambiguës et imprécises. Ajoutons que l'interprétation des données est influencée par plusieurs facteurs externes tels que les informations contextuelles fournies par la personne surveillée. En conséquence la prise de décisions et l'analyse des informations extraite sont influencées.

Tout d'abord une technique de collecte de données est proposée. Celle-ci a pour intérêt de réduire la quantité de données collectée et la consommation d'énergie. Dans le modèle proposé, l'énergie consommée par les nœuds capteurs sans fil pour capter et pour transmettre les signes vitaux est particulièrement ciblée. Il s'agit à la fois d'un mécanisme temps-réel pour l'adaptation du taux d'échantillonnage et d'un système de détection local permettant aux nœuds de transmettre uniquement les données indiquant un changement dans l'état de santé de la personne. Les résultats montrent qu'une réduction de plus que 50% des données est atteinte au niveau de l'acquisition et qu'une réduction de plus que 80% des données est atteinte au niveau de la transmission avec une perte d'information négligeable (erreur quadratique moyenne $\approx 0,05$) et que sur une heure de surveillance continue, la consommation d'énergie est en moyenne réduite de 10 fois.

Deuxièmement, un modèle de fusion de données pour l'évaluation de l'état de santé de la personne surveillée est proposé. Les données fusionnées sont les signes vitaux de la personne qui proviennent de plusieurs capteurs. Ces données sont interprétées de manière humaine et sont caractérisées par l'ambiguïté et l'imprécision. Ainsi, nous proposons d'utiliser un système d'inférence floue ayant comme entrée le score agrégé des signes vitaux et comme sortie l'évaluation de l'état de santé sur une échelle de 0 à 1. L'approche proposée est comparée à une autre approche existante et elle est validée par un expert en soins de santé.

Ensuite, nous proposons d'évaluer l'état de santé de la personne surveillée tout en prenant en compte le contexte dans lequel elle se trouve. Étant donné que les signes vitaux de l'être humain ainsi que son contexte tels que: son activité physique, son dossier médical et ses informations personnelles sont fortement corrélés, l'interprétation des signes vitaux est largement influencée. Plus particulièrement, nous proposons d'utiliser les ensembles flous hésitants pour déterminer subjectivement l'intensité de l'activité physique de la personne. L'approche proposée prend en considération le profil de la personne ainsi que les caractéristiques de l'activité physique en cours. Les résultats montrent que l'approche proposée évalue différemment les activités qui sont théoriquement classés selon leur intensités. Ceci est due au fait que le profil de la personne est pris en considération lors de l'évaluation des activités physiques. De plus, les résultats montrent que la fusion des signes vitaux et de l'information disponible à propos de l'activité physique réduit les fausses alertes et améliore l'évaluation de l'état de santé de la personne.

Finalement, une application médicale spécifique est ciblée. Nous proposons de détecter et d'évaluer le stress en temps réel tout en considérant la consommation d'énergie. Shimmer 3 GSR + est utilisé comme capteur sans fil pour capter le signal Photoplethysmogram (PPG) et la conductance cutanée. Une application mobile Android est développée pour extraire du signal PPG les signes vitaux qui sont corrélés au stress tels que la fréquence cardiaque, la fréquence respiratoire et la pression artérielle. Les résultats préliminaires sont prometteurs.

MOTS-CLÉS : Évaluation de l'état de santé, Aide à la décision, Consommation d'énergie, Sensibilisation au contexte, Surveillance du stress, Logique Floue, Courbe de Bezier, Ensembles Flous Hésitants, Score d'alerte précoce, Données imprécises et ambiguës, One-way ANOVA, Fisher Test.

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*"Man cannot discover new oceans unless he has the courage to lose sight of the shore."
- André Gide*

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INTRODUCTION

INTRODUCTION

1. GENERAL INTRODUCTION

Interest in pervasive and ubiquitous healthcare solutions is currently increasing given the potential they have and the benefits they bring to people's everyday life. Wireless Body Sensor Networks (WBSNs) play a major role in this field since they ensure remote and continuous health monitoring at a low cost and reduce unnecessary hospitalization as well as healthcare expenditure. WBSNs have the potential to detect and even prevent life-threatening health problems such as a heart attack. Many healthcare and well-being applications can be fulfilled using WBSNs such as: emergency detection, health assessment, disease prevention, medical diagnosis, tracking physical activity, mental health support etc, thus several populations are concerned: elderly, patients suffering from chronic diseases, acutely-ill patients, athletes and even any average person who is interested in continuously monitoring his/her health. These healthcare applications must satisfy multiple requirements to ensure user satisfaction such as good quality of service and accuracy.

A WBSN is composed of wireless sensor nodes called biosensors and a coordinator. The former can be invasive or non-invasive. They sense and collect physiological signals such as Electrocardiogram (ECG), Electroencephalogram (EEG) and Photoplethysmogram (PPG) etc. and vital signs such as Heart Rate (HR), Respiration Rate (RR), skin temperature, blood pressure (BP), oxygen saturation (SpO₂) etc. The latter is usually the person's smart phone or any other portable device. It manages the network, receives the collected signals/measurements and performs the data analysis and fusion to reach the healthcare's application goal.

However, several constraints exist in WBSNs such as the limited resources of biosensors and the environmental interference which make collected signals noisy. In this dissertation, we take into consideration that biosensors have limited energy, processing and memory resources and that data transmission is the most power hungry task especially that WBSNs are usually periodic and huge amounts of heterogeneous data are periodically collected. Therefore, extending the network's lifetime, reducing the amount of collected data, early detecting anomalies in vital signs, and providing a continuous health assessment and decision-support to patients and doctors are the core motivation of this dissertation. Hence, the following two challenging tasks have been identified:

- **Data collection** which includes the data acquisition, processing and transmission while taking into consideration the constraints that are present in WBSNs.
- **Data fusion** which includes the analysis and the extraction of knowledge and meaningful information from the collected data. The data fusion model to be proposed must take into consideration that the fusion must be made in real-time and that the collected data is characterized by a heterogeneous, imprecise and ambiguous nature (different vital signs, personal information, context information etc.).

The objective of this thesis is then to propose data collection and fusion models for WBSNs while taking into consideration the constraints and challenges that exist in such networks.

2. MAIN CONTRIBUTIONS OF THIS DISSERTATION

The main contributions in this dissertation fall within the aforementioned data management aspects. They fulfill the previously mentioned requirements while taking into consideration the constraints that are present in WBSNs and the characteristics of the collected data. We summarize the main contributions of our research as follows:

1. First, a self-adaptive data collection technique was proposed at the level of the biosensor nodes in order to allow them to adapt their sampling rate in real-time while locally detecting emergencies. Our proposal mainly targets the energy consumed by sensor nodes to sense vital signs as well as the energy consumed to transmit them to the coordinator. Thus, the proposed approach is two-fold: (1) the sampling rate of the sensor node is adapted in real-time based on the evolution of the vital sign of interest over time and the severity of the patient's health condition, (2) using an early warning score system, only the measurements indicating changes in the status of the vital sign of interest are sent to the coordinator. First, the evolution of vital signs over time is studied by applying the One-way ANOVA (Analysis of Variance) coupled with Fisher statistical test on the sensed measurements during several consecutive periods. Then, the adaptation of the wireless sensor node's sampling rate is done using a Quadratic Bezier function. As a result, oversampling and undersampling are minimized where the former has an impact on the network's lifetime and considerably increases the amount of collected data and the latter has an impact on the loss of information. Furthermore, the amount of data transmitted to the coordinator is considerably decreased since only representative measurements are sent and redundant information is minimized. Extensive simulations have been made to test and validate the proposed data collection technique in terms of data reduction, energy consumption and loss of information.
2. Second, data fusion in WBSNs has been tackled. Indeed, a health assessment should be provided by the coordinator of the WBSN in a real-time fashion and continuously. The health assessment is inferred based on the fusion of the vital signs that are collected by different biosensor nodes. It gives the possibility to keep track of the evolution of the patient's health condition whether it is stable, improving or deteriorating. Moreover, it allows the coordinator to detect emergencies and to make decisions such as giving medical advice or taking actions. In this context, we have proposed a multi-sensor fusion model for health assessment based on Fuzzy Inference Systems (FIS) and Early Warning Score systems (EWS). This model is characterized by: (1) a certain flexibility given that the input membership functions of the FIS are dynamically defined in terms of the number of monitored vital signs, (2) a human-reasoning of ambiguous data given that it employs fuzzy logic, (3) a smoothing of sudden deviations of vital signs by weighting the persistence of a vital sign in a given state, and (4) a knowledge-driven modeling given that it requires EWSs put by healthcare experts to evaluate vital signs. The proposed model is compared against a data-driven, data-mining based approach from the literature

in terms of energy consumption, data reduction, vital sign assessment and health assessment. Moreover, the proposed health assessment model is validated by healthcare experts.

3. Knowing that the patient's context such as his/her personal information and his/her physical activities greatly influences vital signs, we have decided to make the proposed health assessment model context-aware. Thus, the interpretation of vital signs is made based on the person's current physical activity. More specifically, we have added another input to the FIS defining the intensity level of the person's physical activity on a scale from 0 to 1. We proposed to use Hesitant Fuzzy Sets (HFS) in order to subjectively evaluate the intensity level of physical activities (PAs) such that the decision-makers are the person's attributes constituting his/her profile. An example of these attributes are: age, body mass index, the person's diet such as his/her alcohol consumption per week, the person's fitness level such as the amount of exercise per week in minutes etc. Whereas an example of the PA's characteristics that are to be evaluated include: speed and inclination at which the PA is performed, duration of the PA, additional weights carried by the person etc. The results show that theoretically intensity-based classified PAs are evaluated differently for different profiles. This is due to the fact that the proposed approach takes into consideration the person's personal information when evaluating PAs rather than assuming their intensities. Moreover, the results show that fusing vital signs with the information the coordinator has about the current PA being performed by the person reduces false alarms and improves health assessment.
4. Lastly, a specific monitoring scenario has been targeted by the proposal of a stress detection and evaluation approach followed by a real-implementation. Shimmer 3 GSR+ has been used as a mote and an Android application has been developed to test the proposed approach in a real experimental setup. Given that skin impedance is an indicator/detector of stress episodes, it has been considered as a triggering event for the transmission of the PPG signal. Therefore, periodic transmission has been reduced in order to ensure energy-efficiency. The following vital signs are extracted from the PPG signal: the heart rate, the blood pressure and the respiration rate. Knowing that stress and the previously mentioned vital signs are correlated, the coordinator can then evaluate the stress level of the person using a FIS. Preliminary results are promising.

3. DISSERTATION OUTLINE

The dissertation is organized as follows: Chapter 1 gives an overview about biosensors and healthcare applications. Chapters 2 and 3 expose respectively the domains of data collection and fusion in WBSNs by presenting the scientific background and going through some scientific research that have been made and have investigated these two domains. Chapter 4 presents the first contribution resumed by a self-adaptive data collection technique at the level of sensor nodes. Chapter 5 presents the second contribution resumed by a multi-sensor fusion model providing health assessment. Chapter 6 presents the third contribution resumed by a context-aware health assessment approach based on multi-sensor fusion and the fusion of data coming from different sources. Chapter 7 presents the fourth contribution resumed by a stress detection and evaluation approach and its real implementation. Chapter 8 concludes the work that has been done in this thesis.



WBSNs: FROM DATA COLLECTION TO FUSION

This part discusses the scientific background of Wireless Body Sensor Networks (WBSNs) by presenting recent advances in this field and focusing on the two challenging tasks that have been identified: data collection and data fusion. It is composed of three chapters. In the first chapter, WBSNs including the architecture, biosensor nodes, health-care applications and their requirements are covered. In the second chapter, energy-efficient data collection in WBSNs is explored by going through significant research that has been made in this domain. In the third chapter, the domain of data fusion in WBSNs is investigated by presenting some of the most relevant scientific research that has been made so far, particularly in multi-sensor fusion.

ADVANCES IN WBSNs AND THEIR APPLICATION

This chapter explores WBSNs by presenting biosensors and focusing on their potential in ensuring a wide variety of healthcare applications. The most commonly used biosensors in WBSNs as well as some of the available commercial and research oriented sensor nodes are listed. A special focus is brought to the requirements that should be satisfied by any application to ensure user satisfaction and attain the desired outcomes. Furthermore, a discussion is made to highlight that several healthcare applications can be tackled based on the monitoring phenomenon of interest and the target population.

1.1/ INTRODUCTION

In the past decade, wireless body sensor networks (WBSNs) emerged as a low-cost solution allowing the continuous monitoring of physical and physiological parameters of the human body. A lot of research has been made and is still being made in the design of medical accurate invasive and non invasive sensors and the design of comfortable wearable health monitoring systems. In this chapter, firstly we go through the most commonly employed sensors in WBSNs. These sensors capture physiological parameters including vital signs and physiological signals as well as physical parameters related to body movement. Additionally, we list and discuss the differences of several commercially available wearable sensor nodes on the market. Having health related data being continuously collected leads to a palette of body sensor network (BSN) applications. A particular focus is given to healthcare applications given that it is the main focus of this thesis. All types of population can benefit from BSN healthcare applications, starting from toddlers to elderly, depending on the monitoring phenomenon of interest. Furthermore, diverse monitoring tasks can be achieved such as event detection, prediction, diagnosis etc., thus we provide a discussion about these tasks and depict them as a function of three different dimensions: the type of user, the type of processing and the monitoring location. However, BSN healthcare applications should meet a set of requirements in order to achieve user satisfaction, perform as desired, have an impact on people's life and ensure continuity, especially that WBSNs have limited resources, are subject to interference and faulty measurements and that we are dealing with sensitive medical data.

This chapter provides an overview of biosensors and BSN healthcare applications. In Section 1.2, the components and the architecture of WBSNs is presented. In Section

1.3, a classification of biosensors based on wearability is given and the most commonly used biosensors in WBSNs as well as some of the commercially available sensors on the market are listed and discussed. Then, in Section 1.4, we highlight the potential of BSN healthcare applications by discussing the monitoring tasks that are the mostly studied in the literature. Furthermore, we discuss the list of requirements any healthcare application should meet in order to be accepted by people and to have the desired performance.

1.2/ WBSN ARCHITECTURE

A WBSN is composed of biosensor nodes and a coordinator (c.f. Figure 1.1). The former are deployed on the person's body. They can be either implanted inside the human body or attached/placed on it. They continuously sense physiological signals, vital signs and/or body movement. An example of physiological signals include ECG, EEG and PPG etc. Whereas an example of vital signs include heart rate, respiration rate, temperature, blood pressure and oxygen saturation etc. The acquired data is periodically and wirelessly transmitted to the coordinator of the network. The latter can be any portable device close to the person's body such as his/her smartphone or PDA. Its role is to manage the network and perform the fusion of the collected data. Thus, emergencies, abnormal events as well as the continuous follow-up of the person's health condition can be ensured by the coordinator. Moreover, it can provide the person advice, reminders and take action in emergency situations such as call the doctor. The collected data as well as the results of the fusion process are sent by the coordinator to the medical center (healthcare experts, doctors) where further processing can be made.

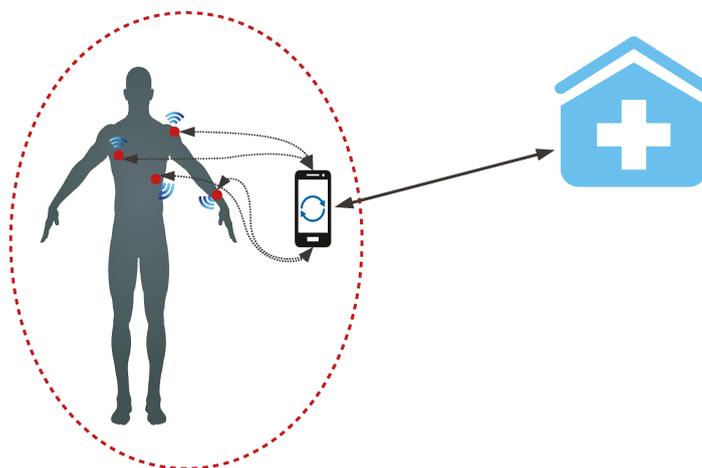


Figure 1.1: The architecture of the WBSN.

1.3/ BIOSENSORS

Biosensors are miniature, lightweight, low power, limited-resources and intelligent sensor nodes that sense, process and transmit human physiological parameters such as the ECG, the heart rate, the body temperature, the body movement etc. Figure 1.2 shows the components of a wireless biosensor node. It is composed of three units powered by a battery: the sensing unit, the processing unit and the transmission unit. All three units need power to perform their tasks. Yet, transmission is considered to be the most power-hungry task. The sensing unit is composed of the sensor and the ADC which converts the analog signal, which is sensed with a given frequency (Nyquist-Shannon), into a digital signal. The latter is fed to the processing unit (processor and memory) where the processing algorithms are run. Furthermore, the processor controls the sensing and the transmission units and it activates and/or changes their status according to the application and the used protocol.

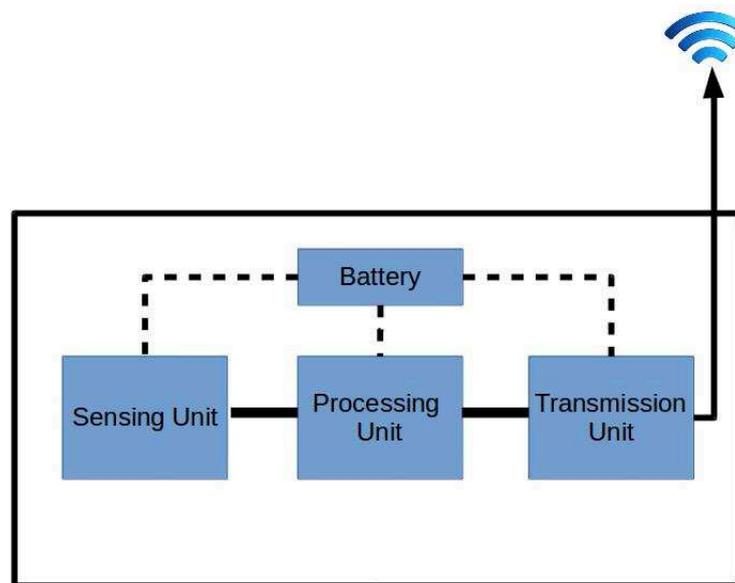


Figure 1.2: The components of a biosensor node.

As shown in Figure 1.3, based on the wearability, biosensor nodes can be regrouped under two categories: invasive (or implantable) and non-invasive (or wearable). The latter can take several forms e.g. accessory (watch, bracelet, glasses, ring etc.), clothe (smart shirts, gloves, shoes) and patch [116].

Table 1.1 summarizes some of the commonly used biosensors in WBSNs [163, 60, 136]. Based on the physiological parameter that they capture, they can be categorized under two types : electrical and non-electrical signals. The former can sense electrical signals such as the ECG, EEG, EMG etc. While the latter can sense physical and chemical signals such as the 3-axis acceleration and the blood sugar. Unobtrusive sensing can be achieved by means of two different methods : capacitive sensing and photoplethysmographic (PPG) sensing [95]. Capacitive sensing employs adhesive electrodes and is used to measure biopotentials such as the ECG, EEG, and EMG. PPG sensing involves a light source emitting light into the tissue and a photo-detector collecting the light that is reflected from or transmitted through the tissue. It is used for measuring vital signs

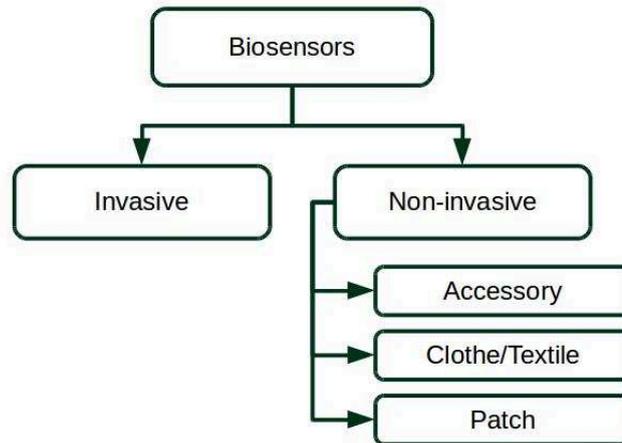


Figure 1.3: Classification of biosensors based on wearability.

such as the SpO₂, the heart rate, the respiration rate and the blood pressure. In this dissertation we refer to electrical signals as physiological signals while we refer to other physiological parameters, which are most of the time extracted from these signals, as vital signs. Vital signs include the heart rate, the respiration rate, the systolic blood pressure, the diastolic blood pressure, the oxygen saturation, the body temperature etc.

Table 1.2 reports some of the commercially available sensor nodes. Some of them only target body movement while others also target physiological parameters. We are mainly interested in those who enable the continuous monitoring of physiological parameters especially vital signs. Except Vitalpatch [5] and Hexoskin smart shirts [2], all the reported sensor nodes are programmable and all of them allow the access to the raw measurements of physiological signals (except Vitalpatch) which extends their potential and their versatility given the diverse palette of healthcare applications. Hexoskin smart shirts allow a continuous data collection but an offline data processing whereas Shimmer sensors [4] and Movisens sensors [3] allow a real-time data collection and data processing which make them suitable for real-time healthcare applications.

Table 1.1: Commonly used biosensors in Wireless Body Sensors Networks.

Sensors	Function	Placement	Signal Type	Data Rate	Power consumption
Accelerometer	Obtains acceleration on the x,y and z axis to measure body posture, falling etc.	Wearable	Continuous	High	Low
Gyroscope	Obtains angular momentum to measure body movement and orientation	Wearable	Continuous	High	Low
Blood pressure	Measures systolic and diastolic blood pressure	Wearable	Discrete	Low	Low
ECG	Measures electrical activity of the heart by measuring voltage difference between two electrodes placed on the surface of the body	Wearable	Continuous	High	High
EEG	Measures electrical activity of the brain by measuring voltage difference between two electrodes placed on the surface of the body	Wearable	Continuous	High	High
EMG	Measures electrical activity of the muscles by measuring voltage difference between two electrodes placed on the surface of the body	Wearable	Continuous	Very High	High
Pulse oximetry (SpO2)	Measures blood oxygen saturation by absorption ratio of red and infrared light passing through a thin part of body	Wearable	Discrete	Low	High
Temperature	Measures temperature of the human body	Wearable	Discrete	Very Low	Low
Respiration	Measures respiration parameters indirectly by detecting the expansion and the contraction of chest abdomen	Wearable	Continuous	High	High
Heart rate	counts the number of heart contractions per minute	Wearable	Continuous	High	High
Camera pill	Detects gastrointestinal tract by wireless endoscope technique	Implantable	Continuous	High	High
Blood sugar	Measures blood sugar level without pricking the finger	Implantable	Discrete	High	Extremely low
Brain pacemaker	Measures electrical signals of the brain in the form of low frequency and high frequency waves	Implantable	Discrete	Low	Low

Table 1.2: Commercially available sensor nodes on the market.

Model	Company	Description	Firmware
<i>Exclusively Body movement</i>			
Move 3	Movisens	3-axis accelerometer, barometric air pressure and temperature.	Programmable
Shimmer 3 IMU	Shimmer	inertial sensing via accelerometer, gyroscope, and magnetometer.	Programmable
<i>Body movement & Physiological parameters</i>			
EdaMove 3	Movisens	Electrical dermal activity, 3-axis accelerometer, barometric air pressure and temperature.	Programmable
EcgMove 3	Movisens	ECG signal to detect heart rate and respiration rate, 3-axis accelerometer, barometric air pressure and temperature.	Programmable
Shimmer 3 ECG	Shimmer	ECG signal to detect heart rate and respiration rate, and inertial sensing via accelerometer, gyroscope and magnetometer.	Programmable
Shimmer 3 GSR+	Shimmer	PPG signal to detect heart rate, respiration rate and blood pressure, and inertial sensing via accelerometer, gyroscope and magnetometer.	Programmable
Vitalpatch	Vitalconnect	ECG electrodes to detect heart rate, 3-axis MEMS accelerometer to detect motion, Thermistor to detect skin temperature	Non-programmable
Hexoskin Smart Shirts	Hexoskin	Cardiac sensors: ECG signal, Heart rate, heart rate variability, RR interval, QRS detection Breathing sensors: breathing, breathing rate, tidal volume, minute ventilation and inspiration and expiration events Movement sensors: 3-axis acceleration, activity level, step counting, cadence and energy expenditure	Non-programmable

1.4/ HEALTHCARE APPLICATIONS

BSN applications are diverse and can be regrouped under two categories healthcare applications and non-medical applications. Non-medical applications are found in the entertainment field and in consumer electronics. They allow more realism in the user experience such as in video games, virtual reality applications and movies. Whereas healthcare applications concerns all health monitoring applications whether they were employed in critical or non-critical monitoring scenarios. All healthcare applications that aim to provide a continuous monitoring of physiological parameters in order to capture

life-threatening events and enable early interventions [116] as well as applications that provide medical assistance for patients fall within the category of critical monitoring scenarios. For instance, these applications include: medical care applications, rehabilitation applications and medicine intake applications. Other types of healthcare applications concern non-critical scenarios which are not related to patient monitoring such as fitness and sports and ambient assisted living. Therefore, different populations are targeted given the diversity of BSN applications. Based on the monitoring scenario and application needs, healthcare applications mainly target elderly, chronically-ill patients, acutely-ill patients, wheelchair users, athletes, elderly and people in general seeking for pervasive assistance and desiring to continuously monitor their health. Figure 1.4 provides an overview of the main healthcare applications monitoring tasks which are dominantly studied in the literature [54]. Three dimensions are used to represent the different aspects which are tackled: the monitoring setting, the type of subject concerned and how data is processed. Six aspects are identified: event detection, health/situation assessment, decision-support, prediction and diagnosis.

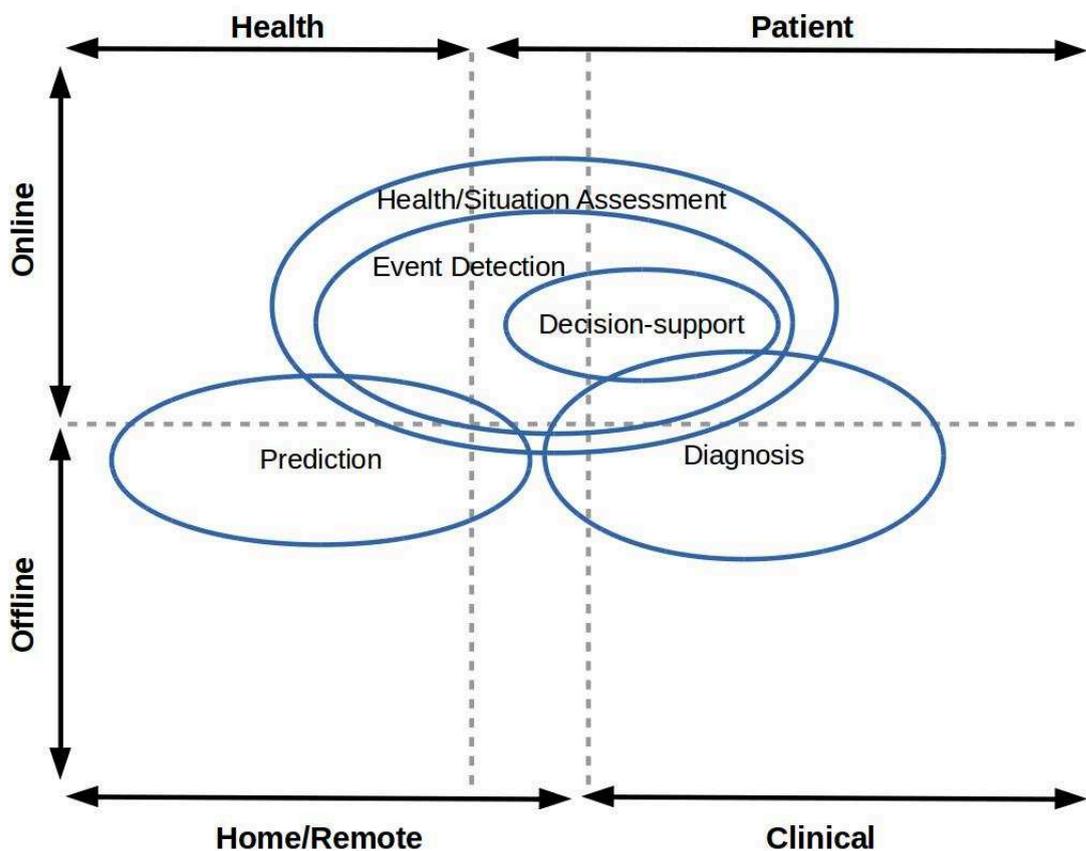


Figure 1.4: Targeted monitoring tasks in healthcare applications based on Wireless body sensor networks (inspired from [54]).

decision-support, event prevention, event prediction and diagnosis.

- **Health/situation assessment:** It refers to the continuous assessment of an event of interest using scoring systems, a scale/grade metric to provide the patient and doctors with an overview of the patient's situation over time. For instance the assessment of illness [76], emotional/mental state [90, 92], physical activity/inactivity

state [153, 117], patient's health condition namely the deterioration, improving and stability state based on vital signs monitoring [164], stress evaluation [141] etc. are examples of this category.

- **Event detection:** It refers to the identification of unusual patterns, outliers and critical conditions which do not conform to normality. For instance, typical examples of healthcare applications that target event detection include: fall detection, emergency detection based on vital signs monitoring and disease-related symptom detection such as tachycardia in heart attack [103].
- **Decision-support:** It refers to monitoring systems that aim to provide patients with local and fast decisions based on the identified emergency or health related event. Thus, ensuring a better medical intervention and preventing the worsening of the patient's health condition. The decisions can take the form of medical advice such as *'to rest'*, triggering actions such as a *'phonecall to doctor or family'* and reminders such as *'drink water'*.
- **Event prediction:** allows to identify events which have not yet occurred. Thus, it helps in preventing the development of chronic illness and could help doctors to make a prognosis. Several healthcare prediction applications have been proposed in the literature such as: blood glucose level prediction, mortality prediction [45], heart disease status prediction [162], the prediction of severe clinical events [142] etc.
- **Diagnosis:** is often based on the retrieval of knowledge from vital signs which are monitored by WBSNs and other medical information such as electronic health records and metadata. Thus, it needs more robust information rather than only physiological parameters collected by WBSNs. For instance, in [159], a model for diagnosing cardiovascular autonomic nerve dysfunction is proposed and in [155] a model for the diagnosis of non-polyp, adenoma and hyperplasi is proposed.

1.4.1/ HEALTHCARE APPLICATION REQUIREMENTS

From a user point of view, BSN healthcare applications must meet a list of requirements in order to be accepted, adopted by societies and for their advantageous integration in everyday life. We believe that any healthcare application, regardless of the targeted population and the specific monitoring task that it performs (c.f. Section 1.4), should respect the following requirements in order to achieve good monitoring and ensure satisfactory towards the users and the medical community.

- **Acceptable delay:** Ensuring an acceptable delay between data collection and their analysis is crucial. Especially in critical monitoring and when sudden life-threatening events occur where emergencies should be quickly reported to the medical team or family. Therefore, data acquisition, processing and transmission at the level of sensor nodes should not be time consuming and complex. Furthermore, the algorithms that process the collected data at the coordinator level for fusion and analysis should run in real-time and respect delay in order not to miss any important events and to provide alarms in critical monitoring.
- **Quality of Service (QoS):** Huge amounts of physiological data are collected continuously in WBSNs. Furthermore, not all the data contain critical or emergency

information. Thus, ensuring quality of service is very important in BSN healthcare applications in order to give priority to critical data rather than normal data.

- **Mobility:** BSN healthcare applications should take into consideration the mobility of the user. Thus, the wearable systems should not be bulky and should be comfortable. Furthermore, interference due to body movement makes pre-processing of data an important step in data processing. Moreover, when different WBSNs are communicating, efficient routing protocols should be proposed in order to cope with the mobility of the user from one location to another.
- **Accuracy:** Health monitoring requires by nature good accuracy due to possible life-threatening events. Thus, the algorithms proposed for data collection and fusion should ensure a good accuracy by the detection of all critical events and the inference of correct knowledge compatible with the reality.
- **Robustness:** WBSNs can be subject to malfunctioning sensor nodes, energy depleted sensor nodes or malattachment of sensor nodes. This leads to erroneous measurements and missing information. Thus, BSN healthcare applications which rely on multi-sensor fusion ensures robustness as well as data availability and authenticity.
- **Security:** Dealing with medical data demands establishing secure systems. Security is of major importance in BSN healthcare applications. It is ensured by integrating security protocols in order to ensure safe data collection and fusion.
- **Confidentiality/Privacy:** Similarly medical data requires confidentiality and privacy. Thus, BSN healthcare applications should integrate privacy mechanisms in order to get user acceptance.

1.5/ CONCLUSION

In this chapter, an overview about biosensors that are used in WBSNs has been provided. On the one hand, different types of biosensors exist depending on wearability and the type of signal. A lot of research is still needed in order to design more accurate and fine-grained biosensors that take advantage of different sensing technologies such as capacitive sensing and PPG sensing. Furthermore, smart watches, textiles and patches are currently gaining a lot of interest due to their ease of wearability and their future potential in healthcare applications. On the other hand, WBSN enable the development of diverse healthcare applications. These applications are able to provide different monitoring tasks. This thesis particularly tackles health assessment, event detection and decision-support. However, healthcare applications should meet several requirements given that WBSNs have many constraints and that we are dealing with medical data.

ENERGY-EFFICIENT DATA COLLECTION

Energy management in WBSNs is of paramount importance especially that biosensors have limited energy resources and that healthcare applications are supposed to run autonomously for long periods of time. Therefore, the data collection including the sensing, processing and transmission of measurements should ensure energy-efficiency without putting at cost the requirements that any healthcare application should satisfy. In this chapter, we cover the most relevant energy-efficient mechanisms in data collection and their impact on the performance of the WBSNs as well as we discuss energy harvesting techniques.

2.1/ INTRODUCTION

Designing long-lasting WBSNs is a challenging matter. First, WBSNs are expected to run autonomously and continuously for long periods of time. Second, they are designed for specific healthcare monitoring applications, thus they have to satisfy a group of requirements that vary from one application to another [88]. Indeed, the batteries of the resource-constrained wireless sensor nodes are rapidly depleted with the continuous sensing, processing and transmission tasks and their frequent replacement is not favoured especially that we want to encourage the acceptance of this technology by people [149]. Therefore, energy management is of paramount importance in WBSNs. On the one hand, several energy-efficient data collection mechanisms have been proposed in the literature so far. Transmission is considered to be the most power-hungry task. However, it has been shown that continuous sensing may consume a greater amount of energy [149, 109]. Whereas, locally processing raw data is often possible by adopting lightweight algorithms in order to manage the energy consumption of the node. In this Chapter, We survey papers that target energy-efficiency in any of these data collection steps: sensing/acquisition, processing and communication. On the other hand, energy harvesting has been gaining a lot of attention especially that the human body produces heat and that movement is a source of energy [132].

This chapter explores energy-efficient data collection in WBSNs. In Section 2.2, a classification of energy-efficient mechanisms is given and relevant papers from the literature are investigated. Then, in Section 2.3 the potential of energy harvesting in WBSNs is highlighted and some major work that has been proposed in the literature is exposed. Finally, we discuss the impact of energy-efficient mechanisms on the requirements that are imposed by healthcare applications such as accuracy, delay, quality of service, confiden-

tiality etc. Moreover, we highlight the potential of combining energy-efficient mechanisms with energy harvesting in WBSNs.

2.2/ ENERGY-EFFICIENT MECHANISMS

Inspired from [149, 88, 109], energy-efficient mechanisms can be classified under the following three categories: sensing, communication and processing (c.f. Figure 2.1). These categories represent the energy-consuming tasks performed by the node to ensure continuous health monitoring. The techniques that aim at adjusting the power-on time of biosensor nodes fall within the first category. Indeed, these techniques reduce unnecessary sensing by turning off the sensors. Based on the surveyed papers that propose energy-efficient data collection in WBSNs, energy-efficient sensing is ensured by adopting either sensor set selection or context-based pull requests. Whereas, techniques that focus on ensuring efficient transmission of sensor nodes fall within the second category. These techniques mainly try to reduce the energy consumed by biosensor nodes for transmission. Energy-efficient communication is reached by means of data reduction techniques, radio optimization, energy-efficient routing protocols and sleep/wakeup schemes. Some other techniques aim to reduce the amount of processing performed by biosensor nodes. Feature selection and adaptive classifier selection are common methods to ensure energy-efficient processing.

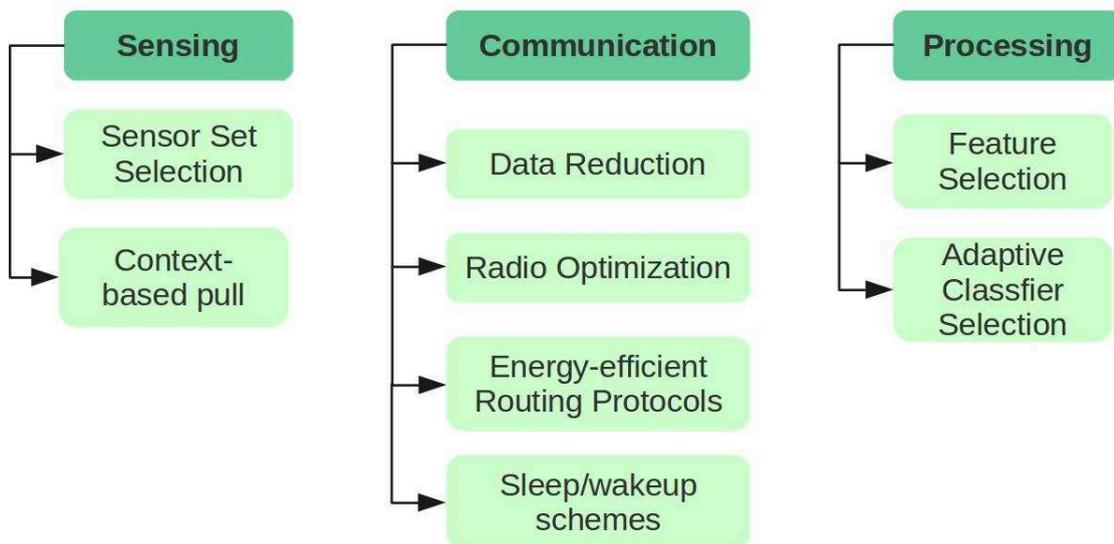


Figure 2.1: Classification of energy-efficient data collection techniques.

2.2.1/ ENERGY-EFFICIENT SENSING

In this section, we cover some of the works in the literature that have tackled energy-efficient sensing in WBSNs. As previously mentioned, we have identified two different categories: sensor set selection and context-based pull messaging. These techniques focus on reducing the sensing time of sensor nodes in order to preserve their energy

level. Consequently, the sensor nodes' unit(s) including the radio, CPU and sensor(s) are turned off to reduce the energy consumed to perform their tasks.

- **Sensor set selection:** The techniques in this category focus on achieving a good trade-off between the number of activated sensors and the classification accuracy. Their ultimate goal is to maximize the WBSN's lifetime while keeping a good detection performance. The sensor set selection could be made prior to deployment or in real-time. Such an approach is used in activity detection applications [71, 147] as well as in diseases detection applications [37]. In the latter case, the authors build their proposal on the fact that each diseases has its specific relevant symptoms, thus not all the sensor nodes should continuously send their measurements. Information gain and sensor selection are combined in order to design the sensor selection algorithm.
- **Context-based pull:** Exploiting the correlation between contexts is another approach to reduce the energy consumption due to data acquisition [64, 145]. The context aware energy management is often based on activity recognition. Instead of adopting the current paradigm where the data is continuously streamed from the sensor nodes to the coordinator, a pull-based asynchronous model is employed. Thus, the coordinator requests relevant data from the sensor nodes depending on the identified user context. As a result, the energy consumption of continuous data acquisition and collection is reduced without compromising the requirements of the application.

2.2.2/ ENERGY-EFFICIENT COMMUNICATION

In this section, a review of some of the existing work that aim to reduce the energy consumption due to communication is exposed. Energy-efficient communication schemes either focus on reducing the amount of transmitted data, reducing idle states, reducing re-transmission or by adequately selecting the communication technology.

- **Data Reduction:** This approach aims to reduce the amount of data to be transmitted to the coordinator. Several techniques exist namely: *on node-processing*, *adaptive sampling* and *compression* specifically *compressive sensing*. Compressive sensing and adaptive sampling limit the amount of unneeded samples, thus ensuring efficient sensing and transmission.

The logic behind *on-node processing* is that processing consumes less energy than data transmission. Therefore, a sensor node performs signal processing and feature extraction and only transmits the extracted features instead of the raw data [104, 115]. Computationally inexpensive features which are representative of the phenomena to be detected should be identified. For example in [104], some of the selected features, based on the analysis of the accelerometer sensor data during handshake, were: Zero Crossing (ZC), Root Mean Square (RMS), Amplitude (A), Mean (M) and Standard Deviation (SD) etc. For instance in [115], the authors suggested to perform anomaly-driven transmission such as the sensor nodes perform on-node signal processing in order to identify critical time intervals and transmit data from these intervals. Although on-node processing leads to an increase in the energy consumed for computation, however it considerably reduces the energy consumed for data transmission. This is especially true when the transmission rate

of the sensor nodes are high (for example ECG, EEG etc.) and important events such as a heart attack are rare.

In the *adaptive sampling schemes*, the main concern is to reduce the amount of acquired data by either adapting the sensing frequency of sensor nodes to the recognized context or on the basis of spatial and/or temporal correlations among data [101, 52, 35] while keeping the sensing accuracy within the acceptable level. Thus, by reducing the amount of sensed data, the data transmission is reduced and the sensor node's lifetime is prolonged. In such approaches, it is assumed that the energy consumption of continuous sensing is greater than the energy consumed for transmission and that unneeded samples affect the communication and the processing resources. In [119], the authors motivate the use of low sampling rates to recognize the effects on battery's lifetime without compromising the signal quality.

In the recent years, *compressive sensing* (CS) theory emerged as an energy-efficient approach for wireless communication. Capitalizing on signal sparsity, CS guarantees an accurate signal reconstruction by sampling signals at a much lower rate than the traditional Shannon-Nyquist theorem. Thus, it has the potential to dramatically reduce the power consumption since the amount of wirelessly transmitted data is considerably reduced. Furthermore, it reduces the amount of resources required for processing and storage and it promises significant compression rates while using computationally light linear encoders compared to traditional compression methods. CS theory has been applied in diverse domains including WSNs. Particularly, many contributions based on CS theory have been proposed in the literature so far for WBSNs due to the fact that some biosignals such as the ECG are sparse [129, 41, 62, 82, 63, 33, 152]. Traditional compression techniques have also been used in WBSNs for example in [140] a lossy compression method for ECG was developed and in [38] a novel data compression method based on overhearing was proposed on the basis of exploiting temporal and spatial correlations among the collected data.

- **Radio Optimization:** Radio parameters such as power transmission, antenna direction, modulation schemes and coding have been optimized by researchers in order to reduce the energy consumption of wireless transmission [122, 128, 25, 166]. However, battery preservation should not compromise signal quality.
- **Energy-efficient routing protocols:** Given that the deployment of a WBSN has an impact on the network lifetime, other researchers proposed energy-efficient routing protocols [156]. This approach reduces the energy consumed by wireless sensor nodes for transmission and optimizes the network installation. In [81], the network installation cost and the energy consumed by wireless sensors and relays were taken into consideration to propose a mixed integer linear programming model in order to optimize the number and location of relays as well as the data routing towards the sink. Whereas in [77], the main goal was to reduce the data transmission distances of the sensor nodes by using the uniform cluster structure concepts, thus clusters ensured a load balancing in the network.
- **Sleep/Wakeup schemes:** Medium access control (MAC) layer is of crucial importance in energy management in WBSNs. Thus, the MAC protocol design should ensure efficient energy consumption. The most energy wastage in existing MAC protocols are caused by the four following sources: collisions, overhearing, control packet overhead and idle listening. The majority of the work in this domain

[16, 39, 21] aim to reduce the idle listening time because it dominantly wastes energy. Instead of keeping the nodes awake waiting for potential data coming from the coordinator of the network, a sleep mode is defined in order to put them into the sleep state. This is done by turning off their radios when there is no data sent by the coordinator. When in sleep mode, the node is inactive, it cannot receive data and is unable to hear broadcasts. Energy is then saved and the life of the sensor nodes is extended. A good sleep mode must ensure an acceptable trade-off between flexibility and energy efficiency. Particularly, WBSNs clearly manifest a wide range of traffic variations given that physiological signals are collected at different rates (such as the ECG and Temperature), thus the authors of [39] have been motivated to dynamically adapt the wake-up intervals of sensor nodes based on traffic status. Whereas in [21], the authors suggested to achieve time synchronization between sensor nodes based on the human beat rhythm instead of using traditional periodic timing information received by the coordinator of the network. Another aspect of duty-cycling is presented in [165] where the authors present a proportional feed-forward controller in order to dynamically tune the sampling rate of the inertial measurement unit (IMU) and the orientation estimation update rate of the Madgwick filter (MF). Other works [146] focused on providing time synchronized channel hopping in order to reduce collisions and avoid interference in transmission. Furthermore, wake-up radio based mechanism was used in [148, 145] to control sleep and active modes of sensor nodes in order to save energy.

2.2.3/ ENERGY-EFFICIENT PROCESSING

Healthcare applications such as activity recognition and disease detection require power-hungry and complex algorithms to process and classify the signals. In this section, some of the existing work that aim to reduce the energy consumption due to processing is exposed. Two different approaches are covered: feature selection and adaptive classifier selection.

- **Feature Selection:** The selection of features impacts the performance of the classifier. On the one hand, using a lot of features enhances the accuracy but consumes a great deal of energy and requires a lot of computation. On the other hand, using a reduced number of features reduces computation and energy consumption at the cost of a lower accuracy. Thus, there is a trade-off between delay and accuracy [107, 66]. In [107] a real-time feature selection model is proposed taking into account the energy cost of individual features, thus studying the trade-off between the WBSN's power efficiency and classification accuracy of an activity recognition application.
- **Adaptive classifier selection:** Different types of classifiers exist which are different in terms of delay, memory and computation requirements. Therefore, in the context of power-aware computation, some researchers have proposed to adapt the classifier choice to the monitored person's context, battery level of the sensor nodes, available resources such as CPU load, available memory and the application's requirements [29, 46]. The adaptation can be either made statically or dynamically.

2.3/ ENERGY HARVESTING

Recent advances in technology have introduced two battery charging mechanisms : wireless power transfer [19] and energy harvesting [151]. On the one hand, the former requires wirelessly transferring energy using methods such as inductive coupling, magnetic resonant coupling, and electromagnetic radiation. However, this battery charging approach presents many limitations, given the deployment characteristics of a WBSN. It requires the wearer to be in proximity (several meters) of the energy transmitter, to ensure line of sight and to have a constant electrical source. On the other hand, energy harvesting involves scavenging power from a multitude ambient and body sources, thus enabling real-time monitoring of different physiological parameters and ensuring a self-sustainable network [135]. This solution can be considered as a green energy supply since it reduces system costs and electrical waste. Furthermore, it contributes in reducing the energy constraints of WBSNs. The energy sources can be classified into the two following categories: ambient sources and human body sources [133]. Ambient sources can be of several types such as light, heat, vibration and RF radiation. Human body sources can be either biochemical (enzymes such as glucose, lactate etc.) or biomechanical which can be voluntary such as body movement or involuntary such as heartbeat, blood pressure and breathing. Biochemical energy harvesting presents many drawbacks. For instance, the techniques are still immature and limited, small amount of energy can be currently produced from these sources and their application-specific utilization is finite. Moreover, biomechanical energy harvesting sources can cause discomfort and present exploiting challenges such as the size of the harvester and the effect of a poor health condition on the correct functioning of the harvesting technique. Involuntary sources can provide low levels of energy whereas voluntary sources can provide sufficient amount of energy but are dependant of the physical activity of the person and are only available when they are performed. Concerning ambient sources, their main drawback persists in the fact that they cannot be harvested whenever required and might not be constantly available.

2.4/ DISCUSSION

In this section, we discuss the trade-offs between energy-efficient mechanisms and the requirements any healthcare application must ensure. Then, we investigate the potential and the advantages of combining different energy management strategies and using cross-layer approaches. Finally, we highlight the importance of complementing energy-efficient mechanisms by energy harvesting methods in order to achieve a self-sustainable WBSN.

2.4.1/ ENERGY-EFFICIENT MECHANISMS V.S. HEALTHCARE APPLICATION REQUIREMENTS

As previously mentioned in Chapter 1, any healthcare application should ensure an acceptable delay, QoS, mobility, accuracy, robustness, security and confidentiality. Table 2.1 reports all the energy-efficient methods that have been discussed and their effect on delay, QoS, mobility and accuracy. The ✓ refers to the verb "ensures" and the X refers to the verb "impacts". We do not cover the confidentiality and security aspects given that

they can be ensured respectively by encryption and privacy techniques which we do not treat. Furthermore, robustness is achieved by means of radio optimization. As it is shown in Table 2.1, most energy-efficient methods impact accuracy. Thus, it is essential that any proposal in these methods does not compromise accuracy.

Table 2.1: Trade-off between Energy-efficiency and healthcare application requirements.

Energy-efficient methods	Delay	QoS	Mobility	Accuracy
Sensor set selection		✓		✗
Context-based pull		✓		✗
Adaptive sampling	✓			✗
Compressive sensing	✗			✓
On-node processing	✗	✓		✗
Radio optimization	✗			✗
Energy-efficient routing protocols	✓	✓	✓	
Sleep/wakeup schemes	✗	✗		
Feature selection	✓			✗
Adaptive classifier selection	✓			✗

Delay is potentially ensured by the following methods:

- Adaptive sampling: because the number of unneeded samples is reduced and thus transmission is decreased leading to less traffic on the network.
- Energy-efficient routing protocols: since a star-topology architecture is mostly adopted for WBSNs.
- Energy-efficient processing methods: because lightweight algorithms are implemented at the node level taking into consideration delay and complexity.

QoS is mostly ensured by the following methods:

- Sensor set selection: because only sensors that are related to the identified user context (physical activity or disease detection) are powered on, thus prioritizing physical or physiological parameters.
- Context-based pull: because the coordinator only requests relevant parameters to the monitoring application and to the identified user situation, thus eliminating periodic transmission and irrelevant data.
- On-node processing: through the use of lightweight algorithms allowing the nodes to locally detect emergencies, reduce transmission and sending only critical measurements.
- Energy-efficient routing protocols: by using 1-hop communication and prioritizing packets depending on their status which can contain emergency or normal data.

Mobility is mostly ensured by energy-efficient routing protocols through the management of multi-WBSNs and the communication among nodes and relays.

Accuracy is ensured by means of compressive sensing since it is a lossless compression technique and does not affect the signal of interest.

2.4.2/ CROSS-LAYER APPROACHES AND COMBINING DIFFERENT ENERGY-EFFICIENT MECHANISMS

A lot of research has been conducted to tackle energy consumption at multiple layers, especially at the network, MAC and physical layers. Energy-efficiency and versatility with changing environments can be significantly improved by an integrated cross-layer design. Indeed, the requirements that a healthcare application should meet are closely linked and related to each other. Cross-layer solutions allow to study such interdependence [88]. Moreover, much research have jointly exploited different energy-efficient mechanisms, thus addressing the energy consumption at the different data collection steps to optimize the power-aware management. For instance, in [145], the authors combine wake-up radio with a context-based pull approach to provide power management, thus combining a hardware and a software solution to tackle the energy consumption due to sensing and communication. Similarly, in [115] compressive sensing, anomaly-driven transmission (on-node processing) and sample aggregation have been combined to ensure accuracy and QoS, and Bluetooth Low Energy (BLE) has been chosen as the low power communication protocol. Thus, maximizing energy-efficiency in data collection. In [104], energy-efficiency was tackled by combining a context-based pull mechanism (handshake detection), on-node processing and feature selection allowing the node to extract a set of selected features from raw accelerometer data, thus reducing sensing, processing and transmission. Of course combining different techniques is not always possible, it is dependant on the application. For example, in activity recognition applications requiring a single accelerometer sensor, sensor set selection is not applicable. However, on-node processing and feature selection could be used to reduce transmission.

2.4.3/ COMBINING ENERGY HARVESTING AND ENERGY-EFFICIENT MECHANISMS

Using energy harvesting techniques in WBSNs is alone not sufficient to make the network self-sustainable, especially that most healthcare applications require continuous monitoring and limited amount of energy can be harvested over time based on available sources. Therefore, the energy provision technique should be complemented by an energy-efficient mechanism. Much research has jointly studied energy provision and management in WBSNs [109]. As a consequence, energy harvesting needs are reduced and the sensor nodes are able to perform their tasks more frequently with the scavenged energy [124, 131]. Furthermore, given that some energy harvesting sources are dependent of the user context (body movement, health condition etc.) and others are dependant of the surrounding ambient environment (solar, heat, light etc.), a combination of different energy harvesting techniques should be adopted to scavenge energy in order to exploit different energy sources based on their availability.

2.5/ CONCLUSION

In this chapter, we have covered the most common energy-efficient mechanisms that are employed in WBSNs. We have categorized them into three categories : sensing, processing and transmission, depending on which energy consuming data collection task is mainly targeted. Furthermore, we have highlighted the potential of energy harvesting

techniques which are still in their early age and still need effort to ensure long lasting sensor nodes. Finally, a discussion has been made regarding the trade-off between energy-efficiency and delay, QoS, mobility and accuracy. We have concluded the chapter by shedding the light on cross layer approaches, the potential of combining different energy-efficient mechanisms with energy harvesting. In our opinion, any energy-efficient data collection technique must not compromise data accuracy, especially that we are dealing with healthcare applications and sensitive data. Furthermore, we believe that combining different techniques and/or technologies to maximize power efficiency has a great potential in maximizing the network's lifetime and ensuring continuous health monitoring.

DATA FUSION

As already mentioned, we are interested in providing continuous health monitoring using WBSNs. Thus, proposing models for combining and fusing heterogeneous data collected from different biosensor nodes is one of the main objectives of this thesis. Multi-sensor fusion is a very challenging task in WBSNs that impacts the accuracy and performance of healthcare applications. This chapter explores the different aspects of multi-sensor fusion from the relationship among data sources, to the processing architectures that are found in the literature and the level at which the data is processed for fusion. Several data-related challenges exist in WBSNs that influence the chosen technique for the fusion. Moreover, high-level fusion is gaining increasing attention due to its potential and openings. Thus, we discuss the most relevant fusion algorithms and discuss their limitations.

3.1/ INTRODUCTION

Currently, developing intelligent algorithms for a variety of tasks in healthcare applications has been attracting the research community. Hence, the treatment and processing of the collected data is an important aspect in WBSNs. For instance, data fusion in WBSNs allows to combine, to correlate and to associate physiological data and medical information coming from one or multiple biosensor nodes in order to achieve accurate situation assessments about the monitored person. Particularly, multi-sensor fusion has been gaining an ever-increasing interest driven by its potential in ensuring a unified picture about the health condition of the patient. However, several challenges exist in WBSNs, especially that the collected data is subject to noise, interference and faulty measurements, thus leading to the fusion of imperfect and inconsistent data. Furthermore, real-time fusion and good accuracy, which are two important aspects in healthcare applications, should be satisfied by multi-sensor fusion approaches. Therefore, the choice of high-level fusion techniques such as machine learning, fuzzy logic, case-based reasoning etc., which enable feature-level and decision-level fusion, is very essential and is application-specific.

This chapter explores multi-sensor fusion in WBSNs. First, in Section 3.2 we define data fusion while emphasizing on multi-sensor fusion. In Section 3.3, we motivate the use of multiple sensors in healthcare applications. Then, in Section 3.4, three different categorizations of multi-sensor fusion approaches are presented based on the relationship among data sources, the processing architecture chosen for the fusion and the data processing level at which the fusion is performed. Then, a discussion about the most rel-

evant challenges related to health data is provided in Section 3.5. Moreover, we highlight the difference between low-level fusion and high-level fusion, and discuss the advantages and disadvantages of data-driven and knowledge-driven approaches in Section 3.6. Finally, a discussion about the requirements of multi-sensor fusion approaches regarding the WBSN and the healthcare application is made in Section 3.7. Section 3.8 concludes the chapter.

3.2/ DEFINITIONS

In this section, well-known and approved definitions in the literature for data fusion are given as well as a specific definition for multi-sensor fusion is given. Joint Directors of Laboratories (JDL) define **data fusion** as a

Definition 1: Data fusion

Multi-level process dealing with the association, correlation, combination of data and information from single and multiple sources to achieve refined position, identity estimates and complete and timely assessments of situations, threats and their significance.

Another well-known definition was provided by [6] as follows:

Definition 2: Data fusion

Data fusion techniques combine data from multiple sensors and related information from associated databases to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone.

We agree on the following definition for multi-sensor fusion [111, 58, 55]:

Definition 3: Multi-sensor fusion

Multisensor fusion enables to obtain a unified picture and a global view of the system by combining information from several sources.

In the rest of this chapter, we focus on multi-sensor fusion in WBSNs and investigate relevant research that has been done in this domain.

3.3/ SINGLE SENSOR V.S. MULTI-SENSOR BASED HEALTHCARE APPLICATIONS

Much research has focused on comparing the use of a single sensor with the use of multiple sensors to monitor a specific health related phenomenon such as activity recognition, health assessment, stress detection, disease prediction etc. The multiple sensors at use can be of the same type or can be of different types. An example of the former case is the use of multiple accelerometers placed at different locations on the human body to monitor the physical activity of a person. Whereas an example of the latter case is the deployment of different physiological sensors (such as ECG, Heart rate, blood pressure, temperature etc.) which could also be combined with motion sensors. Multi-sensor fusion improves

detection and decision-making by providing a complete understanding of the situation of interest. It enhances data authenticity and availability and ensures a higher level of confidence and reliability and decreases uncertainty [55, 143]. Given the inconsistency and imperfection of sensor measurements, using redundant or complementary data allow to infer from these measurements high quality information [143, 158]. Particularly, health monitoring applications focus on the use of multiple vital signs in order to perform health assessment, thus achieving robustness [54, 73, 22]. Whereas, the use of a single sensor is limited to the applications that study and analyze a specific physiological parameter such as the ECG [160, 91].

3.4/ CLASSIFICATION OF MULTI-SENSOR FUSION APPROACHES

In this section, three different classifications of multi-sensor fusion approaches are presented [143].

3.4.1/ RELATIONSHIP AMONG DATA SOURCES

Based on the relationship among the sensors that are deployed on the person's body, the multi-sensor fusion can be categorized into three different groups according to [143]: *competitive*, *complementary* and *cooperative* as depicted in Figure 3.1. The competi-

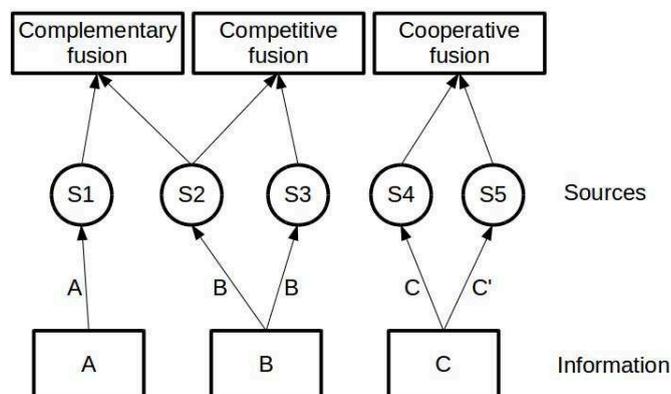


Figure 3.1: Relationship among data sources.

tive fusion involves the use of multiple homogeneous sensor nodes that provide through their sensing capabilities the same information. It is used to obtain redundancy and self-calibration. This type of fusion is not very common in WBSNs because any wearable system should not be bulky and should be comfortable to wear. In physical activity monitoring applications, equivalent sensors are deployed on different locations of the human body (arm, chest, leg etc.) and hence do not provide competitive information but rather complementary. Concerning the complementary fusion, it consists of employing sensors that capture different aspects of the monitored phenomena. It is used to refine the accuracy and reliability of the application. For instance, in activity recognition applications, the motion data sensed by an accelerometer and a gyroscope capture two different aspects of physical activities. Their joint analysis enables to obtain a high-level information and

improves accuracy and reliability. We talk about cooperative fusion when multiple physiological and/or physical parameters are required in order to obtain information that could not be achieved by analyzing any of these parameters independently. For instance, the health assessment of acute patients requires the simultaneous monitoring of several vital signs in order to detect emergencies and to have information about the severity of the patient's health condition. This type of fusion is the most common in WBSNs.

3.4.2/ PROCESSING ARCHITECTURE

In [143], three different data fusion approaches based on the processing architecture are identified : *centralized*, *distributed* and *hybrid*. The centralized approach depends on a fusion center where all the processing is performed. A distributed approach is adopted when the sensor nodes perform independent processing on the data they have captured and transmit the results to a fusion node. In this case, the fusion node executes a global analysis based on the results sent by all the sensor nodes [69, 105]. Finally, hybrid fusion concerns approaches where the sensor nodes only perform pre-processing and/or perform partial lightweight computation on the collected data in a distributed approach fashion while a central node fuses the gathered data and performs high-level fusion [104].

3.4.3/ DATA PROCESSING LEVEL

The authors in [143] have also categorized the multi-sensor fusion based on what level the fusion is performed. Three categories were identified: *data-level*, *feature-level* and *decision-level*. Data-level fusion is the combination of multiple homogeneous sources of raw sensory data in order to improve the accuracy and the inferred information. Specifically, data can come from different channels of the same sensor (ex: 3-axis accelerometer, ECG leads etc.) or from competitive sensors which is rare in WBSNs [67, 75, 167]. Feature-level fusion involves the combination of several feature sets extracted from different sensor nodes to create a new high-dimension feature vector [44, 22, 56, 114, 154]. Generally, the latter constitutes the input of the classification/pattern recognition step. The features could be in the time domain (such as mean, standard deviation, variance etc.) and/or frequency domain (such as low/high frequency, spectral energy etc.) and/or other type of features (such as drift from normality, rule-based features etc.). In decision-level fusion, a unique decision is obtained based on local or weaker decisions of multiple sensor nodes [104, 108, 75, 161, 97]. For instance, it allows to enhance robustness and accuracy, and is mainly used to detect anomalies or to enforce the detection of the phenomena of interest. Most importantly, it allows to fuse the physiological data whose measurement domains have been differently processed using different algorithms.

3.5/ CHALLENGING ASPECTS IN DATA

The collected data in WBSNs present many challenging aspects given that (1) sensor nodes are deployed in a noisy environment, thus the sensed signals are affected and may be corrupted, (2) the collected data is subject to data loss due to interference, (3) the collected data can present inconsistency due to poorly attached or uncalibrated or low battery level sensors , (4) sensor nodes capture physiological signals that are medically

interpreted following a human-reasoning logic, thus characterizing the collected data by imprecision. In this section, we discuss the data-centric taxonomy inspired from [58]. Data fusion techniques and algorithms can be categorized based on the following data-challenging aspects: *imperfection*, *correlation*, *inconsistency* and *disparateness*. It is notable that no single algorithm can solve all these challenges. We chose to discuss uncertainty, imprecision and outlier since the data collected in WBSNs exhibits these challenges and thus they are the mostly tackled in the literature (c.f. Figure 3.2).

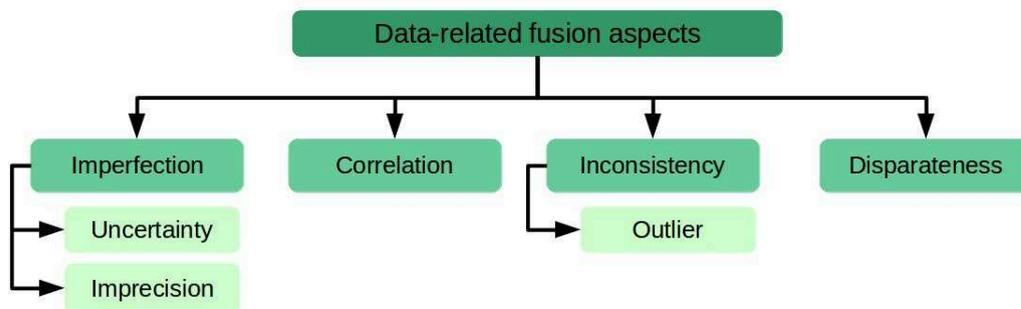


Figure 3.2: Data-centric taxonomy based on the data challenging aspects.

Below is a definition provided for each of the aspects of the aforementioned data-related challenges as depicted in Figure 3.2 to distinguish among them:

- **Uncertainty:** if the associated confidence degree about what is stated by the data is less than 1, then data is uncertain. Probabilistic methods are used to express this uncertainty such as the Bayes estimator, kalman filter, Monte Carlo simulation-based techniques as well as Dempster–Shafer evidence theory [168, 157].
- **Imprecision:** if data refers to several objects rather than only one object, then data is imprecise. Imprecision can take several forms: vagueness, ambiguity and incompleteness. Each of these forms will be explained by an example. For instance ambiguity can be explained by the following sentence: "the normal heart rate is between 51 and 90 bpm", a well-defined yet imprecise interval is assigned to the heart rate. Contrariwise, vagueness is characterized by ill-defined attributes. For example, in the sentence "the blood pressure is high", the assigned attribute "high" is not well-defined and can be interpreted subjectively. An imprecise data that is missing information is called incomplete. For example, in the sentence "the person has fever", only the upper limit on the degree of confidence is given. To deal with the aforementioned data-related challenges many popular data fusion techniques exist in the literature. On the one hand, evidential belief reasoning enables the fusion of uncertain and ambiguous data [168, 157, 138]. On the other hand, fuzzy reasoning is an established approach to deal with vague and ambiguous data especially human generated data [75, 48, 134, 126]. Finally, possibilistic theory enables to tackle incomplete data [123, 34].
- **Outlier:** Data collected by sensor nodes may be spurious due to permanent failures, not well attached sensor nodes or low energy level. Thus, pre-processing techniques are applied on the acquired signals, anomaly detection techniques and other sensor validation techniques are proposed in the literature to deal with this problem and prevent the fusion of such data with correct data [67, 108, 72, 120].

3.6/ HIGH-LEVEL FUSION: DATA-DRIVEN VS KNOWLEDGE-DRIVEN APPROACHES

Currently, high-level fusion is gaining more attention especially that low-level fusion has attained maturity. Low-level fusion concerns data-level fusion tasks which mainly address the data-related challenges that were discussed in Section 3.5. However, feature-level and decision-level fusion are adopted in order to infer high-level information. In this category, multiple approaches are exploited especially supervised machine learning such as Decision trees, Bayesian Networks, Naive Bayes, Support Vector Machine, Neural Networks and unsupervised machine learning such as clustering algorithms. Furthermore, other reasoning approaches are used such as rule-based algorithms, fuzzy inference systems and case-base reasoning. As it is noticed, the approaches are divided between data-driven approaches and knowledge-driven approaches. Obviously, data-driven approaches are considered to be self-contained because they rely on the observations and their assumed model: no external input is required. They are mainly used when the interactions between data is not understood. In the context of WBSNs, these approaches are extensively used in activity recognition applications and are also used for prediction and diagnosis healthcare applications. However, they require a training phase and an extensive amount of data to be validated. The former requires data collection for a long period of time which consumes the energy resources of sensor nodes in a real deployment scenario, and an enough number of participants (greater than 40) in order to build an application-specific model rather than a patient-specific model. The latter is an important factor to consider when a real implementation and test of the application are not feasible. In that particular case, procuring enough datasets concerning a specific application such as stress monitoring, health assessment through vital sign monitoring, emergency detection and disease prevention is unattainable. Knowledge-based approaches make use of prior knowledge such as rules, knowledge databases, solved cases and known medical facts put by healthcare experts. They have the advantage of being semantically clear and understandable by humans. However, they are weak in handling uncertainty and temporal information and could be viewed as static or incomplete [40, 121, 70].

3.7/ DISCUSSION

The choice of sensor nodes namely their type and location on the human body depends on the monitoring phenomenon. For instance, acute illness requires the continuous and simultaneous monitoring of five vital signs: the heart rate, the respiration rate, the systolic blood pressure, the temperature and the oxygen saturation [47], while stress is detectable by monitoring the heart rate, the respiration rate, the blood pressure and the skin conductance. Thus, the type of fusion, which is discussed in Section 3.4.1, is determined by the monitoring phenomenon. For instance, in these examples the type of fusion is cooperative since each sensor provides a different aspect of the same phenomenon. Similarly, the choice of the fusion level, which is discussed in Section 3.4.3, is determined by the monitoring phenomenon. For instance, in [104] the authors propose collaborative WB-SNs that detect handshakes based on joint decisions and in [108] the authors propose to detect anomalies based on the majority voting of different sensor nodes sensing different vital signs.

Based on the healthcare application in hand, a subset of data-related challenges is addressed. Indeed, there is not a single algorithm that could solve all the issues discussed in Section 3.5. Researchers combine different techniques at low-level fusion as well as high-level fusion in order to solve different data-related challenges [75, 44, 157]. However, any multi-sensor fusion approach should be capable of ensuring real-time monitoring, should take into consideration the memory, processing and energy constraints existing in WBSNs namely at both the sensor nodes and the coordinator levels, and should be evaluated in terms of accuracy. The requirement for real-time monitoring application guide the selection of the high-level fusion algorithm. For example frequency analysis and neural networks are not efficient due to computational complexity while rule-based, decision trees, temporal analysis and statistical techniques are capable of satisfying the online data processing requirements. In [54], the authors report the lifetime of sensor nodes and mobile phones (coordinator) for different architectures found in the literature in hours of operation. It is noticed that the lifetime of mobile phones is shorter than the lifetime of sensor nodes and that their energy is depleted faster. An explanation for this observation is that mobile phones have to ensure different services other than performing multi-sensor fusion tasks such as text messaging, phone call and web browsing. Therefore, the energy consumption and processing capabilities of the coordinator should be taken into consideration when proposing a multi-sensor fusion approach, selecting techniques and algorithms, and choosing the processing level of the fusion (c.f. Section 3.4.2). The evaluation of a fusion algorithm is not only affected by its efficiency but also by the quality of the input data. There is no standard or a well established evaluation framework enabling the assessment of the performance of data fusion algorithms. In fact, it is hard to predict the performance of algorithms in real-life applications because most of the work is done in a simulated environment with idealized assumptions. However, most of the multi-sensor fusion approaches in the literature are validated in terms of accuracy especially when it employs machine learning. Validation is made either by computing the classification accuracy based on provided datasets and/or simulated testing or is made by collaborating with healthcare experts.

An additional usage of contextual information is gaining an increasing interest in data fusion. It could include meta information about persons such as personal information (ex: age, sex, weight, height etc.), medical history, fitness level and activities of daily living. Contextual information ensures ubiquity and autonomy, as well as it enhances data interpretation and decision-making thus making healthcare applications more robust, dynamic and flexible given the changing conditions of people. Furthermore, adding context-awareness provides a palette of services such as lifestyle recommendation/suggestions, medical advice and assessment of healthy habits.

3.8/ CONCLUSION

In this chapter, we have defined multi-sensor fusion and motivated the use of multiple sensors in healthcare applications instead of a single sensor. This is driven by the fact that it enhances robustness, data availability and authenticity, and reduces uncertainty in the inferred information. The different categorization strategies of multi-sensor fusion approaches have been presented. Moreover, a distinction between low-level fusion and high-level fusion has been made by presenting the most common data related challenges in WBSNs, i.e. uncertainty, imprecision and outlier, as well as by discussing the advan-

tages and disadvantages of data-driven and knowledge-driven approaches. Finally, a discussion has been made concerning the potential of combining different multi-sensor fusion approaches, the impact of continuous data fusion on the energy consumption of the coordinator and the evaluation of these approaches.



CONTRIBUTION

SELF-ADAPTIVE DATA COLLECTION

In WBSNs, biosensors periodically collect vital signs and send them to the coordinator. In this chapter, we target data reduction and energy consumption. We propose a two-fold adaptive data collection approach. First, the sampling rates of biosensors are locally adapted in real-time based on the variations of the monitored vital sign and the monitoring importance given to it. Second, an early warning score system is used by biosensor nodes to optimize data transmission. To evaluate our approach, we have conducted multiple series of simulations on real sensor data. The results show that our approach reduces the amount of collected data while maintaining data integrity, thus implying a reduction of the energy consumption.

4.1/ INTRODUCTION

Patient monitoring involves periodic transmission of routine vital signs and alerting signals when vital signs cross a certain threshold. We assume a network of biosensor nodes placed on or implanted in the body of patients. They continuously send the sensed data to the coordinator of the network. The latter is located on or near the body and is assigned the fusion of the collected data. It forwards the data as well as the inferred information such as decisions to a sink node. The decisions include detected emergencies, advice given to the patients as well as taken actions in case of emergency. The sink node then sends the received data to the healthcare center or any other destination for further processing and storage [100]. As discussed in Chapter 2, many challenges arise in WBSNs, which are the energy consumption due to periodic transmission and the huge amount of heterogeneous raw data captured by biosensor nodes. In this chapter we address the energy consumption and data reduction issues which are directly related to one another by proposing an energy-efficient data collection scheme.

Vital signs can vary from critical values to normal values and vice versa. Moreover, the dynamics of the monitored conditions can slow down or speed up regarding the patient's situation. For this purpose and to reduce the energy consumption, the sampling rate in periodic data collection networks, such as WBSNs, must depend on how fast the condition varies and at what rate the characteristics need to be captured [113, 61, 112]. Furthermore, most of the existing work in Wireless Sensor Networks (WSN) considers that data acquisition and processing have energy consumption negligible compared to communication. Unfortunately, this assumption is not true for all type of applications and especially for WBSNs where sensors are used periodically. Therefore, adapting the sam-

pling rate is an effective method to reduce the energy consumption in WBSNs due not only to transmission but also to sensing and processing the data. Likewise, we are specifically interested in establishing an early warning system, where the biosensor nodes are capable of locally detecting emergencies and sending measurements to the coordinator only when a change in the status of the vital sign is observed. Thus, reducing redundant information and improving power efficiency. In our work, we propose an adaptive sampling rate scheme having a direct impact on the sensing and processing tasks of the biosensor node. Using a Quadratic Bezier Curve as a Behavior (BV) Function, it takes into account two parameters : the evolution of the monitored vital sign over time and its monitoring importance. The first parameter is determined by studying the variances of the sensed measurements over time using One-way Analysis of Variance (ANOVA) coupled with Fisher test. Whereas, the second parameter is represented by a value named risk level which is medically judged based on the patient's health condition. However, the overall health condition of a patient, being continuously and remotely monitored on a long-term basis, changes over time. It is subject to many health events which can be acute or even chronic. Thus, it can vary from day to day as well as from an improvement state into a deterioration state and vice versa especially that acute disease go through many different stages. As a consequence, the monitoring importance given for each vital sign should be adapted with these changing conditions. This matter, has a direct influence on data collection, therefore on the energy consumption of the WBSN and the early detection of critical events. Thus, we propose to dynamically adapt the risk level of a vital sign according to the changing health condition of the patient.

The following of the chapter is organized as follows. Section 4.2 presents the related work. In Section 4.3 early warning score systems are defined. In Section 4.4, the local emergency detection algorithm is introduced. In section 4.5, the adaptive sampling rate model is explained and the algorithm regrouping this model and the local emergency mechanism is presented. The risk level of the sensor node is defined and its adaptation is explained in Section 4.5.2. Experimental results are given in Section 4.7. Section 4.8 concludes the chapter.

4.2/ RELATED WORK

Various aspects and needs in WBSNs have been studied and discussed in the literature. Some of them treated routing issues and QoS such as in [96] and in [74]. Others focused on analyzing and fusing the sensed data in order to produce useful information [104, 28]. Several solutions for supporting emergency messages in WBSNs have been proposed in the literature so far [106, 87, 24, 78]. In [87] the authors propose to locally classify the captured reading of the vital sign, based on a preset thresholds at each sensor. If the value of the vital sign is in the normal range, the corresponding packet is classified as a normal packet and is put in a normal queue, otherwise it is classified as a prioritized packet and is put in a precedence queue. A scheduler chooses first the packets in the priority queue and puts it in a transmission queue. The authors in [24] developed a platform, Dexter Net, that allows local processing of data both at the sensor mote and smartphone levels. Although they stipulate that the framework, based on SPINE, allows local data processing they did not focus on the detection of emergency events. In [106], the authors propose a system to help finding the abnormalities of heart beat rate and also medicine intake by the patient using Bayesian algorithm. The aforementioned work

highlights the need of personal caring given to the patient by the hospital, thus reducing unnecessary delay in providing treatment to a patient. It also concentrates on the network lifetime maximization and distance metrics while moving from one network to another network.

Unfortunately, the above related work assume that data acquisition and processing have an energy consumption that is negligible compared to the radio communication. Consequently, their researches aim only at minimizing radio transmission. On the other hand, in almost all the previous solutions there was no particular attention related to the optimization of raw data transmission and local emergency detection on the sensor node level. The studies just focused on detecting the emergency at the base station level where all the data is received from different sensors. For instance, some previous work [112, 113, 18] propose an adaptive sampling algorithm in order to reduce the sensors activity of periodic sensor networks. However, data transmission is still a significant issue and emergency detection is not being handled. Indeed, an early emergency detection along with energy saving and reduction of the huge amount of raw data captured by the sensors are the major challenges of WBSNs. In [80], the authors propose the Local Emergency Detection (*LED**) algorithm which consists of detecting early emergencies while saving energy. In this approach the authors suggest that sensor nodes send all critical values, which are outside the normal range, to the coordinator. However, this approach does not reduce the amount of transmitted data in critical health monitoring where all captured measurements are critical. Furthermore, redundant information is not taken into consideration in this approach where a vital sign could be stable in a critical state for a long period of time. As a consequence, the sensor node in this approach would send all the critical captured measurements without checking the redundancy of the information.

In this chapter, we propose to bring some modification to the *LED** algorithm to further reduce the energy consumption and extend the lifetime of the network. Furthermore, the BehaVior (BV) function used for the sampling rate adaptation is extensively explained by adapting its equations based on the requirements of vital signs monitoring in terms of having a minimum sampling rate. Moreover, we propose to dynamically adapt the monitoring importance given to a vital sign with the changing health condition of the patient, which impacts data collection. Extensive simulations on real health sensory data is carried out to study and validate our proposal.

4.3/ EARLY WARNING SCORE SYSTEM

An early warning score system (EWS) is a guide used by emergency medical services staff in hospitals to determine the degree of criticality of patient situation. An EWS is used as a systematic protocol to measure simple physiological parameters in all patients to allow early recognition of those presenting an acute illness or who are deteriorating [43]. For each vital sign, a normal healthy range is defined. Measured values outside of this range are allocated a score which is weighted and color-coded on the observation chart according to the magnitude of deviation from the normal range. The weighting reflects the severity of the physiological disturbance. Such scoring systems can give the biosensor node the ability to locally evaluate the severity level of the vital sign being monitored and to assign to it a score.

Figure 4.1 shows the National EWS (NEWS) [47], a standard that is employed in all

National Early Warning Score (NEWS)*

PHYSIOLOGICAL PARAMETERS	3	2	1	0	1	2	3
Respiration Rate	≤8		9 - 11	12 - 20		21 - 24	≥25
Oxygen Saturations	≤91	92 - 93	94 - 95	≥96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤35.0		35.1 - 36.0	36.1 - 38.0	38.1 - 39.0	≥39.1	
Systolic BP	≤90	91 - 100	101 - 110	111 - 219			≥220
Heart Rate	≤40		41 - 50	51 - 90	91 - 110	111 - 130	≥131
Level of Consciousness				A			V, P, or U

*The NEWS initiative flowed from the Royal College of Physicians' NEWS Development and Implementation Group (NEWSDIG) report, and was jointly developed and funded in collaboration with the Royal College of Physicians, Royal College of Nursing, National Outreach Forum and NHS Training for Innovation

Please see next page for explanatory text about this chart.



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Figure 4.1: Early Warning Score System

the hospitals of the United Kingdom (UK) for the assessment of acute-illness. We have used NEWS in our experimental tests and examples in order to evaluate the severity level of each of the following vital signs: temperature, heart rate, respiration rate, oxygen saturation and systolic blood pressure. A score of 0 is assigned to the measurement if it is in the normal range and a score of 1, 2 or 3, according to its magnitude of deviation from the normal range, where 3 indicates the highest level of criticality. In the next section, we will show how an EWS can be used by a local emergency detection algorithm.

4.4/ LOCAL EMERGENCY DETECTION

A WBSN is composed of biosensor nodes and a coordinator. The former is defined as a traditional sensor node equipped with sensors that monitor vital signs such as the heart rate (HR), respiration rate (RR), blood pressure (BP), Temperature (Temp) etc. We suppose that each biosensor node is sensing one vital sign. In a traditional WBSN, each biosensor node collects data and sends them to the coordinator in a periodic manner. Thus, a huge amount of data is collected and sent every period to the coordinator. Therefore, we must find a model which reduces the amount of data while guaranteeing integrity and in the same time optimizes data transmission to reduce the energy consumption on nodes. The first intuition is to send the first captured measurement during a period as well as all the critical measurements to the coordinator as proposed in [80] and known as Local Emergency Detection (LED) algorithm. Detection of abnormal situations is allowed by providing a local warning system on each node. Thus, the score of each captured

data is calculated, which allow to early and locally detect any emergency represented by a score different from zero. However, data transmission can be further optimized. Indeed, when an emergency is detected it is not always useful to send all the critical data. For instance, suppose a biosensor node capturing the respiration rate is running the LED algorithm. This latter, will send huge amounts of critical data if the respiration rate of the patient is abnormal for a long time. This case is very common in unstable and deteriorating health conditions where all the data sensed by the biosensor nodes are critical and redundant. Therefore, we propose to modify the *LED* algorithm in order to further optimize data transmission and further reduce the energy consumption of the biosensor nodes and extend their lifetime.

Suppose $V = (v_0, \dots, v_n)$ is a series of sensed data at a R_t rate, during a period p , belonging to a given vital sign and $V_{scores} = (score(v_0), \dots, score(v_n))$ is the series of their corresponding scores computed using an EWS. The biosensor sends a sensed data v_i only if its score $score(v_i)$ is different from the score of the previously sent data in the same period (cf Algorithm 1). Therefore, the transmission is optimized by eliminating the transmission of consecutive sensed data having the same score while maintaining data integrity by sending data each time a new score is detected. For example, suppose $V = (v_0, v_1, v_2, v_3, v_4, v_5, v_6, v_7)$ is a series of 8 consecutive measurements for a given vital sign, $V_{scores} = (1, 1, 0, 2, 2, 2, 2, 0)$ is the series of the corresponding consecutive scores. By using *Modified LED* (c.f. Algorithm 1) only the following series (v_0, v_2, v_3, v_7) is sent to the coordinator. The latter is able to regenerate the original data series since it considers the last value received at time t as the current one while it has not received any new measurement at time $t + 1$ from the biosensor node during the same period.

Algorithm 1 Modified Local Emergency Detection Algorithm *Modified LED*

Require: SR_t (Instantaneous Sampling Rate), EWS for the vital sign of interest.

```

while Energy > 0 do
2:   for each period do
       Take first measurement  $v_0$ 
4:     Store first measurement  $V[0] \leftarrow v_0$ 
       Send first measurement  $v_0$ 
6:     Get score  $score(v_0)$ 
        $S = score(v_0)$ 
8:     while end of period not reached do
       Take measurement  $v_i$  at rate  $SR_t$ 
10:    Store measurement  $V[i] \leftarrow v_i$ 
       Get score  $score(v_i)$ 
12:    if  $score(v_i) \neq S$  then
       Send measurement  $v_i$ 
14:     $S = score(v_i)$ 
       end if
16:    end while
       end for
18: end while

```

Several approaches for energy saving in WSNs are proposed in the literature. However, the majority of these works consider that data sensing and processing have an energy consumption that is negligible compared to data transmission. Consequently, these approaches try to minimize the network's communications. However, this assumption is not always correct especially when the sensors collect data periodically, thus, a huge amount of sensing data is collected. Moreover, medical applications require spe-

cific sensors whose power consumption cannot be neglected [9]. For instance, popular radio equipment used in sensor nodes "CC1000" produced by "Texas Instruments" consumes $42mW$ (at $0dBm$) for transmission and $29mW$ for reception. On the other hand, an accelerometer "iMEMS" by "ADI" consumes $30mW$. Therefore, if we consider that the data acquisition phase is longer than the transmission phase, we can conclude that some sensors may consume more energy than radio communications. As such, the *Modified LED* algorithm which aims to minimize the communication in the network needs to be complemented by an efficient energy management of the sensors by considering the energy consumed for data sensing. In the next section, we show how we can adapt the sampling rate in order to save more energy at the the biosensor node level.

4.5/ ADAPTIVE SAMPLING

In this section, we suggest an adaptive sampling rate scheme that adapts the sampling rates of the sensors to the vital sign dynamic evolution. Therefore, the sampling rate is adapted based on the sensed data variation as explained in [61]. For instance, if a vital sign is unstable then the sensor node's sampling rate should better be set to a maximum in order not to miss any important changes and to record all variations. However, if the vital sign is somewhat stable, then the sensor node's sampling rate should better be set to a minimum in order to preserve its energy level. Furthermore, we take another parameter into consideration: the monitoring importance given to a vital sign v_i (critical/uncritical) which we call risk level r_i . The idea here is to apply the One-way ANalysis Of VAriance (ANOVA) with Fisher test in order to verify during a specific period if there is high variation in the captured measurements. In the affirmative case the sampling rate must be set to its maximum otherwise the sampling rate is adapted according to the variations presented by the vital sign and its monitoring importance. Our goal is to minimize the sensing activity and to reduce the amount of raw data sent to the coordinator. In the following, the Fisher test with one-way ANOVA is firstly presented and the monitoring importance of vital signs is defined. Then, the behavior function we have proposed for the sampling rate adaptation is described and the proposed adaptive local emergency detection algorithm is presented.

4.5.1/ FISHER TEST WITH ONE-WAY ANOVA

The Fisher test with One-way ANOVA is used to evaluate whether the expected values of a quantitative variable in several pre-defined groups vary from each other. We propose to test the following null hypothesis: The means of the measurements of the last h consecutive periods are equal. In order to do so, we compute the Fisher test with one-way ANOVA statistic test using the following formula:

$$F = \frac{\frac{SF}{(h-1)}}{\frac{SR}{(N-h)}} \quad (4.1)$$

where SF is the between period variation, SR is the within period variation, h is the total of consecutive periods and N is total of measurements. SF and SR are calculated as follows:

$$SF = \sum_{j=1}^h n_j \times (\bar{Y}_j - \bar{Y})^2 \quad (4.2)$$

$$SR = \sum_{j=1}^h \sum_{i=1}^{n_j} (y_{ji} - \bar{Y}_j)^2 \quad (4.3)$$

where y_{ji} is the i^{th} measurement of the j^{th} period, n_j is the total of measurements of the j^{th} period, \bar{Y}_j is their mean and \bar{Y} is the mean of all the measurements taken during the h consecutive periods. When the hypothesis is accepted the Fisher statistic follows the F-distribution with $(h-1, N-h)$ degrees of freedom. If F is greater than the critical value $F_t = F_{\alpha}(h-1, N-h)$ that is defined for a given Fisher risk α (false-rejection probability), then the hypothesis is rejected. Otherwise the hypothesis is accepted. Thus, the decision is based on F and F_t . Three situations are possible:

- $F > F_t \Rightarrow$ the variance between periods is significant and the sampling rate is balanced to the maximum sampling rate.
- $F \leq F_t \Rightarrow$ the sampling rate is adapted depending on the Fisher test F and the vital sign's risk level.
- If $N < h$ the sampling rate is balanced to the maximum sampling rate.

4.5.2/ MONITORING IMPORTANCE OF VITAL SIGN: RISK LEVEL r

The monitoring importance given to a specific vital sign is represented by a quantitative variable (risk level r) which can take values between 0 and 1 indicating low and high risk levels respectively. It is set by healthcare experts based on the health monitoring scenario. Two risk level ranges are defined:

- **Low Risk:** r is assigned a low value (< 0.5), indicating a low monitoring importance, if the following conditions are met:
 - If the vital sign generally does not present many variations and is usually stable.
 - If the medical expert thinks that a low sampling rate is sufficient to capture any important variation.
 - If the variations do not have a drastic impact on the patient's health.

For example, the temperature, the galvanic skin response and the oxygen saturation meet these requirements. In this case, the biosensor nodes will preserve energy by sampling at a low rate.

- **High Risk:** r is assigned a high value (≥ 0.5), indicating a high monitoring importance, if the following conditions are met:
 - If the vital sign usually presents many variations.
 - If the medical expert thinks that a high sampling rate is essential to capture any important variation.

- If any variation can have a drastic impact on the patient's health.

For example, the heart rate, the blood pressure and the respiration rate meet these requirements. In this case, the biosensors will be assigned high sampling rates.

Having the result of the one-way ANOVA and Fisher test as well as the risk level r , the behavior function used for adapting the sampling rate of the sensor node is explained in the following section.

4.5.3/ BEHAVIOR FUNCTION

Bezier curves are flexible parametric curves that define shapes by having knowledge about some points of interest [113]. Quadratic bezier curves are defined using three points. They are limited by the two points P_0 (start point) and P_2 (end point) and their curvature is controlled by the point P_1 . We define the coordinates of the three points as follows: $P_0(0; l_y)$, $P_1(b_x; b_y)$ and $P_2(h_x; h_y)$ such as $0 < b_x < h_x$ and $l_y < b_y < h_y$.

Since P_1 moves on the diagonal [AB] of the behavior rectangle where $A(0; h_y)$ and $B(h_x; l_y)$, the coordinates b_x and b_y of P_1 satisfy the equation of [AB] which is defined as follows:

$$y = \frac{l_y - h_y}{h_x} \times x + h_y \quad (4.4)$$

In our approach, the patient's risk level r determines the position of P_1 and thus the curvature of the BV function:

$$\begin{aligned} B_r : [0; 1] &\mapsto [0; h_x] \times [l_y; h_y] \\ r &\mapsto (b_x; b_y) \end{aligned}$$

Thus, the following equations can be derived to find the coordinates b_x and b_y of the behavior point P_1 :

$$B_r(r) = \begin{cases} b_x = (1 - r) \times h_x \\ b_y = l_y + r \times (h_y - l_y) \end{cases} \quad (4.5)$$

The closer the value of r is to 1 the more patient's health condition is judged to be critical.

Finally, the BV function curve can be drawn using the following quadratic bezier curve functions:

$$BV(F) = \begin{cases} \frac{h_x + l_y - 2b_y}{4b_x^2} F^2 + \frac{h_y - l_y}{h_x} F + l_y, & h_x = 2b_x \\ (h_y + l_y - 2b_y)\alpha(F)^2 + \\ 2(b_y - l_y)\alpha(F) + l_y, & otherwise \end{cases}$$

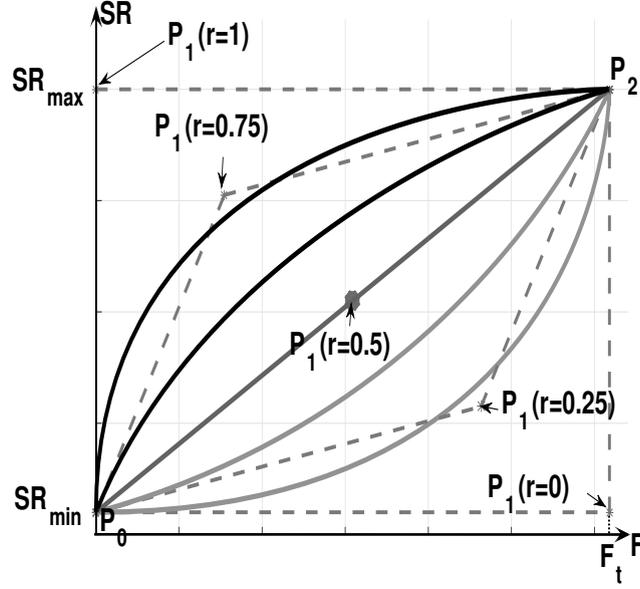


Figure 4.2: Behavior Function: Quadratic Bezier Curves

with $\alpha(F) = -b_x + \frac{\sqrt{b_x^2 - 2b_x F + h_x F}}{h_x - 2b_x}$, such as $0 \leq b_x \leq h_x$, $0 \leq F \leq h_x$ and $h_x > 0$.

Figure 4.2 shows the BV function which is used to adapt the sampling rate according to the Fisher test result F and the risk level r . The x-axis represents the result of Fisher Test F and the y-axis represents the sampling rate SR . The start point P_0 corresponds to $F = 0$ and $SR = SR_{min}$ and the end point P_2 corresponds to $F = F_t$ and $SR = SR_{max}$ where F_t corresponds to the critical value given by the Fisher Test for N collected samples during h periods. Having a maximum sampling rate SR_{max} and a minimum sampling rate SR_{min} , depending on the application's requirements, and the critical value F_t given by the Fisher Test, the BV function is then defined as follows:

$$BV(SR_{max}, SR_{min}, r, F, F_t) = SR \quad (4.6)$$

The closer F is to F_t , the more the acquired measurements in h periods present variations. Therefore, the higher the sampling rate given to the sensor node is in order not to miss any important variations. Whereas, the closer F is to 0, the less the acquired measurements in h periods present variations. Therefore, the lower the sampling rate given to the sensor node is in order to preserve its energy level. For each risk level value, a curve is associated. The higher the risk level value, the greater the sampling rate values and the lower the risk value, the lower the sampling rate values. As shown in Figure 4.3, for the same value of F , if the vital sign has a low risk level r , the sensor node's sampling rate will take a lower value if the vital sign has a high risk level r . Thus, in the first case, the sensor node will preserve its energy and will sense data and process measurements at a lower rate. However, in the latter case, the biosensor node, which is monitoring a vital sign being medically judged as essential regarding the patient's health condition, will be assigned a higher sampling rate in order not to miss important measurements and events. As a consequence, the sensing and processing tasks of the sensor node are affected: the number of sensed samples during a time period p can be increased or

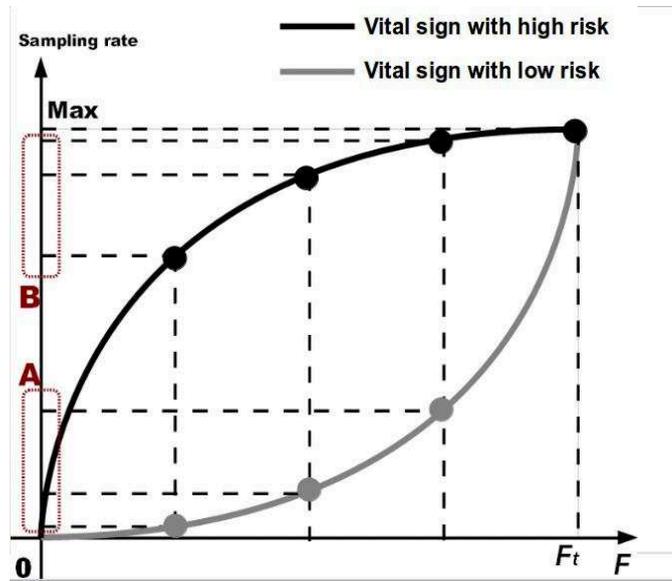


Figure 4.3: Sampling rate adaptation according to the vital sign's risk level

decreased depending on the sensor node's sampling rate.

4.5.4/ ADAPTIVE LED ALGORITHM

In this section, the algorithm that allows biosensor nodes to locally detect changes in vital signs including emergencies as well as to adapt their sampling rates in real-time is presented. The proposed algorithm, called *Modified LED** (c.f. Algorithm 2), is to be locally performed on each biosensor node of the WBSN. The sampling rate adaptation is performed each round k such as $Round_k = \sum_{i=k}^{h+k-1} p_i$ where $k \in \mathbb{N}, h \in \mathbb{N}$ and p is the time period. In other words, it is performed at end of each period based on the measurements that were acquired during the last h periods (sliding window of h consecutive periods with an overlap of $h - 1$ periods). The sampling rate adaption depends on the result of Fisher test F . If the means of the measurements of the last h consecutive periods are equal, thus suggesting that the vital sign is somewhat stable, then the sampling rate is adapted using the BV function. The latter requires the result of the Fisher Test F and the monitoring importance given to the vital sign r . Otherwise, the sampling rate is set to its maximum since the null hypothesis was rejected which means that the vital sign is varying.

Algorithm 2 Modified Local Emergency Detection with Adaptive Sampling Algorithm *Modified LED**

Require: h (1 round = h periods), SR_{max} (maximum sampling rate), SR_{min} (minimum sampling rate), r (risk level).

Ensure: SR_t (instantaneous sampling rate).

```

 $SR_t \leftarrow SR_{max}$ 
for  $h$  periods do
3:   Run Modified LED
      Store measurements in  $V$ 
end for
6:  $SR_t \leftarrow SR\_ADAPT(V, h)$ 
while  $Energy > 0$  do
      for each period do
9:       Run Modified LED
          Store measurements in  $V$ 
      end for
12:   $SR_t \leftarrow SR\_ADAPT(V, h)$ 
end while

function  $SR\_ADAPT(Mes, h)$ 
15:  Compute  $SR, SF$  and  $F$  using the measurements of the last  $h$  periods.
      if  $N < h$  then
           $SR_t \leftarrow SR_{max}$ 
18:  else
          Find  $F_t$ 
          if  $F < F_t$  then
21:        $SR_t \leftarrow BV(F, F_t, r, SR_{max}, SR_{min})$  (BV function).
          else
               $SR_t \leftarrow SR_{max}$ 
24:  end if
          end if
      return ( $SR$ )
27: end function

```

4.6/ RISK LEVEL ADAPTATION

In this section, we propose to dynamically adapt the risk level r values of all the monitored vital signs over time according to the patient's health condition. First, the motivation for doing so is presented then risk level evaluation function is described.

4.6.1/ SCENARIO

Tom is an elderly person living in a nursing home. In order to keep track of his health condition, he is being remotely and continuously monitored by a WBSN. We suppose that the WBSN is composed of n biosensor nodes, where each node monitors one vital sign. At first, the monitoring importance for each vital sign is medically judged by the medical team. Accordingly, the risk levels r for all the vital signs are chosen. Tom's health condition can change with time, he can become sick or be subject to dangerous health events. Thus, the risk levels r should be adapted by the WBSN with Tom's changing health condition. Higher values should be given to the nodes in order to increase their sampling

rate and capture important measurements and when the patient's health condition is at a lower risk and when it is normal, lower risk values should be given to the nodes in order to preserve their energy level. Next, we give a proper definition to the risk level r and discuss its initial setup.

4.6.2/ RISK LEVEL EVALUATION FUNCTION

We propose to adapt the risk level r of a vital sign, throughout the life of the WBSN, according to the patient's changing health condition. Let r_{global} represent the patient's overall health condition where $r_{global} \in [0; 1]$ and $r_{global} \in \mathbb{R}$. r_{global} is referred as the patient's global risk level and it indicates the severity level of his/her health condition. r_{global} is evaluated by the coordinator based on the multi-sensor data fusion which will be presented in Chapter 5. Let \bar{S} be the average score of the sensed measurements for a given vital sign during one round R , such as $R = h \times p$ where p is a time period and $h \in \mathbb{N}$, and S_{max} be the maximum score that a measurement can have according to the used EWS (cf. Section 4.3). Then, the risk level evaluation function $Eval : (r_{global}, \bar{S}) \mapsto [0; 1]$ is defined as follows:

$$Eval(r_{global}, \bar{S}) = \alpha \times r_{global} + \beta \times \frac{\bar{S}}{S_{max}} \quad (4.7)$$

where α and β are weight coefficients such as : $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$ and $\alpha + \beta = 1$. The Score ratio $\frac{\bar{S}}{S_{max}}$ is equal to the mean score of the sensed measurements over the maximum score that can be given to a measurement. It represents the situation of a vital sign (its criticality) compared to the worst case (highest criticality level). \bar{S} is calculated as follows:

$$\bar{S} = \frac{1}{m} \times \sum_{i=1}^m s_i \quad (4.8)$$

where m is the total number of sensed measurements and s_i is the score of the i^{th} measurement.

Figure 4.4 shows the output of the proposed risk level evaluation function for two different parameter setups. The blue surface corresponds to a parameterization of $\alpha = \beta = 0.5$, whereas the pink surface corresponds to a parameterization of $\alpha = 0.2$ and $\beta = 0.8$. In the former case, both the score ratio and the overall health condition of the patient are given equal weights. Thus, both are equally important. In the latter case, the score ratio is given a greater importance than the overall health condition. For example, for both cases, the lower the global risk and the higher the score ratio, then the higher the risk level. However, in the latter case the risk level will have higher values than the former case for the same global risk value, since the impact of the score ratio is greater than the impact of the global risk. The α and β values are to be judged and parameterized by the healthcare experts, depending on whether the overall health condition of the patient or the status of the vital sign itself is more essential given the monitoring needs. For instance, some viruses such as flu or infections are accompanied by fever. Therefore, the temperature should be given a higher monitoring importance given its impact on the these types of sickness and given that healthcare experts are interested in monitoring its variations over time. Thus, β better have a higher value than α in order to give a higher importance to the score ratio of the temperature rather than the overall health condition regrouping all the vital signs being monitored.

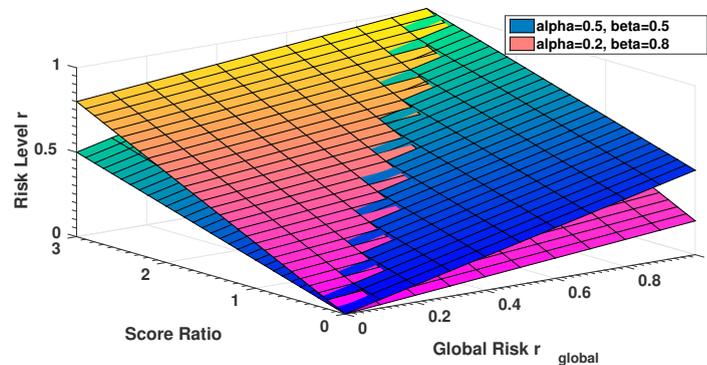


Figure 4.4: Risk Level Evaluation Function

4.7/ EXPERIMENTAL RESULTS

To verify our suggested approaches, we conducted multiple series of simulations using a custom Java based simulator. The objective of these simulations is two-fold:

- Firstly, we confirm that the proposed self-adaptive data collection technique can successfully detect locally any emergency while taking into consideration desirable energy conservation objectives.
- Secondly, we evaluate the performance of the proposed risk level adaptation model and study the effect of dynamically adapting the risk levels of nodes over time on the sampling rate adaptation scheme and its outcomes on the WBSN.

4.7.1/ SELF-ADAPTIVE DATA COLLECTION

In this section, the performance of the adaptive sampling scheme coupled with local emergency detection is evaluated. Therefore, in our simulations we used real medical readings collected from the online MIMIC Database [7].

We have run the different algorithms during 70 periods (approximately 2 hours) using a *Fisher risk* $\alpha = 0.05$. In the reported results, we are interested in two fields of biosensor measurements (vital signs): the respiration rate and the body temperature. We have taken into consideration two different risk levels given to vital signs, low and high risks respectively. We have evaluated the performance of the approach using the following parameters: a) h the number of periods per round; b) r the risk level of a vital sign. Three metrics are used in our simulations:

- The instantaneous sampling rate after each period which reflects the amount of data reduction
- The energy consumption
- The data integrity

4.7.1.1/ INSTANTANEOUS SAMPLING RATE AND DATA REDUCTION

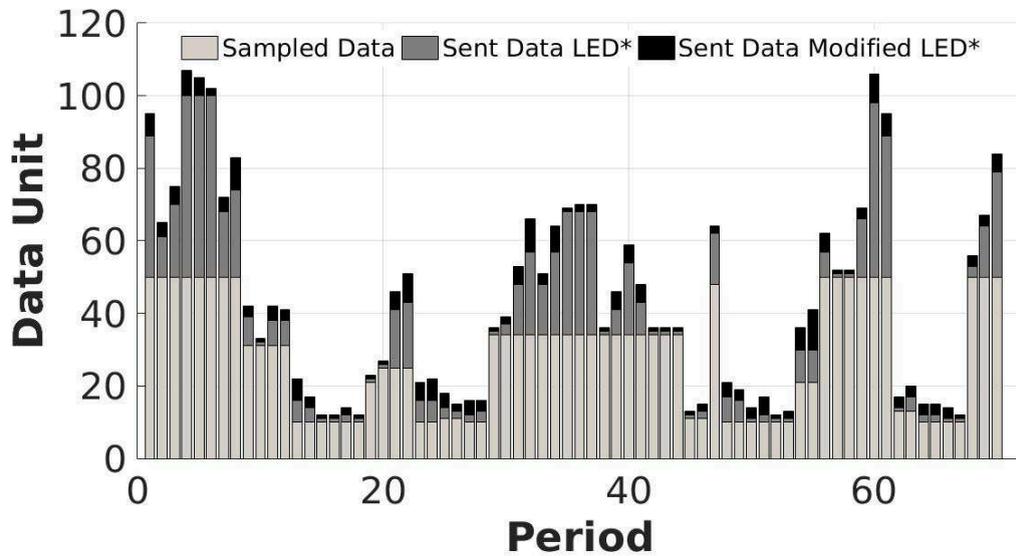
The main goal of this section is to show how our algorithm is able to reduce and adapt the biosensor node's sampling rate according to the monitoring importance of the vital sign. We consider two situations, a low risk vital sign ($r = 0.4$) and a high risk vital sign ($r = 0.9$). In the following, we will use the terms normal and critical vital sign to identify these two monitoring importance cases respectively.

In Figures 4.5, 4.6, 4.7 and 4.8, we show the number of sampled data in each period. We have fixed the maximum sampling rate to 50 measurements per period and the minimum sampling rate to 10 measurements per period. Then, we compare the quantity of sent data between *LED** (LED coupled with the adaptive sampling) proposed in [80] and the proposed *Modified LED** (*Modified LED* coupled with adaptive sampling, c.f. Algorithm 2).

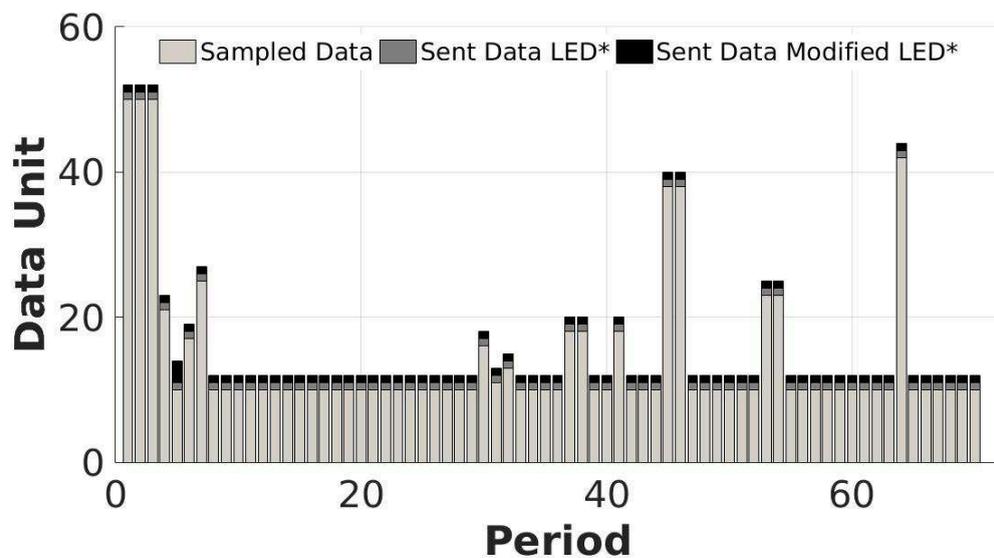
First, it is clear to see that our approach adapts the sampling rate according to the monitoring importance of the vital sign. We compare the results obtained for a normal vital sign ($r = 0.4$) and a critical vital sign ($r = 0.9$). When comparing Figures 4.5a and 4.6a, we can see that the sampling rate in the case of a critical vital sign presents higher values over the periods where the sampling rate is adapted. For example at period 9, the sampling rate is decreased to 47 in the case of a critical respiration rate, however it is decreased to 31 when the the monitoring importance of the respiration rate is low. In fact, when the monitoring importance given to a vital sign is high, it is a necessity to monitor it with a higher sampling rate, in order to keep track of any changes which might have effects on the patient's health.

Second, another parameter we took into consideration in our simulations is the number h of periods per round. This parameter indicates to the bio-sensor nodes after how many consecutive periods they must apply the ANOVA model to find the instantaneous sampling rate. We compare the results of our approach while assigning the values 2 and 3 to h . These comparisons can be seen by comparing Figures 4.5 and 4.7 as well as by comparing Figures 4.6 and 4.8. We can observe that the sampling rate varies much more for low values of h (2 in our case) than high values. This means that when h increases ($h = 3$), the variation between the sensed measurements increases also. The sampling rate becomes constant near the maximum sampling rate especially when there is high variations in the monitored vital sign. For example, if we consider the respiration rate (critical case): when $h = 2$ ($round = 2 \times period$), the variation between the measurements remains important but without high variations contrary to when $h = 3$ ($round = 3 \times period$). Therefore, when $h = 2$, the sampling rate varies more precisely with the monitoring needs of the biosensor. This is due to having a standard deviation between the measurements lower than the one when $h = 3$.

Third, we compare the quantity of sent data in each period when adopting *LED** and *Modified LED**. We can observe that both algorithms minimize the amount of data transmitted to the coordinator (not all the sampled data are sent). In the case of the temperature, *LED** and *Modified LED** have the same performance since the vital sign present stable normal score measurements over the 70 periods. In both algorithms only the first sensed data in a period is sent. However, in the respiration rate case, *Modified LED** algorithm outperforms *LED** and allows data reduction 50% more than *LED** and from the sampled data. The reason behind, is that the respiration rate of this patient is outside the normal range and presents critical scores for the majority of the periods. *LED**



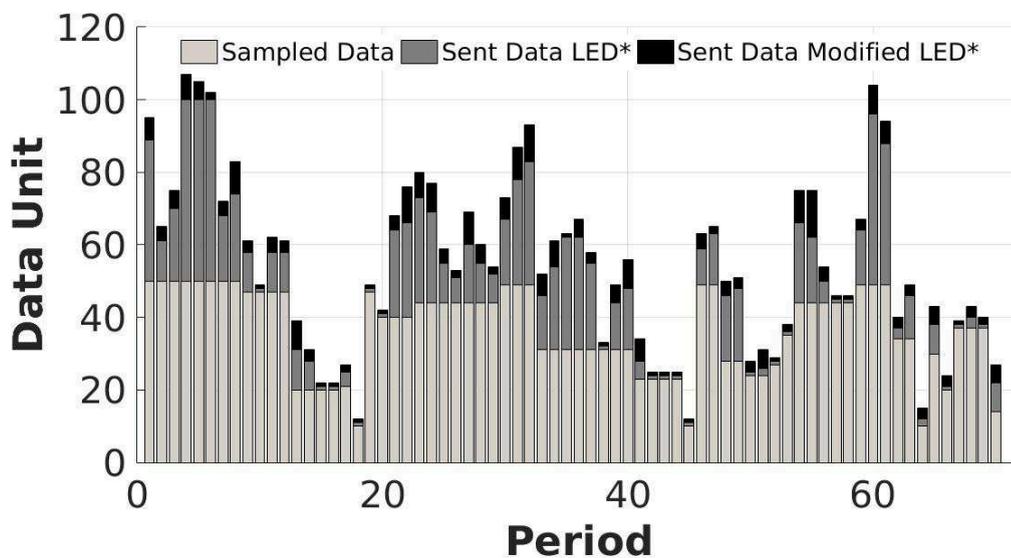
(a) Respiration Rate (Normal)



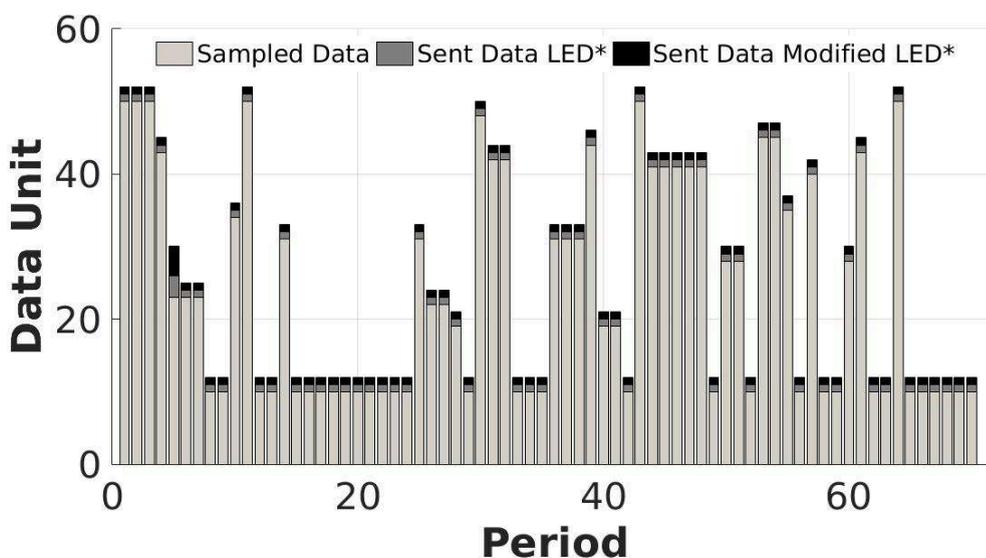
(b) Temperature (Normal)

Figure 4.5: Results of the Fisher Test applied on each two consecutive periods ($h = 2$) for a normal vital sign.

sends all the critical sensed data during a period and therefore it is not reducing the transmitted data compared to the sensing data in this case. However, *Modified LED** sends only the measurements indicating changes in the respiration rate state and therefore reduces redundancy and optimizes the transmission. Data integrity is studied in Section 4.7.1.3 by showing the impact of applying adaptive sampling for collecting the data on the sensor node level.



(a) Respiration Rate (Critical)

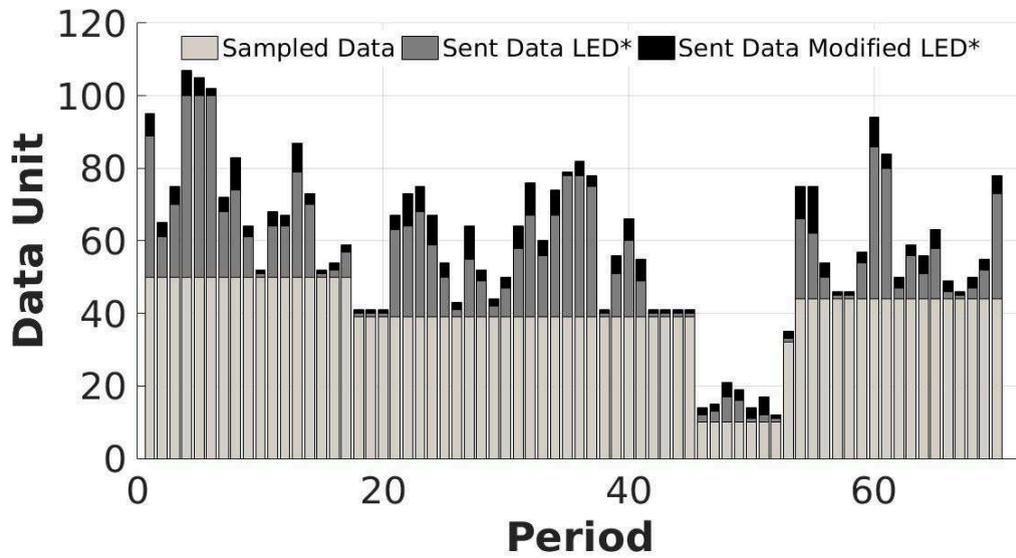


(b) Temperature (Critical)

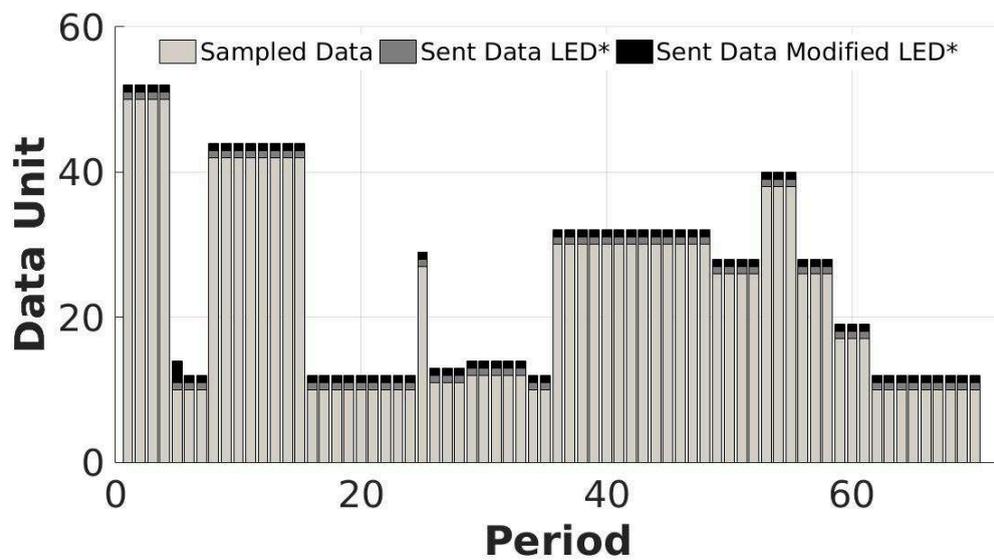
Figure 4.6: Results of the Fisher Test applied on each two consecutive periods ($h = 2$) for a critical vital sign.

4.7.1.2/ ENERGY CONSUMPTION

Figure 4.9 illustrates the energy consumption on the node responsible of capturing the respiration rate. We assume that the node has an energy level arbitrarily fixed to 700 units. Each captured and sent measurement consumes 0.3 and 1 unit respectively. The values correspond to a normal patient over 24 periods (40 minutes). We have compared our algorithm *Modified LED** to *A** and *LED**. All of the three algorithms adapt the sampling rate of the node to the respiration rate dynamic evolution (Fisher Test $h = 2$ and $\alpha = 0.05$). However in *A** all the sensed data are sent, in *LED** all the critical data are sent and in *Modified LED** the sent data is determined by *Modified LED* (cf Algorithm 1). As



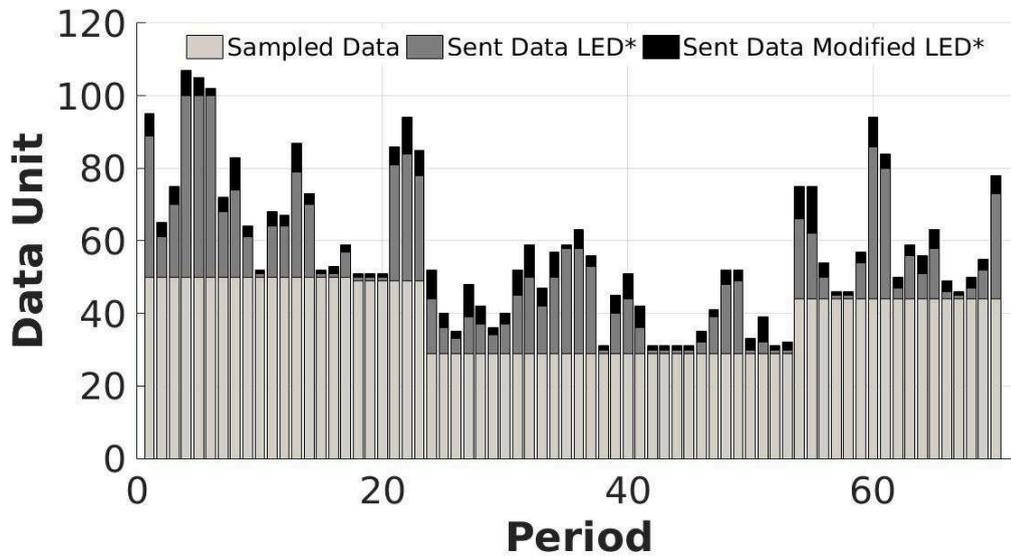
(a) Respiration Rate (Normal)



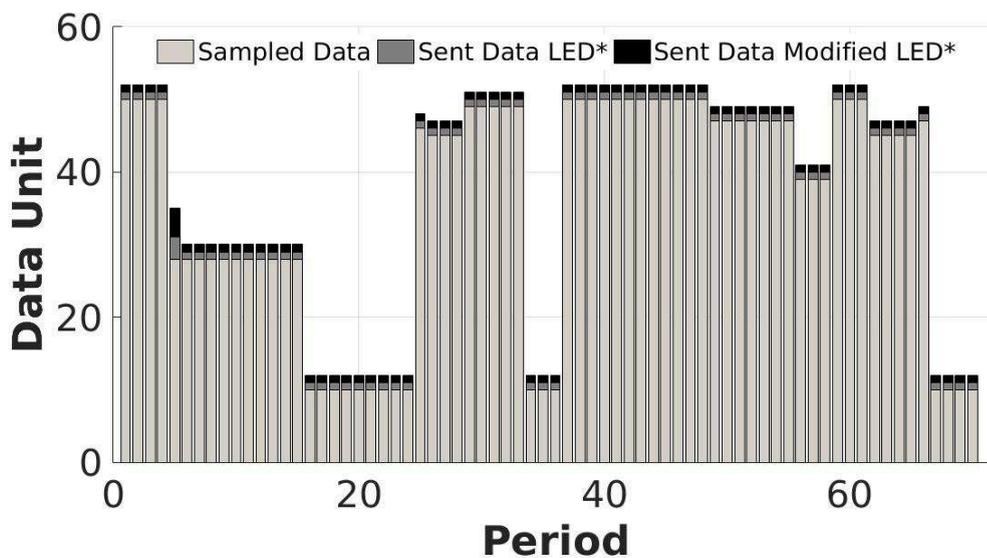
(b) Temperature (Normal)

Figure 4.7: Results of the Fisher Test applied on each three consecutive periods ($h = 3$) for a normal vital sign.

shown in figure 4.9, the *Modified LED** algorithm consumes less energy than *LED** and *A** algorithms since the transmission is optimized. We can see that our algorithm saves energy up to 3 to 4 times more than *LED** and up to 7 times more than *A**.



(a) Respiration Rate (Critical)



(b) Temperature (Critical)

Figure 4.8: Results of the Fisher Test applied on each three consecutive periods ($h = 3$) for a critical vital sign.

4.7.1.3/ DATA INTEGRITY

In this section, we examine the effect of adaptive sampling on data integrity. We have run the adaptive sampling algorithm ($h = 2$ see Section 4.5) for 70 consecutive periods (approximately 2 hours). We have fixed the maximum sampling rate to 50 measurements/period and the minimum sampling rate to 10 measurements/period. Then, we have compared the data that is sensed at each period to the data that is sensed when we do not apply adaptive sampling on the node. This is done by comparing the distribution of scores (NEWS). Originally, the sensed data = 100 measurements/period (no adaptive sampling case).

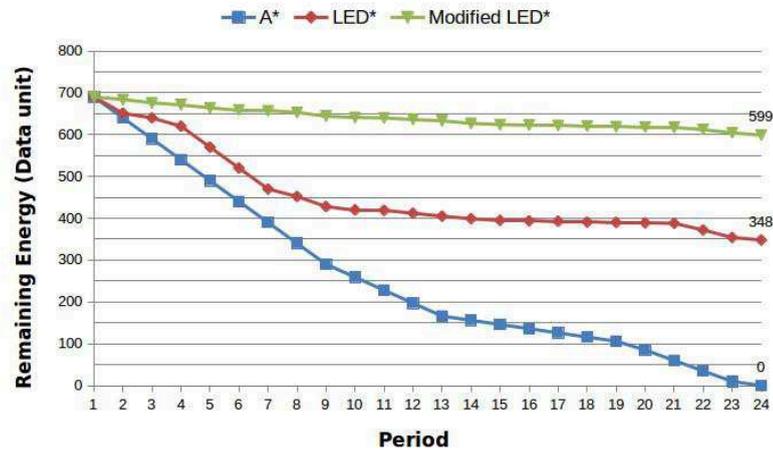


Figure 4.9: Comparison of Remaining Energy on the Respiration Rate Node

Risk Level	Respiration Rate		Temperature	
	0.4	0.9	0.4	0.9
Average of difference between scores of adaptive sampled data and non sampled data during one period	4.5%	2.9%	0.02%	0.02%
Data Reduction	71.8%	63.5%	85.7%	75.8%

Table 4.1: Data reduction and Average of difference between the distributions of scores in the adaptive sampling case and the no adaptation of sampling case during one period

In Table 4.1, we can clearly see that the adaptive sampling does not influence considerably on the distribution of scores and therefore on the integrity of data and information required for the decision making. Since the temperature of the patient is normal over the 70 periods, when adapting the sampling rate we do not lose information (Average difference in distribution= 0.02%) and we reduce data to 75.8% when $r = 0.9$ and to 85.7% when $r = 0.4$. However, the respiration rate of the patient is unstable and presents many variations and critical scores. Therefore, it is very important to make sure that when applying adaptive sampling, we do not lose important measurements and change the distribution of scores during periods. Our results show (see table 4.1) that the average difference between the distribution of scores obtained when we apply adaptive sampling and when we do not is only 4.5% during one period. While data reduction is about 71.8%.

Figure 4.10 shows the quantity of sensed data (amount of measurements) by the respiration rate node ($r = 0.4$ $h=2$) and the distribution of scores when using adaptive sampling (AS) and when not using adaptive sampling (NS). The results of 8 periods chosen from the 70 periods show that when using the adaptive sampling algorithm we reduce the quantity of sensed data by 64.5% while maintaining 88% of the time very close distributions to the original ones (NS). For example in period 1, AS reduces the sensed data to 50% compared to NS while maintaining approximately the same distributions of scores. Confirming that adaptive sampling has no influence on the taken decisions by the

coordinator.

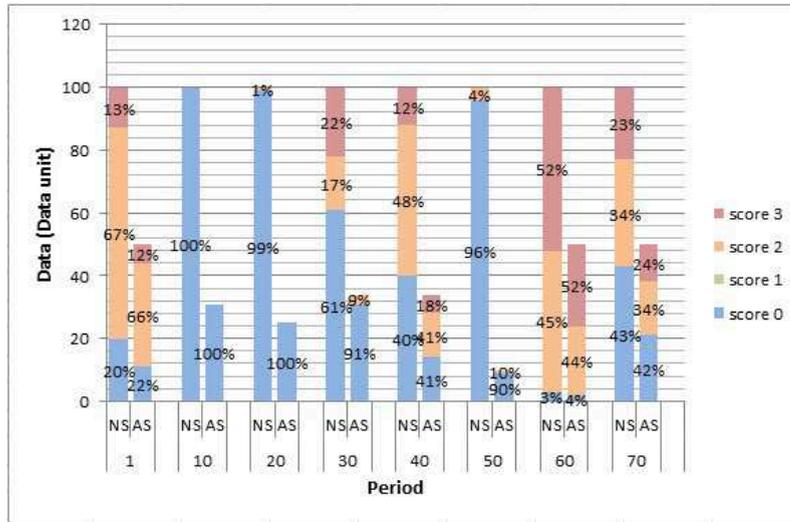


Figure 4.10: Comparison between the quantity of sensed data and the distribution of scores when using adaptive sampling (AS) and when no adaptive sampling is applied (NS) on the respiration rate node

In the next section, we evaluate the performance of the risk level adaptation model and its effects on the WBSN. The proposed local detection technique which optimizes the amount of transmission is not taken into consideration. In the following, we suppose that all the sampled measurements are sent to the coordinator and that the nodes do not employ an EWS to send only the measurements indicating a change in the status of the vital sign. Thus, we specifically study the effects of adapting the risk level of any vital sign over time on the proposed sampling rate adaptation scheme.

4.7.2/ RISK LEVEL ADAPTATION MODEL

In order to evaluate the performance of the proposed approach, patient vital signs datasets are collected from Multiple Intelligent Monitoring in Intensive Care (MIMIC) I and II databases of PhysioNet [7]. We have tested our approach on different patient records as well as different vital signs such as the heart rate (HR), the respiration rate (RESP), the systolic blood pressure (ABP_{sys}), the blood temperature (BLOODT) and the oxygen saturation (SpO₂). The proposed adaptive sampling rate scheme (cf. Algorithm 2) coupled with risk level adaptation is implemented and tested at the level of each node. After running multiple experiments, noting that a minimum of 30 samples is required for the Fisher Test and one-way ANOVA, the parameters settings are chosen as follows:

- Period $p = 100$ sec and Round $R = 2 \times p$.
- Minimum sampling rate $SR_{min} = 1$ samples/3.33 sec (corresponding to 30 samples per period) and Maximum sampling rate $SR_{max} = 1$ sample/1.42 sec (corresponding to 70 samples per period).

- Fisher Risk $\alpha_{fisher} = 0.05$.
- Initial risk level on all sensor nodes is randomly set to $r = 0.4$, indicating that all vital signs are slightly critical and have the same impact on the patient's health.

The global risk level which represents the overall health condition of the patient is determined by the coordinator by performing multi-sensor fusion. The latter approach will be discussed in Chapter 5.

First, we show the risk adaptation over time for different α and β setups and discuss their impact on the risk evaluation. Then we compare the results obtained in terms of data reduction, loss of information and energy consumption for 3 different scenarios : static risk level $r = 0.4$, static risk level $r = 0.9$ and our proposed approach.

4.7.2.1/ RISK ADAPTATION OVER TIME

Figure 4.11 shows the ABPSys sensor node's risk level adaptation over 70 periods for 3 different parameter setups. In our proposed approach, α and β respectively denote the weights accorded for the patient's overall health condition and for the vital sign's severity level. Initially, the sensor node's risk level is set to 0.4, it is clear to see that in the 3 cases the risk evaluation function has yielded most of the time a risk value different than 0.4 and whose values range from low to high risk levels. Hence, pointing out the importance of dynamically adapting the risk level of each sensor node according to the changes in the patient's health condition. When comparing Figures 4.11a and 4.11b, we can clearly see the influence of both parameters on the risk level evaluation. For example, between period 45 and period 60, the risk level is mainly between 0.4 and 0.6 for $\alpha = 0.7$ and $\beta = 0.3$, however it ranges between 0.6 and 0.8 for $\alpha = 0.3$ and $\beta = 0.7$. This is due to the fact that between these periods the severity level of the ABPSys represented by the score ratio is more critical than the patient's overall health condition. Hence, giving the score ratio a higher impact than the overall health condition has yielded a higher risk level (see Figure 4.11c) than in the opposite case (see Figure 4.11b). Whereas, between periods 8 and 18, the results show that the overall health condition is more critical than the severity level of the ABPSys. The risk level ranges between 0.2 and 0.4, in the case of $\alpha = 0.7$ and $\beta = 0.3$ (see Figure 4.11b), however it ranges between 0.1 and 0.2 in the case of $\alpha = 0.3$ and $\beta = 0.7$ (see Figure 4.11c). Hence, the parameters α and β of the risk level evaluation function should be medically judged by the healthcare experts on the basis of the importance given to each of the vital sign's severity level and the patient's overall health condition. In the rest of this section, the results correspond to a setup of $\alpha = \beta = 0.5$.

4.7.2.2/ SAMPLING RATE ADAPTATION AND ENERGY CONSUMPTION

In this section, we compare the sampling rate adaptation and the energy consumption between two cases: static (constant) risk level and our proposal of dynamic risk level. We study the sampling rate adaptation and the energy consumption of the HR sensor node over 70 periods for 2 different patients. Patient 1 corresponds to record s01840-3454-10-24-18-46nm from MIMIC II database whereas patient 2 corresponds to record 276n from MIMIC database . According to the available datasets, all of the 5 vital signs are monitored for patient 1 and only the HR and the ABPSys are monitored for patient 2.

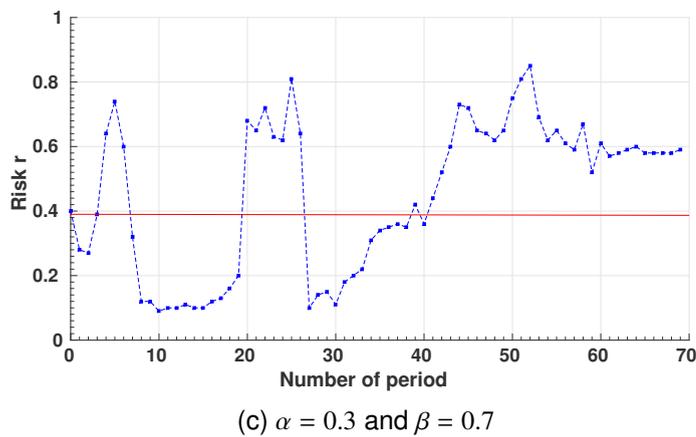
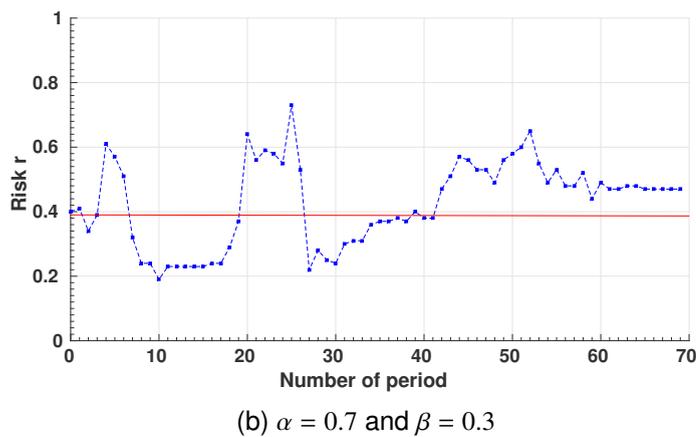
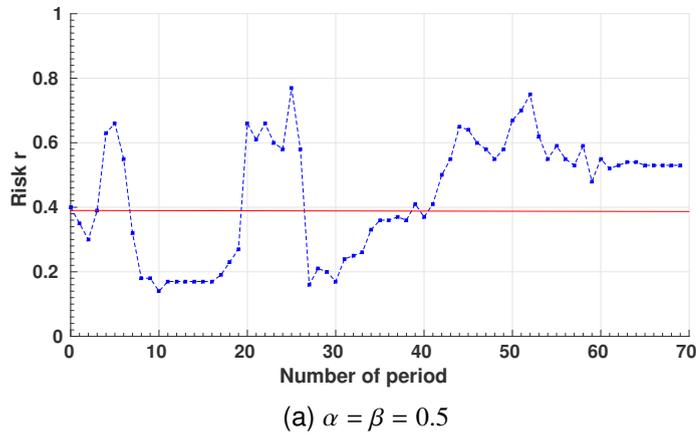


Figure 4.11: ABPSys sensor node's risk level adaptation over 70 periods with different α and β setups

Figure 4.12 shows the sampling rate adaptation of the HR sensor node for both patients for 3 different cases: static risk $r=0.4$, static risk $r=0.9$ and dynamic risk. For both patients, when comparing the two static cases (see Figures 4.12c, 4.12e, 4.12d, 4.12f), we can notice that the sampling rate adaptation results in higher sampling rates when $r = 0.9$ than when $r = 0.4$. For example periods 2 and 10 in Figures 4.12c, 4.12e and from period 50 till period 70 in Figures 4.12d and 4.12f. This is due to the definition of the BV function which results in higher sampling rates for higher risk level values. However, if

we compare the results obtained in the dynamic risk level case with the results of the two static cases for patient 1, we can notice that the total of sampled measurements during the 70 periods are less than the total of sampled measurements in the case of the static risk $r = 0.9$ and slightly less than the case of static risk $r = 0.4$. This indicates that our proposed approach has evaluated the HR risk level around 0.4 (less than 0.9). Thus, the amount of sampled data is reduced during the 70 periods which will have an impact on the energy consumption. While, if we compare the results obtained for patient 2, we can notice that the amount of sampled measurements in the case of dynamic risk is greater than the amount of samples in the case of static risk $r = 0.4$ and less than the amount of samples in the case of static risk $r = 0.9$. This indicates that our proposed approach has evaluated the HR risk level less than 0.9. Thus, the amount of sampled data is reduced during the 70 periods compared to a static risk of 0.9 and slightly increased compared to a static risk of 0.4. Therefore, adapting the risk level value over time has an impact on the Fisher test result since the amount of sampled data changes from one period to another, as well as on the BV function and thus on the output of the sampling rate adaptation scheme. This will have an impact on the energy consumption.

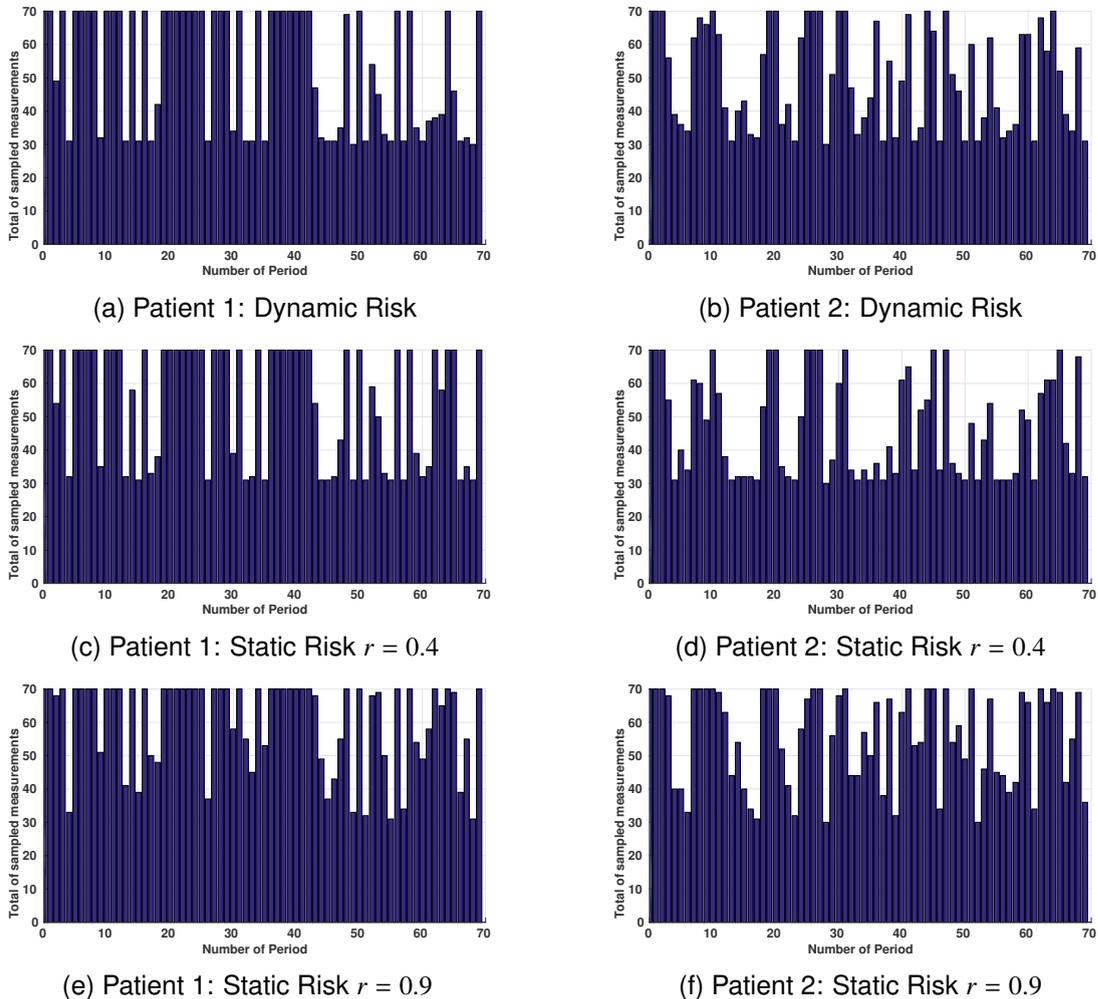
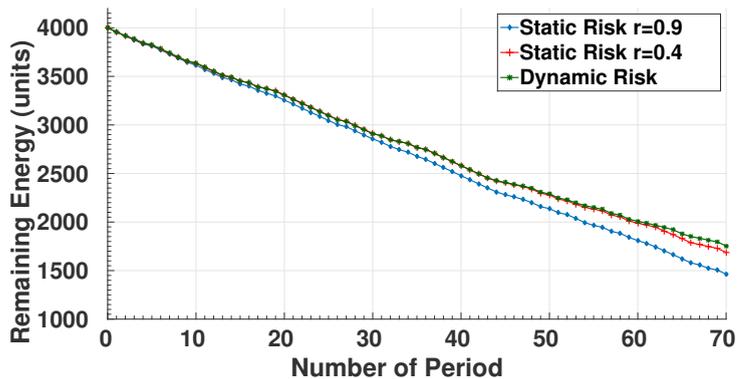


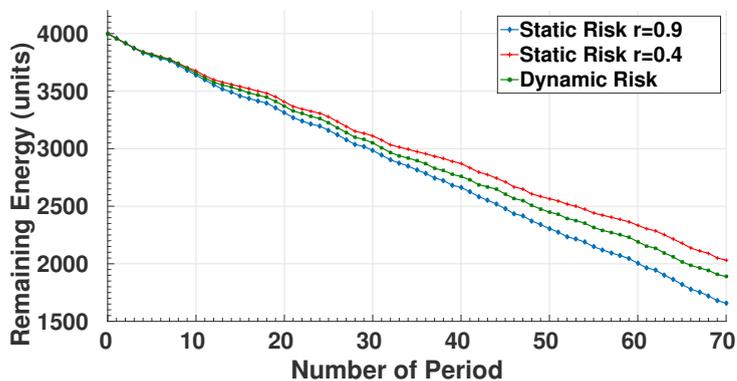
Figure 4.12: Comparison of HR sensor node's sampling rate adaptation over 70 periods between 3 different cases for 2 different patients.

Figure 4.13 shows the HR sensor node's remaining energy at the end of 70 periods

for both patient 1 and 2. We suppose that 1 unit of energy is equal to 152 Joules : the sensing task consumes 6 Joules, the processing task consumes 24 Joules, the transmission task (TX) consumes 60 Joules and the receiving task (RX) consumes 62 Joules [145]. Thus, we suppose that each sampled measurement needs 0.6 units of energy to be sent to the coordinator. It includes 0.04 units of energy for the sensing task, 0.16 units of energy for the processing task and 0.4 units of energy for the transmission task. Having the initial energy randomly set to 4000 units, the dynamic approach has consumed the least energy among the 3 cases in the case of patient 1. The remaining energy is 1463.8 units when setting the risk level to 0.9, is 1687 units when setting the risk level to 0.4 and 1753.6 units when adapting the risk level over the 70 periods. However, the results of the HR sensor node's sampling rate adaptation of patient 2 shows that adapting the risk level over time has reduced the energy consumption compared to setting the risk level value to 0.9 but it has increased the energy consumption compared to setting the risk level value to 0.4. The remaining energy is 1703.2 units when setting the risk level to 0.9, 2031.4 units when setting the risk level to 0.4 and 1888.6 units when adapting the risk level over the 70 periods. Thus, adapting the risk level of a vital sign over time adapts the lifetime of a sensor node to the patient's changing health condition.



(a) Patient 1: Energy Consumption of the HR sensor node over 70 periods



(b) Patient 2: Energy Consumption of the HR sensor node over 70 periods

Figure 4.13: Comparison of the HR sensor node's remaining energy at the end of 70 periods between 3 different cases.

4.7.2.3/ DATA REDUCTION VS LOSS OF INFORMATION

In this section, we study the data reduction performed at the sensor node level following the sampling rate adaptation and discuss its impact on the loss of information. We compare the results obtained for the adaptive sampling rate scheme with static risk level and with dynamic risk level for patient s01840-3454-10-24-18-46nm. Table 4.2 shows the data reduction performed at the level of each sensor node for the three scenarios. Theoretically, if the Fisher Test null hypothesis is rejected for all 70 periods then a data reduction of only 30% is achieved given that the maximum sampling rate is $SR_{max} = 1 \text{ sample}/1.42 \text{ sec}$ (corresponding to 70 samples out of 100 per period). Whereas, if the Fisher Test null hypothesis is accepted for all 70 periods with $F = 0$ then a maximum data reduction of 70% is achieved given that the minimum sampling rate is $SR_{min} = 1 \text{ sample}/3.33 \text{ sec}$ (corresponding to 30 samples out of 100 per period) (cf. Algorithm 2). The results show that for both patients and for all the monitored vital signs the percentage of data reduction is bounded by 30% and 70% such as the data reduction is strictly higher than 30% demonstrating that the F-test is a suitable statistical test for this type of medical data. As shown in Table 4.2, a total data reduction of about 48% compared to the original dataset has been achieved in our approach, of 43% in the case of a static risk $r = 0.9$ and of 47% in the case of a static risk $r = 0.4$. We compare the scores of the measurements of the sampled datasets to the ones of the original dataset in each of the three scenarios, while taking the time granularity of the original dataset (1 sec). We choose the mean-squared error to measure the average of the squares of the errors or deviations given that $MSE = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N (a(i, j) - b(i, j))^2$ where M is the total of monitored vital signs, N is the total of measurements for each vital sign during the simulation, a is the score of the j^{th} measurement of the i^{th} vital sign in the original dataset and b is the score of the j^{th} measurement of the i^{th} vital sign in the sampled dataset. The results (cf. Table 4.3) show that the MSE of the three scenarios are very close to 1, thus the loss of information is negligible. Our approach has reduced the amount of sampled data 5% more than the case of static risk $r = 0.9$ with a MSE difference of 0.0017. Table 4.4 shows the percentage of critical events detected over 70 periods compared to the critical events recorded in the original dataset. As we can see, the percentage is greater than about 70% for all vital signs for the three scenarios. However, it is important to note that the percentage of critical events in the original dataset for each of the HR, SpO2, BLOODT, RESP and ABPSys which do not last more than 2 seconds are respectively 38%, 1%, 20%, 5% and 17%. Thus, in three scenarios and for all vital signs, all of the persistent critical events have been detected. Finally, Figure 4.14 shows the HR sensor node's totals for each score for the 3 different scenarios in comparison with the totals of the original dataset. As we can see, although our proposed approach has reduced the amount of HR sampled data to 47% (cf. Table 4.2), the totals of all scores were conserved. Consequently, our proposed approach allows a sensor node to dynamically adapt its risk level over time based on the state of the vital sign it is monitoring as well as the overall health condition of the patient. Fixing the risk level to a high value when it is not needed increases the energy consumption and the amount of sampled data over time whereas in some scenarios, fixing the risk level to a low value can increase the loss of information and some critical events can be passed unseen.

Table 4.2: Data reduction performed for each monitored vital sign of record s01840-3454-10-24-18-46nm from MIMIC II compared to original dataset in 3 different scenarios.

Risk Level Setup	HR	SpO2	BLOODT	Resp	ABPSys
Static Risk $r = 0.9$	40%	44%	65%	34%	34%
Static Risk $r = 0.4$	45%	48%	65%	37%	37%
Dynamic Risk	47%	48%	65%	38%	38%

Table 4.3: Mean squared error between original dataset and sampled dataset of patient s01840-3454-10-24-18-46nm from MIMIC II for 3 different scenarios.

Risk Level Setup	MSE
Static Risk $r = 0.9$	0.0128
Static Risk $r = 0.4$	0.0144
Dynamic Risk	0.0145

Table 4.4: Percentage of detected critical changes compared to original dataset of patient s01840-3454-10-24-18-46nm from MIMIC II for 3 different scenarios.

Risk Level Setup	HR	SpO2	BLOODT	Resp	ABPSys
Static Risk $r = 0.9$	76%	97%	80%	97%	86%
Static Risk $r = 0.4$	72%	96%	80%	97%	85%
Dynamic Risk	69%	95%	80%	97%	86%

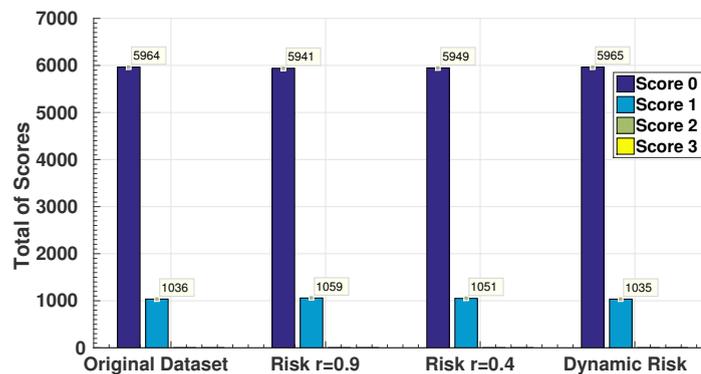


Figure 4.14: The HR sensor node's totals for each score for three different scenarios in comparison with the original dataset.

4.8/ CONCLUSION

In this chapter, we have proposed an energy-efficient data collection approach for WB-SNs. This approach is classified under the data reduction techniques since it reduces the amount of sensed and transmitted data. The proposed *Modified LED** algorithm allows biosensor nodes to adapt their sampling rate in real-time as well as to locally detect changes in vital signs including emergencies. The former is ensured by statistically studying the acquired measurements and taking into consideration the monitoring importance given to vital signs, whereas the latter is made possible by using early warning score systems. We have conducted a series of simulations on real medical data recordings to show the effectiveness of our algorithms and approaches. The results show that our approach reduces considerably the sensed and the transmitted data and the energy consumption while maintaining data integrity.

MULTI-SENSOR FUSION FOR HEALTH ASSESSMENT

In this chapter, a multi-sensor fusion approach for WBSNs is proposed. It allows to perform a health assessment based on vital signs of interest which are collected by biosensor nodes. The approach employs a fuzzy inference system in order to infer from the aggregate score of vital signs the severity level of the patient's health condition. An algorithm, called Health Risk Assessment and Decision-Making (Health-RAD), is proposed at the level of the coordinator. It describes the coordinator's behavior and integrates the proposed model. The proposed multi-sensor fusion approach is tested with the energy-efficient data collection scheme presented in Chapter 2, thus forming a complete framework. It is evaluated on real healthcare datasets and the results are compared with an existing approach in terms of data reduction, energy consumption, assessment of vital signs, the severity assessment of the patient's health condition and accuracy.

5.1/ INTRODUCTION

Several challenges arise in WBSNs. The energy consumed by the biosensor nodes for sensing and transmitting is a highly critical issue, since important physiological variations can be missed out and the data fusion process can be affected if one or more biosensor nodes are dead [9]. Furthermore, the fusion of large amounts of heterogeneous data collected by several biosensor nodes is another challenge in such networks. It enables the coordinator to represent the global situation of the patient and consequently make the corresponding decision. Several data analysis and processing approaches in WBSNs for anomaly detection, prediction and decision making [54, 58] have been proposed in the literature so far. In the majority of these approaches the data fusion techniques require either offline training, high computation resources or do not take into consideration the energy consumption on the sensor nodes level. To the best of our knowledge, no one has so far tackled the problem of monitoring and fusing the vital signs of a patient in order to determine the severity of his/her health condition while taking into consideration data reduction for energy consumption requirements.

The major contributions of this chapter are threefold:

1. A generalized multi-sensor data fusion approach is proposed by defining the input membership functions in terms of the number of vital signs of interest. Thus, presenting a flexible model that can be applied in any health assessment scenario

regardless the number of vital signs of interest. Fuzzy sets are used to deal with uncertainties and ambiguities and a Fuzzy Inference System (FIS) to map the aggregate score of vital signs to the patient's risk level. We believe that the generalization of the multi-sensor fusion model is very promising since it is a flexible knowledge-based model, does not require any training, takes into consideration the uncertainty and the ambiguity that exist in medical data (such as vital signs) that are collected by biosensor nodes through fuzzy sets and assesses patients' health condition following a human reasoning logic through the fuzzy inference system.

2. A Health Risk Assessment and Decision-Making algorithm (Health-RAD) is proposed. It is implemented on the coordinator of the WBSN that is deployed on the patient's body. Health-RAD employs the proposed multi-sensor data fusion model. It assesses the patient's health condition routinely and each time a critical situation is detected and consequently makes an appropriate decision. The decisions are either medical advice or triggered emergency actions. Furthermore, it regularly updates the scores of vital signs and only considers the persistence of a vital sign in a certain state by smoothing sudden deviations.
3. Extensive simulations are performed to validate the proposed multi-sensor data fusion approach. Moreover, it is combined with the energy-efficient data collection technique that is presented in Chapter 4, thus forming a complete framework (from data collection to fusion). It is compared to an existing approach [14] from the literature in order to validate it.

The purpose of our framework is to ensure a continuous and remote monitoring of the vital signs of an acutely ill patient recovering at home after a surgical intervention, present at the hospital or even living in a nursing home in case of the elderly. Indeed, an acute disease requires immediate medical attention and continuous assessment due to life-threatening possibilities. Therefore, Health-RAD allows the early detection of emergencies, deterioration and improving condition of the patient regardless of his/her location. The remainder of the Chapter is organized as follows. Section 5.2 presents the related work. The multi-sensor data fusion model is explained in Section 5.3. Then, Health-RAD is presented in Section 5.4. Experimental results are shown and discussed in Section 5.5. Finally Section 5.6 concludes the chapter.

5.2/ RELATED WORK

Multi-sensor fusion in WBSN is currently gaining more and more attention since it introduces many advantages in a network that suffers from many limitations such as: data loss, inconsistency and affected sensor samples. It has the potential to reduce uncertainty by increasing the confidence of the collected data and the inferred decisions as well as enhancing the robustness of the healthcare application [143]. Assessing the health condition of a patient suffering from a particular disease or an acutely-ill patient, such as in our scenario, requires a continuous collection of multiple vital signs in order to form a complete view of the patient's situation and perform an accurate health assessment. To this end, multi-sensor fusion is a must to combine and infer heterogeneous data.

Diverse applications based on WBSNs, existing in the literature, propose multi-sensor data fusion techniques such as activity recognition applications, mental health related applications and health monitoring applications.

- Activity recognition: Many researchers have proposed approaches to recognize activities by relying on multi-sensor fusion [79, 102, 83]. For instance, [91] has studied the sensor fusion impact on activity recognition in order to determine the best combination of sensors and their positions. Feature extraction and selection accompanied by different supervised classification methods are compared.
- Mental health: [75] has proposed a physiological signal classification technique based on multisensor data fusion and case-based reasoning in order to assess the stress level of the individual being monitored. The matching between cases is done using fuzzy logic [15]. [44] has proposed a smartphone-based driver safety monitoring system. This system is based on data fusion and uses a fuzzy bayesian network to classify the drowsiness level of the driver.
- Health monitoring: [36] has designed an algorithm combining sensor selection and information gain allowing a better management of the WBSN. The information gain is defined as the minimum compact set of features required to identify a disease. [23] has proposed a physiological data fusion model for multisensor wearable health monitoring system (WHMS) called Prognosis. The proposed model generates the prognoses of the patient's health conditions using fuzzy regular language and fuzzy finite-state machine. [14] has proposed a framework that performs real-time analysis of physiological data in order to monitor people's health condition. The framework determines the severity level of the patient being monitored by computing a global risk. It uses historical data and data mining techniques for model building and performs real-time analysis of the collected vital signs measurements. It has been tested on intensive care unit datasets and the results show that simple K-means has acceptable results and can be used as a clustering algorithm. However, energy consumption due to continuous sensing and transmission was not taken into consideration and the network lifetime was not studied. Furthermore, the health assessment is based on the offline training phase which requires enough medically validated datasets.

We chose to compare our proposed multi-sensor fusion approach to the approach presented in [14] in terms of accuracy given that the same problem is targeted: patient health assessment. Both approaches ensure a continuous and real-time assessment of the severity level of the patient's health condition based on vital signs monitoring using a WBSN. Furthermore, our complete framework, including the data collection and fusion, is compared to the framework presented in [14] to demonstrate the effect of data reduction on the fusion and the energy consumption in the WBSN.

5.3/ PROPOSED APPROACH: MULTI-SENSOR DATA FUSION MODEL

In this section, we present the multi-sensor data fusion model having as inputs N vital signs collected by N biosensor nodes and as an output the assessment of the patient's

health condition which we represent by the patient's risk level r_{global} (severity). The proposed model can be classified under the cooperative sensor fusion techniques since multiple sensor signals (N vital signs) are needed in order to assess the patient's health condition. Furthermore, from the processing point of view, the coordinator performs the required fusion of the gathered data by the biosensor nodes, thus the proposed model is centralized. In terms of data processing level of abstraction, the proposed model can be classified under the feature-level fusion category [143] (c.f. Chapter 3).

Figure 5.1 shows the architecture of the proposed model which is composed of the following blocks: the extraction of the up-to-date scores, their aggregation, the mapping to the patient's risk level using a FIS and finally the decision selection. The proposed multi-sensor data fusion approach including all the mentioned blocks (c.f. Figure 5.1) is performed by the coordinator of the WBSN. A FIS can determine the patient's risk level using the information it has about how much the patient's health condition is critical. Fuzzy logic is a widely used technique for representing ambiguity in high-level data fusion tasks [13, 31]. Medical data such as vital signs and physiological signals are characterized by uncertainty and ambiguity given that sensor nodes collecting these types of signals are subject to interference, noise and faulty measurements. Moreover, medical data are interpreted in a human reasoning way which enforces the ambiguity presented in such data. Thus, membership functions (MFs) are defined for the input and the output of the FIS and human-language rules are set. In this chapter, we generalize the membership functions of the input of the FIS in order to make our proposed approach more flexible and applicable for any number of monitored vital signs.

In the following, we first discuss the extraction of the up-to-date scores which is performed at regular time intervals by the coordinator. Then, we discuss the input of the FIS being the aggregate score, its fuzzification and we discuss its output being the patient's risk level. Finally, the whole fuzzy inference system is discussed including the fuzzy rule base as well as the decision-making process.

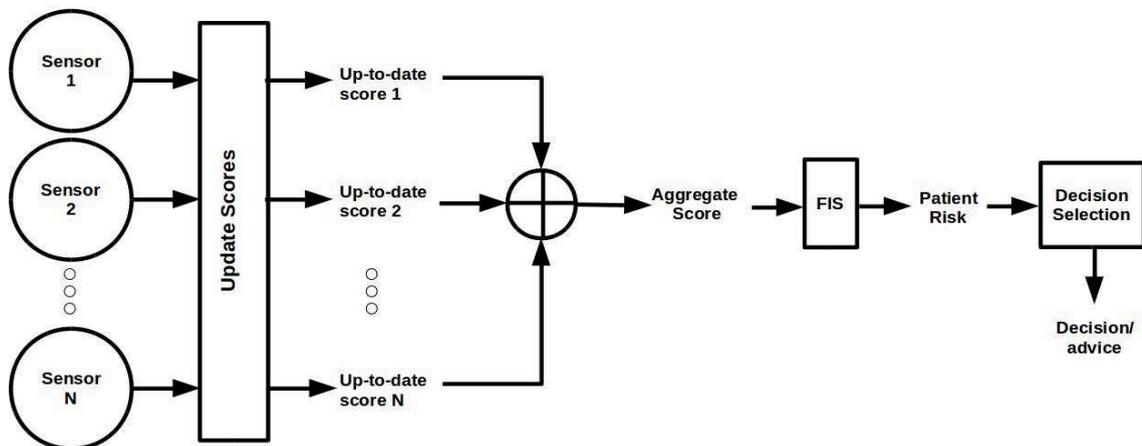


Figure 5.1: Architecture of the Multi-sensor Data Fusion Model

5.3.1/ UP-TO-DATE SCORE

The biosensors running the *Modified LED** algorithm keep the coordinator updated with changes in vital signs (cf. Algorithm 2 in Chapter 4). The latter receives several measurements for each vital sign during one round R where $R = m \times p$, $m \in \mathbb{N}^*$. It calculates the up-to-date score s_t for each vital sign at instant t using an EWS (c.f. Section 4.3 in Chapter 4) as follows:

$$s_t = \frac{s_{t-1} + score_t}{2} \quad (5.1)$$

with $s_0 = score_0$ and where $score_0$ is the score of the first measurement sent during round R , $score_t$ is the vital sign's instantaneous score at time t and s_{t-1} is the score calculated at time $t - 1$. Therefore, the instantaneous score $score_t$ and the score s_{t-1} , representing the history of the vital sign, are given equal weights. For example, suppose that biosensor B_1 sends a score of zero at instant $t = 0$. While no other measurement is received during round R , the score s_t of the vital sign is equal to zero. However, if a new score $score_t = 1$ is received at time t , the new s_t would become 0.5 according to equation (5.1). Supposing that no other measurement is received until the end of round R (stable score), if the coordinator updates the vital sign's score s_t each δ_t , then s_t will converge to 1 depending on δ_t and the remaining time until the end of round R such as:

$$\lim_{s_{t-1} \rightarrow b} s_t = \lim_{s_{t-1} \rightarrow b} \frac{s_{t-1} + b}{2} = b \quad (5.2)$$

where b represents the value of the stable score. Thus, the persistence of a vital sign in the same critical level contributes in the scoring and instantaneous measurements, presenting a deviation, have a lower impact on the scoring.

5.3.2/ AGGREGATE SCORE

Health experts and doctors use the aggregate score of the monitored vital signs of a given patient in order to assess his/her health condition. This total score represents the early warning score. It allows them to determine the criticality level of the patient's condition as well as the intervention mode that should be adopted [11]. The aggregate score is used in our approach as an input into the FIS in order to get as an output the patient's risk level. It is calculated as follows:

$$AggScore = \sum_{i=1}^N s_i \quad (5.3)$$

where s_i is the up-to-date score (see equation 5.1) of the i^{th} vital sign during a round R and N is the number of monitored vital signs (biosensors).

The analysis and the interpretation of medical data is ambiguous and vary from one subject to another, thus we believe that the assessment of the patient's health condition should be done using fuzzy theory. The input of the FIS is the aggregate score *AggScore* (see equation 5.3). First, the input is fuzzified using 3 fuzzy membership functions: Low,

Medium and High. Then, the process of determining the patient's risk level is executed using a set of fuzzy logic rules.

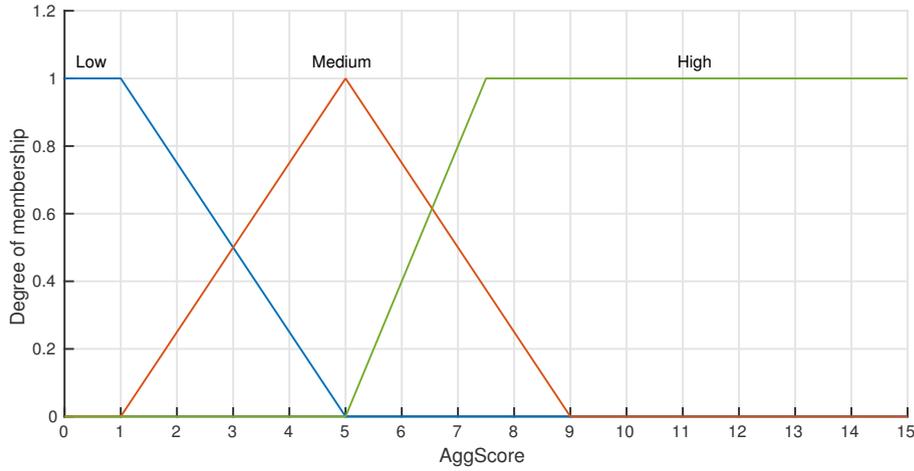


Figure 5.2: Aggregate Score Membership Functions

The aggregate score fuzzy membership functions $f_1(x)$ (Low), $f_2(x)$ (Medium) and $f_3(x)$ (High) are defined as follows:

$$f_1(x) = \begin{cases} 1, & x \leq 1 \\ \frac{1}{1-N}x + \frac{N}{N-1}, & 1 \leq x \leq N \\ 0, & \text{otherwise} \end{cases} \quad (5.4)$$

$$f_2(x) = \begin{cases} \frac{1}{N-1}(x-1), & 1 \leq x \leq N \\ \frac{1}{1-N}(x+1-2 \times N), & N \leq x \leq 2N-1 \\ 0, & \text{otherwise} \end{cases} \quad (5.5)$$

$$f_3(x) = \begin{cases} 2(\frac{x}{N}-1), & N \leq x \leq \frac{3}{2}N \\ 1, & x \geq \frac{3}{2}N \\ 0, & \text{otherwise} \end{cases} \quad (5.6)$$

where x represents the aggregate score $AggScore$ and N is the number of monitored vital signs. The definition of these functions was inspired by EWSs and the medical analysis carried out by doctors when assessing vital signs and physiological measurements. Figure 5.2 shows the MFs for $N = 5$ vital signs. The aggregate score is Low if $0 < AggScore < 5$, Medium if $1 < AggScore < 9$ and High if $AggScore > 5$.

5.3.3/ PATIENT RISK LEVEL

As previously mentioned, the objective of the proposed multi-sensor fusion model is to determine the patient's risk level according to the received measurements of the vital signs which are represented by the aggregate score. The patient's risk level r_{global} is expressed using a quantitative variable and can range from 0 up to 1. It represents the severity of the patient's health condition. The higher the risk value, the more critical/severe the patient's health condition is. The following fuzzy membership functions are defined for

the evaluation of the risk level: Low-Risk, Medium-Risk and High-Risk as shown in Figure 5.3. A patient is at low risk if $0 < r < 0.5$, at medium risk if $0.2 < r < 0.8$ and at high risk if $0.5 < r < 1$.

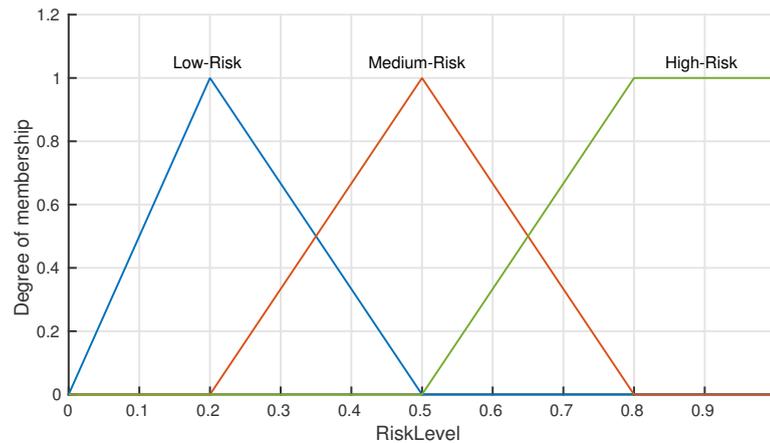


Figure 5.3: Patient Risk Level Membership Functions

5.3.4/ FUZZY INFERENCE SYSTEM AND DECISION-MAKING

Figure 5.4 shows the FIS and decision selection blocks of the proposed multi-sensor data fusion model. Having measurements from the N biosensors, the patient's risk level is computed in order to make a decision. The latter is some predictive or corrective advice given to the patient and could be a trigger to a specific action. The input of the FIS is the aggregate score $AggScore$ of the N monitored vital signs (cf. Section 5.3.2). Its output is the patient's risk level. It uses the fuzzy membership functions described in Section 5.3.2 and a fuzzy rule base to map the input to the output. The fuzzy rule base is shown in

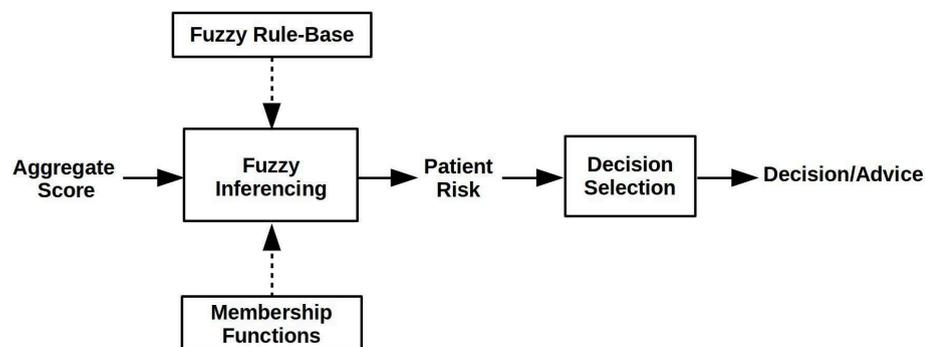


Figure 5.4: Fuzzy Inference System and Decision Selection Blocks

Table 5.1. For example Rule 1 is: *if the aggregate score is Low then the patient's risk level is Low-Risk*. Finally, the risk level is defuzzified using the centroid method to obtain a crisp patient's risk level r_{global} . A decision, some advice or even an action is selected based on the value of r_{global} . It is selected from an association table between the patient's risk values and the decisions (c.f. Table 5.2). Such a table is set by healthcare experts. The

Table 5.1: Fuzzy Rule Base

Rule No.	Agg Score	Patient Risk Level
1	Low	Low-Risk
2	Medium	Medium-Risk
3	High	High-Risk

Table 5.2: Example of an Association Table between patient risk values and decisions

Decisions	Risk value range
d1	$r_{global} < 0.25$
d2	$0.25 \leq r_{global} < 0.4$
d3	$0.4 \leq r_{global} < 0.6$
d4	$0.6 \leq r_{global} < 0.8$
d5	$r_{global} \geq 0.8$

decisions/advice include for example: rest, take medicine, call the doctor etc. depending on the trigger level. For example if $0 \leq r < 0.2$ then decision 1 is taken.

5.4/ HEALTH RISK ASSESSMENT AND DECISION-MAKING ALGORITHM

A Health Risk Assessment and Decision-Making (Health-RAD) algorithm at the coordinator level (cf. Figure 5.5) is proposed based on the data fusion model explained in the previous section. The coordinator receives the measurements sent by different biosensor nodes running *Modified LED**. Its role is to perform the multisensor data fusion in order to obtain meaningful information about the patient's health condition which is represented by the patient's risk level r_{global} . Depending on the value of r_{global} , some advice or a decision is given to the patient. The coordinator sends the collected data and the taken decisions to the medical center. The coordinator operates in rounds where round $R = m \times p$ and where p is the common period of all the biosensors at which they are running *Modified LED** (cf. Algorithm 2) and $m \in \mathbb{N}^*$.

Suppose that 5 different vital signs are being monitored. Let $R_0 = (r_1, r_2, r_3, r_4, r_5)$ be the vector of the first measurements received from the 5 biosensors at the beginning of each round. According to *Modified LED**, these measurements are sensed and sent to the coordinator at the beginning of each period p .

Let $Score_0 = (score_1, score_2, score_3, score_4, score_5)$ be the vector of the computed scores corresponding to R_0 and $S_t = (s_{t1}, s_{t2}, s_{t3}, s_{t4}, s_{t5})$ be the vector of the up-to-date scores at instant t .

At the beginning of each round, the coordinator reads R_0 , computes $Score_0$ and sets $S_0 = Score_0$. Each time, the coordinator receives a measurement, it identifies the sending biosensor B_i in order to compute $score_i$ using an EWS table and to update $Score_t$ and S_t . Then, it checks whether $score_i$ is different from zero. If this is the case, it detects an emergency and sends a query to the other biosensors in order to get their measurements. After receiving them, the coordinator computes $Score_t$ using the EWS, updates S_t (cf. equation 5.1) and calculates the aggregate score $AggScore$ (cf. equation 5.3). The

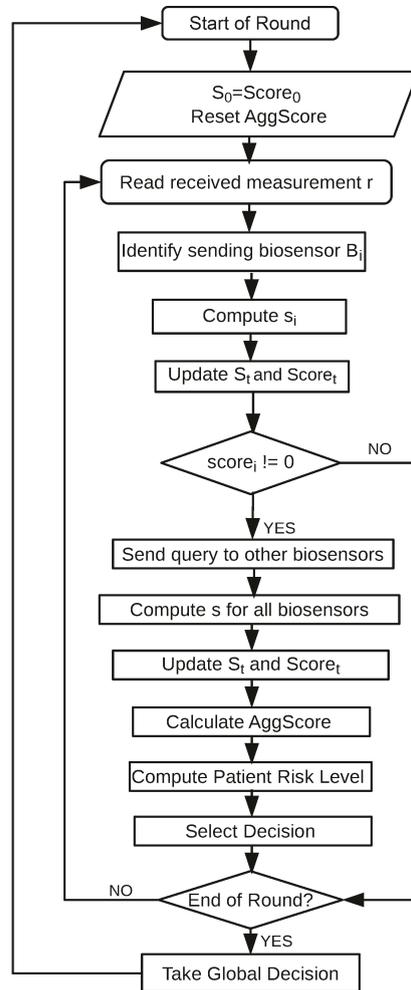


Figure 5.5: Health Risk Assessment and Decision-Making Algorithm Flowchart

latter is the input of the proposed FIS. Finally, a decision is selected depending on the patient's risk level given as an output of the FIS. At the end of each round, the *AggScore* is calculated and a decision is selected based on the result given by the FIS. This decision is a global decision taken routinely, it represents the overall health condition of the patient during one round. Last, S_t is refreshed each δ_t in order to keep track of the patient's condition represented by the scores of his/her vital signs.

5.5/ EXPERIMENTAL RESULTS

Experiments are conducted on real medical datasets using a custom-based Java simulator and Matlab. In order to evaluate the performance of the proposed framework, patient vital signs datasets are collected from Multiple Intelligent Monitoring in Intensive Care (MIMIC) I, II and III databases of PhysioNet [7]. The default number of monitored vital signs is

$N = 5$: heart rate (HR), the respiration rate (RESP), the systolic blood pressure (ABPsys), the blood temperature (BLOODT) and the oxygen saturation (SpO2). Thus, we suppose that 5 biosensors are deployed on the patient's body. In the following, when a different number of vital signs is monitored, the value of N as well as the vital signs of interest will be indicated. *Modified LED** (cf. algorithm 2) is implemented on the biosensor nodes and NEWS (cf. Figure 4.1) is used as a local detection system. The parameters settings for *Modified LED** on all biosensors are set as follows:

- Period $p = 100$ sec and Round $R = 2 \times p$.
- Minimum sampling rate $SR_{min} = 1$ samples/5 sec and Maximum sampling rate $SR_{max} = 1$ sample/2 sec.
- Fisher Risk $\alpha = 0.05$.
- The monitoring importance (risk) of vital signs $r = 0.9$. Indicating that all vital signs are highly critical and have the same impact on the patient's health.

The parameters settings for Health-RAD, which is implemented on the coordinator, are set as follows:

- $N = 5$ vital signs by default.
- Round $R = p = 100$ sec.
- Update interval $\delta_t = 1$ sec.

The existing approach [14] to which the obtained results are compared is implemented in R language. The datasets used in the training phase to build a general intensive care model are taken from MIMIC database and the list is found in [10]. The parameters settings are the following:

- Sampling rate on the sensors: 1 Hz (time granularity of the database 1 measurement/sec).
- Sampling interval on the coordinator: 3 sec.
- Sliding time window size: 10 samples.
- Absolute and Normality thresholds are found in [14].
- k coefficients and h weights for the risk components are found in [10].
- The clustering algorithm: simple K-means.
- The number of risk levels n is set to 3 indicating 4 possible levels (0 to n) : 0, 1, 2 and 3. The higher the level, the more the criticality/severity.
- The number of clusters for the 3 risk components: $C_{max} = 5$

In the rest of the chapter, we refer to the existing approach [14] that is chosen from the literature as data mining based framework.

In the data mining based framework, the signal (vital sign) features: offset, slope and distance are used to compute the following risk components: sharp changes, long-term trends and distance from normal behavior (formulas are found in [14]). Then, the health risk associated to signal (vital sign) x at time t is obtained by combining its risk components as follows

$$risk_x(t) = \frac{\sum_i k_{i,x} C(z_i(x))}{\sum_i k_{i,x}} \times \frac{n}{C_{max}}$$

where i ranges from 1 to 3 for the three z_i risk components, $k_{i,x} \in [0, 1]$ are weights for the i^{th} component of signal x , C_{max} is the number of discrete levels (the same for every risk component) set during model building and $C(z)$ is the function returning the risk level associated to risk component z . The risk function is normalized to return a value indicating the severity level from 0 to n . Finally, the risk levels of each vital sign are combined together in order to obtain a global risk level for the patient as

$$risk(t) = \max_{x \in X} (risk_x(t))$$

where X designates the monitored vital signs.

The two approaches are compared on the following levels, for different patient records and different number of monitored vital signs:

- Data Reduction
- Energy Consumption
- Vital Signs Assessment
- Health Assessment

The proposed approach is validated against the assessment of a medical expert.

First, the data reduction performed by *Modified LED** at the biosensor nodes level is highlighted. For this purpose, the measurements of different monitored vital signs for a given record, being received by the coordinator over time are shown. Furthermore, the percentages of data reduction compared to the data mining approach are reported for different patient records and different number of monitored vital signs.

5.5.1/ DATA REDUCTION

The signals of the original dataset of a given patient are shown in Figure 5.6. The dataset is taken from MIMIC II (s01840-3454-10-24-18-46nm record). The signals show the variation of the 5 vital signs of interest over approximately 2 hours, where the sampling rate is set to 1 Hz for all vital signs. Figure 5.7 shows the signals that are sent to the coordinator over 70 periods, where each signal is sent by a biosensor node sensing the corresponding vital sign. When comparing the original signal of the HR (Figure 5.6), for example, to the sent signal by the HR biosensor (Figure 5.7), it is remarkable to see that the number of small oscillations is considerably reduced while maintaining the general shape and progression of the HR curve over time. This is due to *Modified LED**, where only the 1st measurement and changes in the vital sign's score are sent to the coordinator in a period

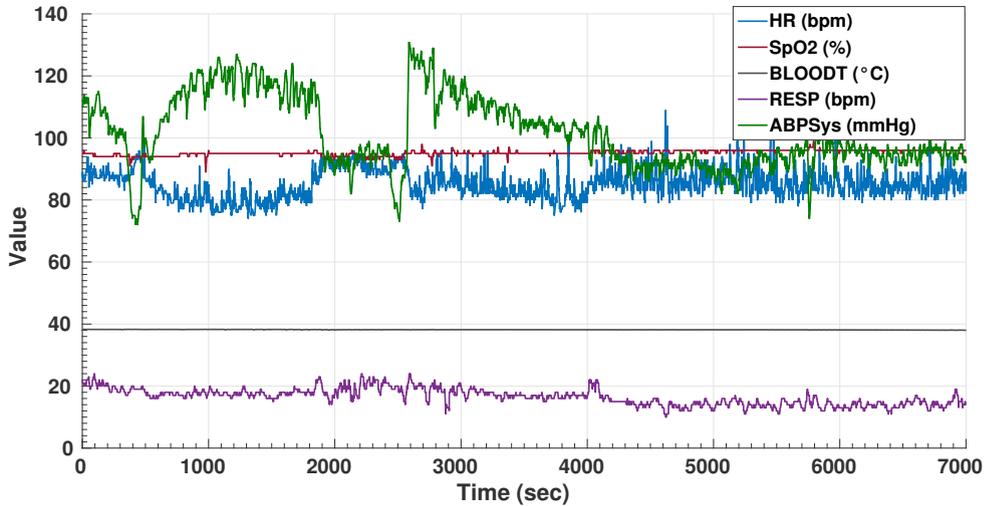


Figure 5.6: Original dataset showing the variation of the 5 vital signs of interest over 2 hours.

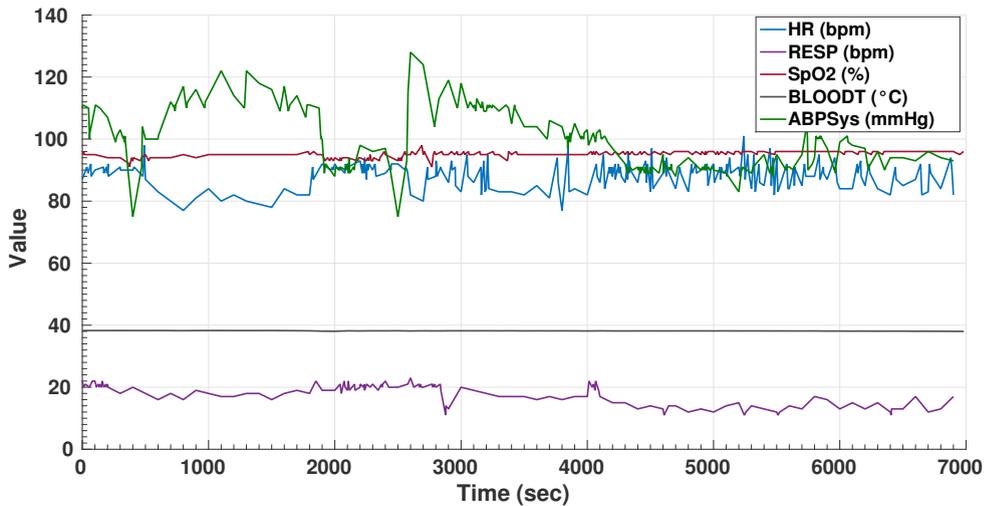


Figure 5.7: The received vital signs signals at the coordinator having been sent by 5 biosensor nodes running the *Modified LED**.

p . Thus, the amount of redundant data in a period p is reduced and only informative measurements, indicating a decrease or an increase in the vital sign's score, are sent. Hence, the shape and the progression of the HR curve over time are conserved. An overall data reduction of about 97% is performed compared to the original dataset, while maintaining information about changes in the 5 vital signs' score.

For different patient records and different number of monitored vital signs, Tables 5.3 and 5.4 show the percentages of data reduction performed at the sensing level and the transmitting level in our framework (biosensor nodes running *Modified LED**) compared to the existing approach [14] in which data are sensed and transmitted each 1 second. The results obtained are over 70 periods (7000 sec). The requests sent by the coordinator running Health-RAD, when critical situations are detected, are taken into consideration in the calculations corresponding to our framework. Missing values in the datasets are

Table 5.3: Data reduction performed for each monitored vital sign of record s01840-3454-10-24-18-46nm from MIMIC II compared to [14].

Vital Sign	Reduction of sensed data (%)	Reduction of transmitted data(%)
HR	63.33	96.91
SpO2	79.58	96.85
BLOODT	64.81	96.93
Resp	72.11	95.56
ABPsys	68.08	95.53

ignored and not taken into consideration.

Table 5.4: Total data reduction of four patient records compared to [14].

Database	Patient Record	Monitored vital signs	Reduction of sensed data (%)	Reduction of transmitted data(%)
MIMIC	276n	HR, ABPsys	69.91	88.03
	039n	HR, SpO2, RESP, ABPsys	69.73	92.2
MIMIC II	s01840-3454-10-24-18-46nm	HR, SpO2, RESP, ABPsys, BLOODT	67.87	94.09
	s15480-2803-10-21-19-54nm	HR, SpO2, RESP, ABPsys, BLOODT	69.57	96.36

5.5.2/ ENERGY CONSUMPTION

We study the energy consumed by the biosensor nodes for sensing and transmitting. The remaining energy after 36 periods in the WBSN in the case of our framework and in the case of the data mining based framework are compared. Figure 5.8 shows the results obtained for patient records s01840-3454-10-24-18-46nm (MIMIC II), 039n (MIMIC I), 3000190 and 3100038 (MIMIC III). We assume that the total initial energy of a sensor node is arbitrarily fixed to 3200 units. The total initial energy in the WBSN is then $N \times 3200$ where N can be equal to 2, 3, 4 or 5. The node consumes 0.04 units for sensing, 0.4 units for transmitting (TX mode) and 0.4 units for receiving (RX mode) [145]. For example, for patient record s01840-3454-10-24-18-46nm, at the end of 36 periods the remaining energy in the WBSN in the case of our framework is about 15010.81 units, however it is only about 8080.0 units in the case of the data mining based framework, suggesting that the energy consumption in the WBSN implementing our framework is about 8 times less than the data mining based framework at the end of 36 periods. The number of vital

signs of interest N has been varied and the results show that: at the end of one hour, the average energy consumption in the WBSN when applying the proposed approach is approximately 6 times less than the energy consumption in the WBSN when applying the data mining based approach such as the vital signs of interest are the following: HR and RESP (record 300190) and is 16 times less such as the vital signs of interest are the following : HR, RESP and SpO2 (record 3100038) and about 10 times less for record 039n where the vital signs of interest are the HR, REP, SpO2 and ABPSys. Therefore, our approach considerably reduces the energy consumption on the biosensor nodes and extends the WBSN lifetime.

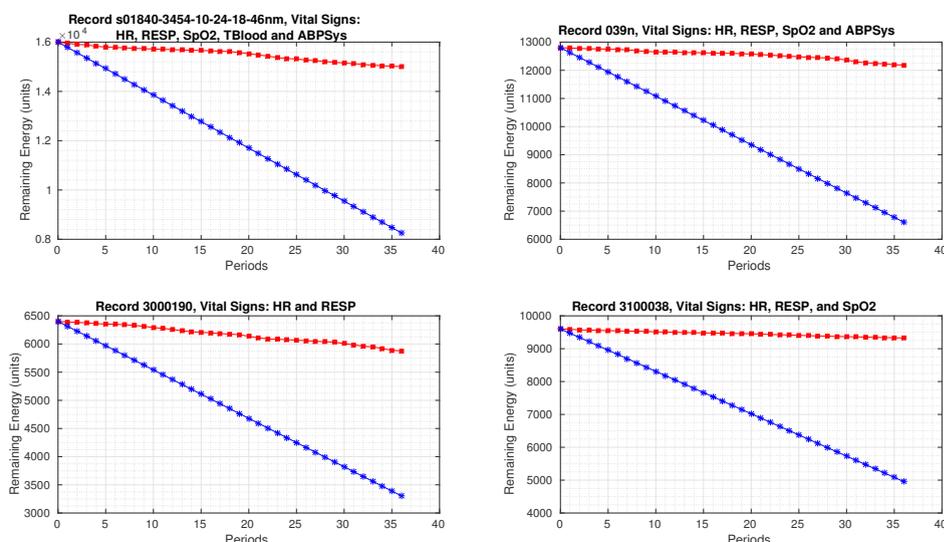


Figure 5.8: Comparison of the remaining energy in the WBSN after 36 periods (1 hour) for different patient records and different number of monitored vital signs: proposed framework (in red) vs data mining based framework (in blue)

In the following, we compare the results of the two multi-sensor data fusion approaches of the two frameworks. We start by comparing the results obtained at the level of the analysis of the measurements for several vital signs for different patients. Then, we compare the results obtained in the assessment of the patient's health condition (severity level) after performing the data fusion in both frameworks.

5.5.3/ A COMPARISON OF THE SEVERITY LEVEL ASSESSMENT OF VITAL SIGNS

In our approach, Health-RAD regularly updates the scores of the monitored vital signs. In addition, the severity level of a given vital sign is represented by a score between 0 and 3 with score $\in \mathbb{R}$. According to the proposed multi-sensor data fusion model, the score of each vital sign is updated each δ_t and each time a measurement is received from a given biosensor node indicating a change in the status of the vital sign including critical situations. Using equation 5.1, the update of the scores is done while taking into consideration the history and the current score of the vital sign during one round R . As for the data mining based framework, the severity level of the vital sign is represented by a risk variable taking values between 0 and $n - 1$, where n is the number of severity levels specified by the user and risk $\in \mathbb{N}$. We set $n = 4$ since the scoring system used

in our approach uses four levels ranged between 0 and 3. Figures 5.9 and 5.10 show the assessment of the HR and the SpO₂ of patient record s01840-3454-10-24-18-46nm during 1000 sec and 2000 sec respectively. The time intervals were chosen randomly. On the one hand, Figures 5.9a and 5.10a show the scores assigned to the HR and SpO₂ respectively, when applying the data mining based framework which relies on feature extraction and clustering (K-Means) for the online classification. On the other hand, Figure 5.9b and 5.10b show the scores assigned to the same vital signs during the same time interval, but when applying Health-RAD. In Figure 5.9b, the score of the HR is stable and is equal to zero from $t_1 = 1400$ sec until $t_2 = 1800$ sec, indicating that it is normal and not critical. Indeed, according to the measurements of the HR between t_1 and t_2 , the values vary between 75 bpm and 87 bpm (cf. 5.9a) which corresponds to the normal range according to NEWS (cf. 4.1). However, Figure 5.9a shows that the score of the HR between t_1 and t_2 vary between 0 and 1 but is, most of the time, equal to 0. Therefore, K-Means has not classified all the HR signal as normal, since at some instants, it was assigned a score of 1. Yet, most of the HR signal between t_1 and t_2 was considered as normal.

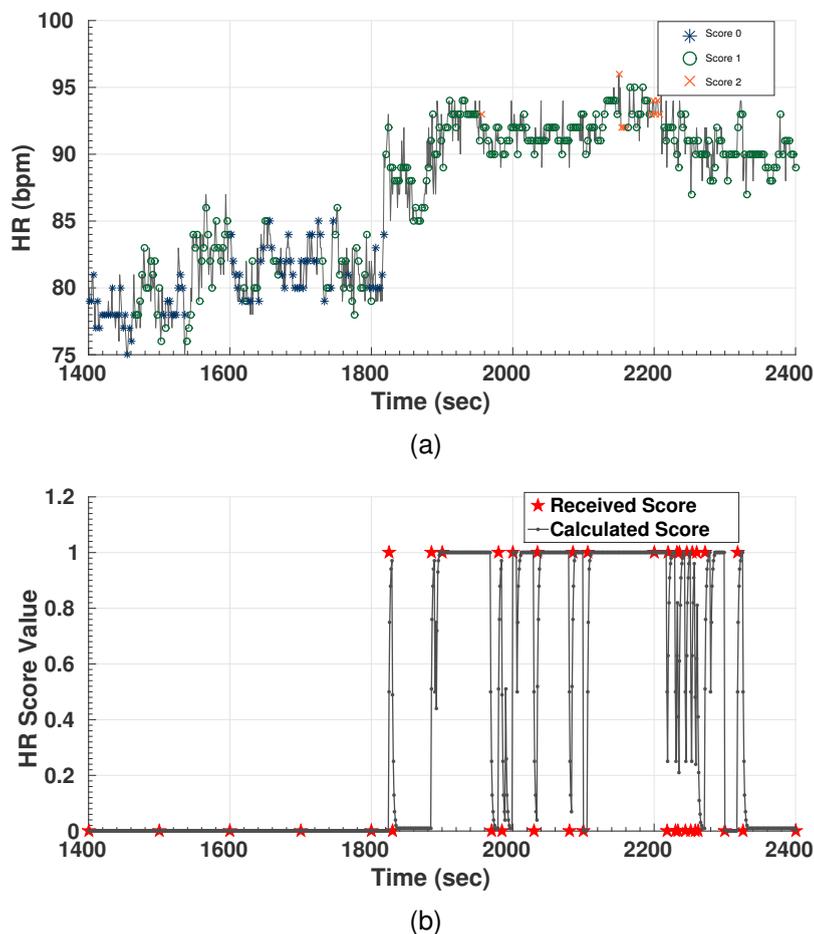


Figure 5.9: Severity level assessment of the HR of patient record s01840-3454-10-24-18-46nm using the data mining based framework [14] (a) and the proposed approach (b)

After $t_2 = 1800$ sec, Figure 5.9b shows that the calculated score values are between 0 and 1. However, for long time intervals and most of the time, it reaches stability and takes a score of 1. This is due to the stabilization of the received score to 1. When a new score is received, Health-RAD does not affect it automatically to the vital sign, instead it computes a new score based on the last calculated score (history) and the new one received. Since, the fact that a patient has an instantaneous measurement in another score range does not necessarily indicate that his/her health condition is degrading or improving. It is his/her persistence in such conditions which contributes to the risk level. The score of the HR reaches 0 for very short time intervals and this is due to the fast alternation of the HR measurements between score 0 and 1. Hence, our approach assigns to the HR scores between 0 and 1 until stability. Figure 5.9a shows that the HR is assigned most of the time a score of 1, which is compatible to the results we obtained in our approach, however K-Means classified it for some instants in a higher risk and assigned it a score of 2. Figures 5.10a and 5.10b show the assessment of the SpO2 during $t_{start} = 2000$ sec and $t_{end} = 4000$ sec. Likewise, both of the approaches assigned alternating scores of 1 and 2 at the beginning. At $t = 2800$ sec, both of them detected a higher level of criticality and assigned a higher score (a score of 3 in the data mining based framework and a score increasing from 2 to 3 in the proposed approach). At $t > 3500$ sec, both of the approaches mostly assigned a score of 1, while the data mining based framework detected some scores of 2. Likewise, Figure 5.11 shows the assesment of the ABPsys of patient record 267n during 1000 seconds. Both approaches detected high levels of criticality between $t_1 = 2500$ sec and $t_2 = 3000$ sec. Health-RAD assigned to the ABPsys a score up to 3 while the other approach assigned a score of 2.

Therefore, the proposed framework analysed and assessed the vital signs of different patients coherently compared to the data mining based approach. However, the proposed approach takes into consideration the limited energy resources requirement in WBSNs. It overcomes the data mining based framework in terms of energy consumption (around 86% less energy consumption) and data reduction (around 70% for sensing and more than 90% for transmission).

5.5.4/ A COMPARISON OF THE PATIENT HEALTH ASSESSMENT: PATIENT SEVERITY LEVEL

In this section, we compare the results regarding the patient's health assessment. In both approaches, this is done by performing a multi-sensor data fusion. Figure 5.12 shows the health assessment of the three following patients 3100038, 3000190 and 039n. The first two records are taken from MIMIC III database and the last record is taken from MIMIC I database. For patient 3000190, only the HR and RESP are being monitored, whereas for patient record 3100038 only the HR, RESP and SpO2 are being monitored and for patient 039n the HR, RESP, SpO2 and ABPsys are being monitored (the energy consumption of these records was reported in Section 5.5.2).

In order to compare the patient's risk value of the proposed approach to the global risk of the data mining approach, Table 5.5 is used. The average patient's risk per period for each record based on the proposed approach is 0.36 (record 3000190), 0.26 (record

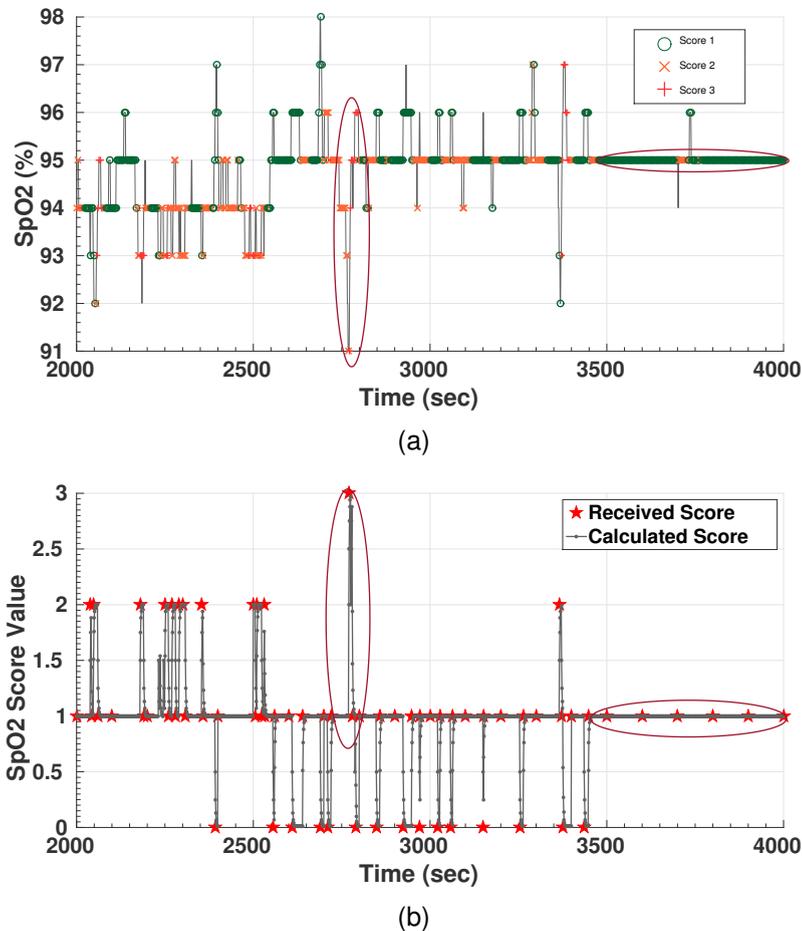


Figure 5.10: Severity level assessment of the SpO2 of patient record s01840-3454-10-24-18-46nm using the data mining based framework [14] (a) and the proposed approach (b)

3100038) and 0.53 (record 039n). Thus, the proposed approach has assigned a global risk of 2 to the records 3000190 and 039n, and a global risk of 1 to the record 3100038. Similarly, the average global risk per period based on the data mining based approach for record 039n is also 2, and it is 1 for record 3100038. However, the average global risk per period based on the data mining based approach for record 3000190 is 1.

As shown in the plots of record 3100038, both approaches have similarly assessed the patient's health condition over time: the majority of the time the global risk was 1 and alternatively 2. Similarly, as shown in the plots of record 039n, both approaches have in the majority of the time given a global risk of 2 whilst the proposed approach after 2000 sec have alternatively assigned a global risk of 3. For patient record 3000190, the plot of the data mining based approach show that in the majority of the time the global risk was equal to 1 and stable for a longer time compared to when it was equal to 2. Whereas, for the same patient record, the plot of the proposed approach show that a score of 3 was given much more times to the patient's health condition than it was given in the data mining based approach. As a consequence, the average patient's risk per period for record 3000190 was not the same in both approaches.

The results show then that both approaches have detected a critical situation over

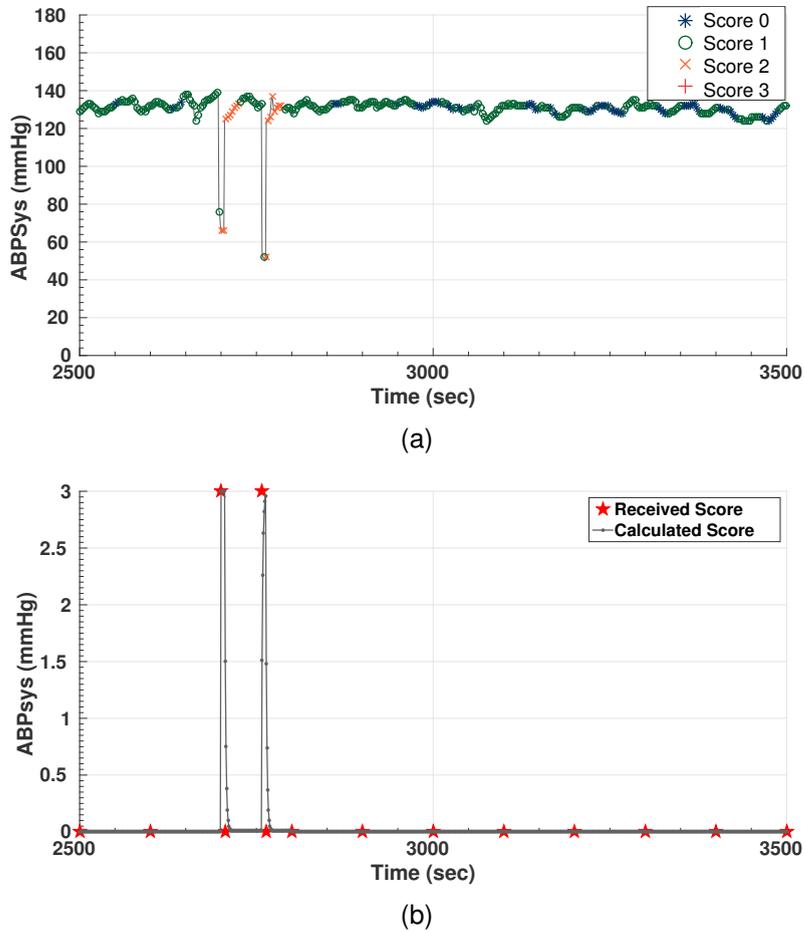


Figure 5.11: Severity level assessment of ABPsys of patient record 267n using the data mining based framework [14] (a) and the proposed approach (b)

1 hour (absence of *patient's risk* < 0.2 and *global risk* $= 0$), that both approaches have similarly assessed the patient's health condition when the vital signs were stable over long periods of time, however the proposed approach reached higher risk values than the data mining based approach when the vital signs presented instability on short time periods and that the data mining based framework is more sensitive to single deviating vital signs.

Table 5.5: Equivalence Table between Patient's Risk of proposed approach and Global Risk of data mining based approach.

Patient's Risk	Global Risk
$[0, 0.2[$	0
$[0.2, 0.35[$	1
$[0.35, 0.65[$	2
$[0.65, 1]$	3

Tables 5.6 and 5.7 show respectively the average patient's risk per period for 10 records where only the HR and RESP are monitored and the average risk per period for 10 other records where only the HR, RESP and SpO2 are monitored based on both

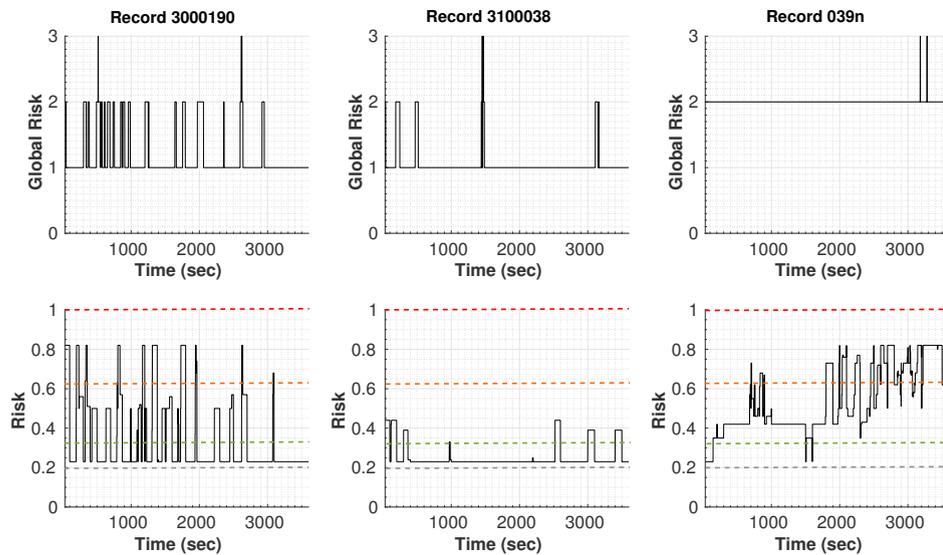


Figure 5.12: Comparison of health assessment during 36 periods (1 hour) for different patient records and different number of monitored vital signs: data mining based framework (second row) vs proposed multi-sensor fusion (second row)

approaches. The results show that 50% of the 2 vital signs monitoring records (cf. Table 5.6) have been similarly assessed by both approaches whereas 90% of the 3 vital signs monitoring records (cf. Table 5.7) have been similarly assessed by both approaches. In all the records where the health assessment was different, the proposed approach has given a higher global risk of one class than the data mining based framework (for example patient record 3000190).

Table 5.6: Average Patient's Risk per period based on the proposed approach and Average Global Risk per period based on the data mining based framework for 10 patient records such as the vital signs of interest are the HR and RESP.

Record	Average Patient's Risk per period	Average Global Risk per period
3000190	0.36	1
3000203	0.33	1
3000598	0.49	2
3000611	0.53	1
3000710	0.27	1
3300295	0.35	1
3300312	0.4	1
3300380	0.23	1
3300430	0.3	1
3300446	0.78	2

Now, a comparison is made based on the default settings of both approaches. In the data mining based framework, the monitored vital signs are the default ones chosen by the authors of [14]: HR, SpO₂, ABPdias and ABPsys. In our approach, as per NEWS, the following five vital signs are chosen to perform the patient's health assessment: HR,

Table 5.7: Average Patient's Risk per period based on the proposed approach and Average Global Risk per period based on the data mining based framework for 10 patient records such as the vital signs of interest are the HR, RESP and SpO2.

Record	Average Patient's Risk per period	Average Global Risk per period
3100038	0.26	1
3100140	0.37	2
3100308	0.23	1
3100331	0.23	1
3100524	0.25	1
3200013	0.33	1
3200059	0.64	2
3200163	0.41	1
3200268	0.26	1
3200359	0.25	1

RESP, ABPsys, BLOODT and SpO2. In the data mining based framework, the patient's health condition is represented by a global risk being the maximum of the scores assigned to the monitored vital signs.

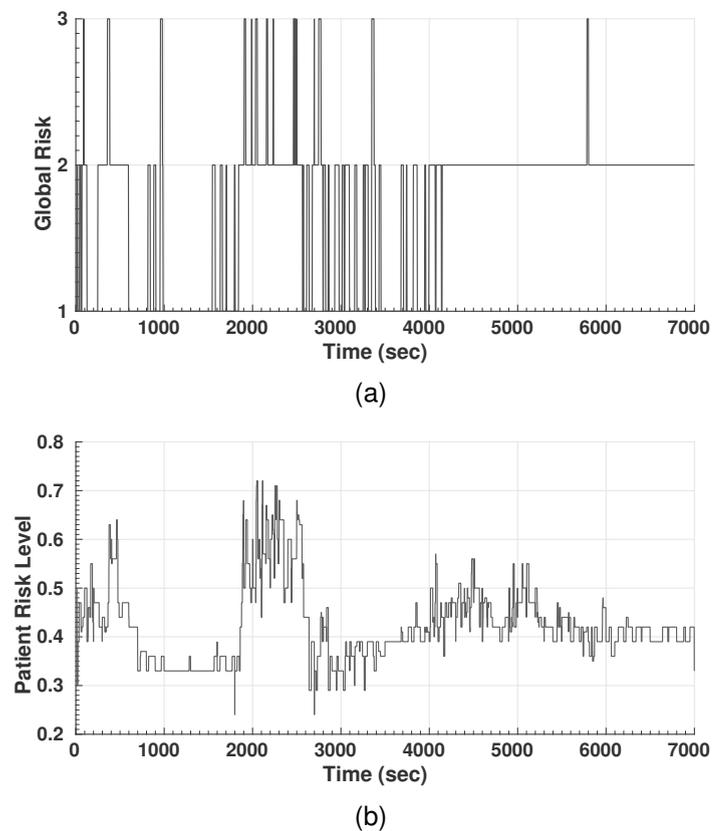


Figure 5.13: The health assessment of patient record s01840-3454-10-24-18-46nm using the data mining based framework [14] (a) and the proposed approach (b)

This could in some cases trigger false alarms, if it is generated by only one deviating vital sign. This usually occurs when a sensor node is collecting faulty measurements. However, our proposed approach represents the patient's health condition by a patient's risk level. For this purpose, our multi-sensor data fusion model aggregates the scores of all monitored vital signs. Then, it uses the aggregate score as an input into a FIS to generate the patient's risk level. Figure 5.13 shows the results of the health assessment of patient record s01840-3454-10-24-18-46nm during 7000 sec using the data mining based framework and the proposed approach. Clearly, the patient presented high severity levels in the same intervals in both approaches between 2000 sec and 2800 sec and medium severity levels between 4000 sec and 5700 sec and lower ones between 1000 sec and 1500 sec. In our approach, a decision/advice or action is triggered according to the range to which the computed patient risk level belongs.

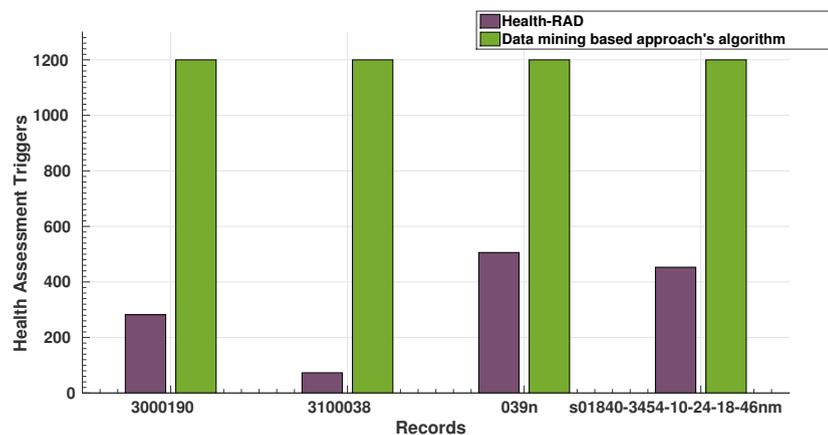


Figure 5.14: Comparison of the total of health assessment triggers over 1 hour between Health-RAD and the real-time assessment algorithm of the data mining based framework.

Finally, Figure 5.14 depicts the total of health assessment triggers over 1 hour for the four patient records : 3000190, 3100038, 039n and s01840-3454-10-24-18-46nm. The health assessment algorithm of the data mining based framework is triggered at a fixed time interval of 3 sec. Whereas, the proposed algorithm Health-RAD which implements the proposed multi-sensor fusion approach is triggered periodically (each 100 sec) and each time a critical situation is detected (cf. Section 5.4). As shown in the results, Health-RAD performs an average of 871,5 health assessments less than the algorithm of the data mining based framework over a time period of 1 hour. Therefore, by using Health-RAD the coordinator's processing resources are less used which extends the coordinator's battery lifetime. This matter did not affect, as shown previously in this section, the health assessment of these patient records because both approaches assessed the health condition of the patients in a similar way.

5.5.5/ MEDICAL DOMAIN EXPERT VALIDATION

The data collection technique and the EWS based vital sign assessment, used in our framework, have been compared to the classification done by an expert in the medical domain. The comparison focuses on detecting critical events: when the measurements

of a given vital sign deviate from the normal range ($score \neq 0$). Table 5.8 shows the results obtained for record s15480-2803-10-21-19-54n for each of the HR, ABPSys and RESP over 28 hours and 46 minutes. It shows the accuracy and false positives of the

Table 5.8: Accuracy of critical events detection and rate of false positives compared to medical domain expert classification.

	HR	ABPSys	RESP
Accuracy (%)	93	85	72
False positives (%)	20	15.4	36.3

detection of critical events. For each vital sign, we have divided the first 100000 sec of the record into 100 time frames each of about 1000 sec. If the time frame contains at least one critical event ($score \neq 0$) then it is counted as a positive event, otherwise it is counted as a negative event. The medical expert has classified the 100 time frames based on the knowledge that the record belongs to an ICU patient of a given sexe and age and based on their used vital signs normality thresholds. All of the critical events were detected by our approach for all the vital signs. An average accuracy of about 83% is achieved compared to the expert's classification. However, an average false alarm rate of about 24% is recorded. This is mainly due to narrower normality ranges, which are used in our system, compared to the expert's classification, making it more sensitive to variations. These thresholds can be easily configured depending on the EWS implemented at both the biosensor nodes and coordinator levels.

5.6/ CONCLUSION

In this chapter, a multi-sensor fusion approach for health assessment was proposed. A health risk assessment and decision-making algorithm has been presented within a complete acute illness monitoring system using a WBSN deployed on the patient's body. A comparison with an existing approach from the literature has been done. The results show that our approach reduces data transmission while preserving the required information. In addition, it reduces the energy consumption due to sensing and transmitting, therefore extending the lifetime of the network of about 10 times over 1 hour of continuous monitoring compared to the other framework proposed in the literature. Furthermore, the assessment of the vital signs and of the global health condition of the patient in both approaches are compatible: risks are detected on time.

CONTEXT-AWARE MULTI-SENSOR FUSION

Changes in vital signs and physiological signals do not always indicate a critical event. In fact, they are influenced by the person's context: personal information, current physical activity and the surrounding environment. In this chapter, a multi-sensor data fusion approach is proposed for the assessment of the person's health condition given his/her context. Hesitant Fuzzy Sets (HFS) are used to subjectively evaluate the intensity of physical activities and a Fuzzy Inference System (FIS) is used to assess the person's health condition given the intensity of his/her current physical activity and his/her vital signs.

6.1/ INTRODUCTION

Context-awareness in pervasive healthcare allows a more robust fusion and interpretation of the collected vital signs [130]. It complements the information one has about the physiological measurements allowing by that a better assessment of the patient's health condition and a better detection of emergencies. It allows the association of the patient's physical activity and the environment with the sensed biosignals and interprets them based on these information [20]. In Chapter 5, we have proposed a multi-sensor data fusion model for the assessment of the patient's health condition based only on vital signs. In this chapter, we propose to assess the monitored person's health condition based on his/her vital signs which are collected by the biosensor nodes and his/her context. More specifically, we target the problem of interpreting vital signs while taking into consideration the person's current physical activity, since they are highly correlated. For instance, an increase of the heart rate indicates a critical event if it occurs when the person is resting, however, it is not a triggering event if the person is running. Using a Fuzzy Inference system (FIS), the severity level of the patient's condition is determined based on the aggregate score of vital signs and the intensity of the person's current physical activity. Knowing that the latter is a subjective classification, we propose a Hesitant Fuzzy Sets (HFS) based evaluation model to assess the intensity of the physical activity performed by the person using its characteristics (speed, duration, incline, additional weights etc.) and his/her personal information (age, Body Mass Index, Alcohol Consumption etc.). The remainder of the chapter is organized as follows. Section 6.2 discusses the related work. The WBSN architecture and the scenario are highlighted in Section 6.3. In Section 6.4, the proposed context-aware health assessment model is presented. Experimental

results are shown and discussed in Section 6.5. Finally Section 6.6 concludes the chapter.

6.2/ RELATED WORK

The definition of context-awareness is given by [8] as:

Definition 4: Context-awareness

Any information that can be used to characterize the situation of an entity, where an entity can be a person, place, or physical or computational object.

Identifying the context of the monitored people is one of the benefits of pervasive healthcare. It enables the understanding of the person's conditions, the identifying of unusual patterns and the making of more precise inferences about any situation [17]. Context-awareness can be achieved by fusing information gathered by several sensors: biosensors, accelerometers, ambient sensors as well as other other type of data such as the patient's personal information and can be extended to monitoring the person's activity on social media [50]. Several context-aware approaches in the domain of pervasive healthcare exist in the literature. These approaches make use of WBSNs to collect people's vital signs, physiological measurements and motion data as well as of smartphones or other portable devices to get additional contextual information such as the temperature, location, personal information etc. Context-aware solutions can target different aspects of a pervasive environment: energy consumption in the WBSN, management of the WBSN, health services providing [32, 42] and complementing biosignals and enriching the health assessment [65]. In [150], the authors propose a solution '*SituMan*' that provides situation awareness to another application '*MoodBuster*', providing mental health assessment based on patient self-assessments. '*SituMan*' is based on a fuzzy inference engine and it identifies the patient's situation (daily routine) using context data gathered from the sensors embedded in mobile devices (location, time and user activity). In [53, 94], the authors propose a pervasive health care system which they name CARA (Context Aware Real-time Assistant) enabling the provision of personalized healthcare services for elderly. The data fusion approach combines context awareness, case-based reasoning, and general domain knowledge in a healthcare reasoning framework. It uses a fuzzy inference engine and case-based reasoning to perform the following reasoning tasks: continuous contextualization of the physical state of a person, prediction of possibly risky situations and notification of emergency situations indicating a health risk, home automation or user prompting within a smart home environment. In [110], the authors present an emergency situation monitoring service using context motion tracking for chronic disease patients. The movement of the user is observed by using cameras and motion sensors. Measurement sensors such as temperature, humidity and illumination sensors are installed in rooms to complete the context of the monitored person. The authors use a semantic inference engine to propose a smart health service to the patient based on the inferred situation. We propose to use context-awareness to complement the information that the coordinator of the WBSN has about the monitored person's vital signs. Assessing the person's health condition based only on his/her vital signs is insufficient. Thus, combining this information with the information the WBSN has about the intensity of the physical activity being performed at the same moment by the person, enriches and solidifies the continuous health assessment and the detection of emergencies when they occur. A

great deal of research has covered real-time activity recognition [49, 84, 86, 59, 118, 51]. Moreover, some research covered the problem of estimating the speed of the person's movement in real-time [85, 98, 12]. Whereas, others proposed to assess the activity level of the monitored person [144, 11, 127]. To the best of our knowledge, nobody proposed to subjectively assess the intensity level of physical activities based on contextual data such as the person's personal information (age, Body Mass Index (BMI), alcohol consumption, smoking rate etc.) and on the characteristics of the physical activity such as speed, inclination, duration, resistance etc.

6.3/ WBSN ARCHITECTURE AND SCENARIO

The goal of the context-aware health assessment model we are proposing in this Chapter is to ensure a continuous health monitoring and to detect emergencies related to abnormal vital signs variations when they occur. The target population of such an application could be elderly in nursing homes, post-surgery patients recovering at home, acutely ill or chronically ill patients. In other words, people who require continuous and remote monitoring because they are at risk of life-threatening emergencies. Furthermore, any average person who requires a continuous follow-up of his/her health condition and fitness can benefit from such an application. The WBSN consists of biosensor nodes and accelerometer(s) placed on the body of the person and a coordinator. These components wirelessly communicate together under a star topology. We suppose that each biosensor node senses at a given sampling rate only one vital sign. Therefore if N vital signs are being monitored then N biosensor nodes are required. The biosensor nodes periodically send to the coordinator the collected measurements for fusion. When the coordinator detects a possible emergency based on the fusion of vital signs (outside normal range or aggregate score of vital signs is greater than a threshold specified by healthcare experts), it sends a request to the accelerometer(s) to get recent acceleration data (acc_x , acc_y and acc_z). This data is collected during the last h consecutive periods such as h is chosen by physicians. The coordinator can then evaluate the intensity of the current physical activity of the person and can assess his/her health condition. Otherwise, the health assessment is made at the end of each round R where $R = m \times p$ where p is the WBSN's common period.

6.4/ CONTEXT-AWARE HEALTH ASSESSMENT MODEL

The context-aware health assessment model (cf. Figure 6.1) is composed of two modules: the physical activity (PA) intensity evaluation model and the health assessment model. First, the intensity level of the PA performed by the person is subjectively evaluated based on the PA's characteristics as well as the person's profile (attributes). Then, the severity of the person's health condition is assessed based on the collected vital signs and the PA's intensity. In the following, we detail the two modules (Sections 6.4.3 and 6.4.4). But first, the definition and the classification of physical activities, as found in the literature, are given in Section 6.4.1 and Hesitant Fuzzy Sets are defined in Section 6.4.2.



Figure 6.1: Context-aware Health Assessment Model Block Diagram.

6.4.1/ CLASSIFICATION OF PHYSICAL ACTIVITIES

Physical activity (PA) is any movement of the body that requires effort to be performed and that uses the energy produced by skeletal muscles. Examples of PAs include: walking, climbing stairs, running, playing soccer and many other examples of being active. We define physical inactivity as the absence of movement. It can indicate multiple states depending on the person's posture: resting, sleeping, sitting, standing still etc. According to the WHO, the intensity of a physical activity refers to the effort required to perform it. Therefore, PAs can be divided into two categories:

- Moderate Intensity: A moderate amount of effort is required which noticeably accelerates the heart rate.
- Vigorous Intensity: A large amount of effort is required which causes rapid breathing and a considerable increase in the heart rate.

Based on Metabolic equivalents (METs), a general classification of PAs into the two categories can be found in the literature. However, the intensity is a subjective classification. It depends on the person's gender, age, Body Mass Index (BMI), medical history, fitness level and lifestyle. Therefore, this classification remains very general and does not take into consideration different populations and human characteristics. For instance, if we only consider the person's age, walking can be evaluated as slightly moderate for a person who is 18 years old, whereas it can be evaluated as quite vigorous for a person who is 70 years old. Furthermore, taking into consideration the PA's characteristics such as speed and duration, the intensity of the PA can be evaluated differently. For example, considering only the duration of a PA, walking for 10 minutes can be evaluated as slightly moderate, whereas walking for 30 minutes can be evaluated as somewhat vigorous. Hence, by fusing the information we have about the patient's current PA and his/her attributes, it is possible to build the context in which the patient is found at a given instant.

6.4.2/ HESITANT FUZZY SETS

A hesitant fuzzy set (HFS) allows the membership to have a set of possible values [93]. Let X be a fixed set, a HFS on X is in terms of a function that when applied to X returns a subset of $[0,1]$. It can be expressed as follows:

$$A = \{ \langle x, h_A(x) \rangle \mid x \in X \} \quad (6.1)$$

where $h_A(x)$ is called Hesitant Fuzzy Element (HFE) and is a set of some values in $[0,1]$ indicating the possible membership degrees of the element $x \in X$ to the set A . HFSs are used in many decision-making problems. They come in help when the decision-makers are usually hesitant and irresolute for one thing or another. Indeed, in this work, we are

dealing with ambiguous and imprecise data such as the person's attributes and the PA's characteristics. Moreover, evaluating a PA's intensity is a subjective matter that follows a human-reasoning logic. Thus, HFSs are used to reach a final agreement about the intensity value that should be given to a particular PA.

6.4.3/ PHYSICAL ACTIVITY INTENSITY EVALUATION MODEL

Let $X = \{x_1, x_2, \dots, x_n\}$ be the set of characteristics that describe a PA where n is the total of characteristics. Examples of such characteristics include: speed, duration, inclination, additional weights, etc.

Let $D = \{d_1, d_2, \dots, d_m\}$ be the set of decision-makers (DM) where m is the total of DMs. In our approach, the person's attributes are the DMs that are going to evaluate the PA's characteristics in order to evaluate its intensity. Examples of such attributes include personal and health information such as: Body Mass Index (BMI), age, alcohol consumption (L/week), smoking status (cigarettes/week) etc. Based on its value, each DM contributes differently in the evaluation of the PA.

For each characteristic x , each DM d is asked to give its evaluation while taking into consideration its own impact. For instance, if the DM age is 50 years old, then evaluating the characteristic speed of 6 km/h would yield a different result than if the DM age is 18 years old.

Then, $h_A(x)$ represents the set of the DMs' opinions regarding the characteristic x of a given PA. In our approach, we refer to *opinion* by the term *evaluation* which reflects how much a given DM d considers a characteristic x of a PA intense. Furthermore, we replace the notation $h_A(x)$ by $h_{PA}(x)$ for more convenience.

Let $h_{PA}(x) = \{e_1, e_2, \dots, e_m\}$ be the set of evaluations given by the m DMs to the characteristic x of a given PA such that $e_i \in [0, 1]$. The closer the value of e_i is to 1, the more the characteristic x is considered intense by the DM d . We define the evaluation function $E(f_1, f_2)$ as follows:

$$e_i = E(f_1, f_2) = \frac{2 \times f_1 + f_2}{3} \quad (6.2)$$

where f_1 and f_2 are features representing the intensity of the characteristic x and the impact of the DM d respectively. Following a human-reasoning logic, we chose to give the PA's characteristic a greater weight than the DM given that we are after all evaluating PAs which differ from each other due to their characteristics. The feature f_1 is defined as follows:

$$f_1 = x / \text{Max}_x \quad (6.3)$$

where Max_x represents the predefined maximum value that can be given to a characteristic x . The closer the value of x is to Max_x the closer f_1 is to 1. The further the value of x is from Max_x the closer f_1 is to zero. For example, if the maximum speed is 12km/h and if the monitored person's current PA's speed is 5km/h, then $f_1 = 0.416$ indicating a more intense speed than if its value is 2km/h where f_1 will be equal to 0.166.

Whereas the feature f_2 is defined as follows:

$$f_2 = \text{Score}(D_i) / \text{MaxScore}_{D_i} \quad (6.4)$$

Table 6.1: Scoring Table of the decision-maker Age.

Age	18-30	31-45	46-60	≥ 60
Score	1	2	3	4

where $Score(D_i)$ is the score of the i^{th} DM and $MaxScore_{D_i}$ is its maximum score given a predefined scoring table put by healthcare experts. The latter assigns a score s for each DM value range such that $s \in \mathbb{N}$. The higher the score is, the more the DM's value is considered as a contributor to a higher intensity and the higher the impact of the DM. For instance, the older the human being gets the more a given PA is considered intense, thus an example of the scoring table related to the DM age can be given in Table 6.1.

Therefore, given the above definitions, we define the HFS of a PA having n attributes and m DM to evaluate its intensity as follows:

$$PA = \{ \langle x_1, e_1, e_2, \dots, e_m \rangle, \langle x_2, e_1, e_2, \dots, e_m \rangle, \dots, \langle x_n, e_1, e_2, \dots, e_m \rangle \} \quad (6.5)$$

We propose the following aggregation function in order to calculate the intensity of the PA based on the DM evaluations:

$$I_{PA} = \sum_{i=1}^n \alpha_i (\max_{j=1}^m (h_{PA}(x_i))) \quad (6.6)$$

For each characteristic x of a given PA, the max function returns the highest intensity evaluation given by the DMs to it. Thus, keeping the highest evaluations given for each characteristic x , suggesting an influence on the person's vital signs. Then, a weighted average is calculated to find the final intensity of the PA. For each characteristic x , a weight factor is fixed given that their influence on the PA's intensity level is not equally judged. For instance, the speed at which a PA is performed influences its intensity level more than the time spent doing it does. The weight factors α_i are set by physicians or healthcare experts such as $\sum_{i=1}^n \alpha_i = 1$

6.4.4/ HEALTH ASSESSMENT MODEL

A Fuzzy Inference System (FIS) uses fuzzy set theory to map inputs to outputs. Fuzzy theory is widely used to represent uncertainty and ambiguity in data fusion techniques [13, 31]. Assessing vital signs and subjectively evaluating PA intensities constitute a high-level data fusion task that requires following the human reasoning and the implication of uncertain and ambiguous data. Such data include vital signs that are collected by the WBSN and PA intensity information deduced from the collected motion data and the person's profile. Figure 6.2 shows the proposed FIS block diagram. The inputs of the FIS are : the aggregate score of the monitored vital signs and the intensity I_{PA} of the person's current physical activity at the moment of the health assessment.

Using Early Warning Score System (EWS), healthcare experts are able to assess vital signs based on their values. In our work, we chose the National Early Warning Score System (NEWS)[47], a standard in the United Kingdom, to assess any of the following

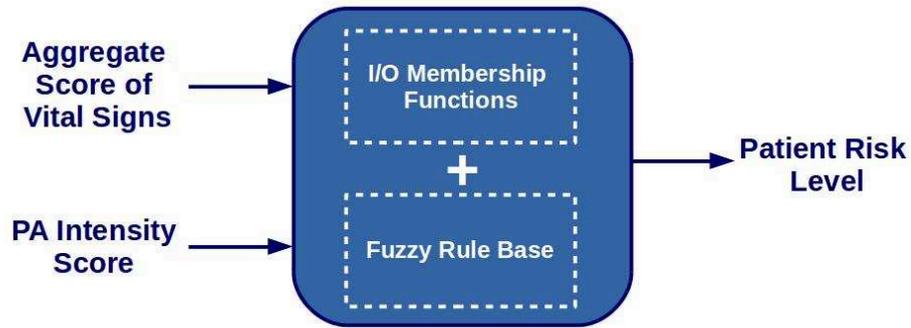


Figure 6.2: Fuzzy Inference System Block Diagram.

vital signs: Heart Rate (HR), Respiration Rate (RR), Systolic Blood Pressure (ABPSys), Temperature (Temp) and Oxygen Saturation (SpO2). The aggregate score can then be calculated as follows:

$$AggScore = \sum_{i=1}^V s_i \quad (6.7)$$

where s_i is the score of the i^{th} vital sign and V is the number of monitored vital signs.

The two inputs of the FIS need to be fuzzified, for this purpose membership functions (MFs) for the $AggScore$ and the I_{PA} are defined. Based on Chapter 5, three MFs are defined for the $AggScore$ in terms of the total number of vital signs N : Low, Medium and High (cf. Figure 6.3). Three other MFs are defined for I_{PA} : Negligible, Moderate and Vigorous (cf. Figure 6.4).

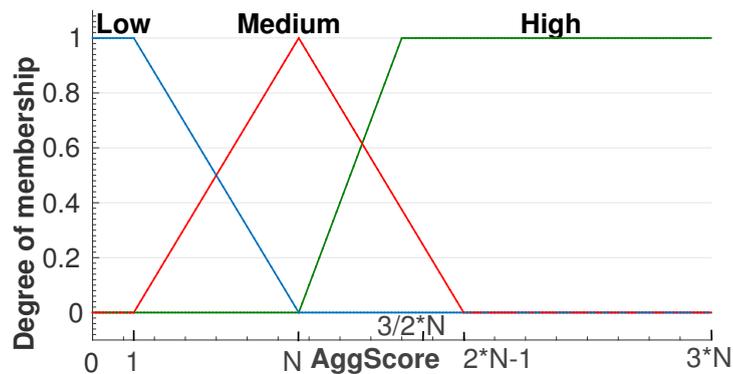


Figure 6.3: Aggregate Score Membership Functions.

As we have previously mentioned in the beginning of this section, the health assessment model assesses the person's health condition using a FIS and based on the PA's intensity I_{PA} and the aggregate score $AggScore$ of the person's monitored vital signs. We define the person's risk level r_{global} as the output of the FIS such as $r_{global} \in [0, 1]$. The closer r_{global} is to 1 the more the person is at risk and is considered in a critical situation. The membership function of the person's risk level r_{global} is shown in Figure 6.5. Two MFs are defined: Low and High.

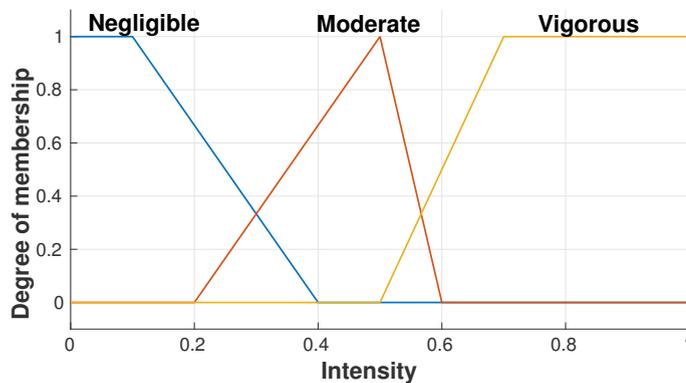


Figure 6.4: Physical Activity Intensity Membership Functions.

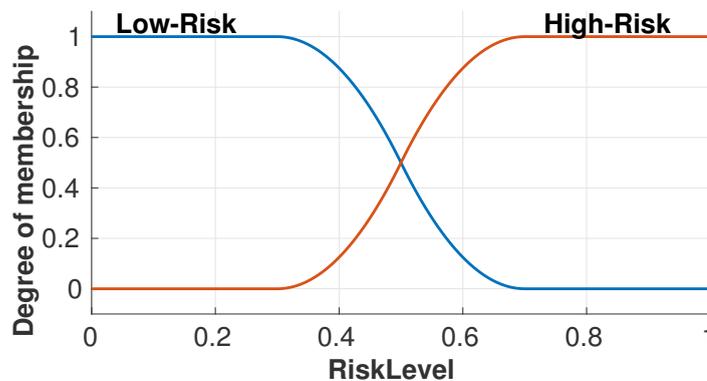


Figure 6.5: Person's Risk Level Membership Functions.

Table 6.2 shows the fuzzy rule base of the FIS. For example *If the AggScore is Low and the I_{PA} is Negligible then the Risk Level is Low*. A typical scenario of such a rule is the health assessment of a person who is resting and whose vital signs are in the normal range suggesting that he is not at risk because its current PA and vital signs match together. Another example of rules is : *If the AggScore is High and the I_{PA} is Negligible then the Risk Level is High*. A typical scenario is the health assessment of a person who is resting and whose vital signs are far from the normal range suggesting that the person is at risk because its current PA and vital signs do not match together. In this case, an emergency should be triggered because an abnormal situation is identified: the person could be having a heart attack for example.

6.5/ EXPERIMENTAL RESULTS

We have run a series of simulations to test and validate the proposed approach using Matlab. Firstly, the proposed PA intensity evaluation approach is tested and its performance is shown by comparing its results to predefined and fixed PA intensities [127]. Indeed in [127], the PAs are supposed to have fixed intensities based on the speed at which they are performed. Thus, we emphasize on the dynamicity and the ability of the proposed approach to take into consideration multiple PA characteristics as well as the

Table 6.2: Fuzzy Rule Base

Aggregate Score	PA Intensity	Risk Level
Low	Negligible	Low
Medium	Moderate	Low
High	Vigorous	Low
Low	Moderate	Low
Medium	Vigorous	Low
High	Negligible	High
Low	Vigorous	High
Medium	Negligible	High
High	Moderate	Low

person's profile (attributes) in evaluating the intensity of any PA. Moreover, the effect of the person's profile on the effort required to perform a PA is highlighted.

Second, the performance of the proposed health assessment model is evaluated. Real medical datasets are collected from the PPG During Exercise database of PhysioNet [7]. This database contains wrist PPG signals as well as a reference chest ECG which are recorded during walking, running and bike riding. The vital signs which are used for the health assessment of the subjects are the Heart Rate (HR) and Respiration Rate (RR). The latter are extracted from the ECG and PPG signals [137]. The results of the two following scenarios are compared:

- Health assessment based only on vital signs (HR and RR).
- Health assessment based on vital signs (HR and RR) and contextual information (Person's profile and PA's characteristics).

Thus, showing the interest in fusing both physiological and contextual information in the detection of abnormalities/emergencies and the identification of low risk and high risk situations.

6.5.1/ PA INTENSITY EVALUATION

In this section, we study the impact of the characteristics of a PA as well as of the person's profile (attributes) on the assessment of the intensity of PAs. Recall that the proposed PA intensity evaluation model generates the PA's intensity as $I_{PA} \in [0, 1]$ such that the closer the value of I_{PA} is to 1, the more the PA is judged to be vigorous. Whereas, the closer its value is to 0, the more the PA is judged to be light/negligible. Table 6.3 shows the association that we have created between the static/predefined PA intensity classification provided in [127] and the proposed PA intensity evaluation model. We assume the following:

- If the PA's intensity $I_{PA} \in [0, 0.5[$, then its is considered to be Light (Negligible).
- If the PA's intensity $I_{PA} \in [0.5, 0.6[$, then its is considered to be Moderate.
- If the PA's intensity $I_{PA} \in [0.6, 1]$, then its is considered to be Vigorous.

Table 6.3: Association table between a fixed PA intensity classification presented in [127] and the PA intensity values of the proposed PA intensity evaluation model.

Activity		Intensity	Intensity Value
Walking	<5 Km/h	Light	[0, 0.5[
Fast Walking	5-6 Km/h	Moderate	[0.5, 0.6[
	7 Km/h	Vigorous	[0.6, 1[
Running	≥ 8 Km/h	Vigorous	[0.6, 1]

Based on the classification provided in [127], Figures 6.6 and 6.7 show the intensity values calculated by the proposed PA intensity evaluation approach. The PA characteristics that were taken into consideration are the following:

- Speed with maximum speed set to 15 Km/h and $\alpha_{speed} = 0.8$ (c.f. Equation 6.6).
- Duration with maximum duration set to 30 min corresponding to the required time for which the intensity of the performed PA becomes stable. $\alpha_{duration} = 0.2$ (c.f. Equation 6.6).
- Inclination of the ground with maximum inclination set to 15° and $\alpha_{incl} = 0$ (c.f. Equation 6.6).

The duration and inclination were respectively fixed to 15 min and 0° during the simulation. Whereas the speed was varied for each PA intensity category. Moreover, the person's attributes (the DMs) that were taken into consideration are the following:

- Age. Please refer to Table 6.1 to view the scoring.
- Body Mass Index (BMI). Table 6.4 shows the scoring that was used based on classification found in the medical literature. If the person's BMI is less than 18.5, then he/she is underweight, if it is between 18.5 and 24.9, then the person is normal, if it is between 25 and 29.9, then the person is overweight and finally if it is greater than 30 then the person is obese.

Table 6.4: Scoring Table of the decision-maker BMI.

BMI Range	<18.5	[18.5-25[[25-30[≥30
Score	2	1	2	3

Figure 6.6 shows the results obtained for a fixed BMI of 22 indicating that the person is normal and a varying age. As shown in Figure 6.6a, for all age ranges and for a speed less than 4 Km/h, the proposed PA intensity evaluation model assessed the PA as light except for a person who is aged over 60 years old. If the latter is walking at a speed of 4Km/h, then our proposal judged his/her PA as moderate. Whereas, walking at a speed of 6 Km/h was only judged as moderate for a person whose age is between 45 and 60. However, it was judged as light for a person whose age is less than 45 and vigorous for a

person whose age is greater than 60 (cf. Figure 6.6b). Finally, Figure 6.6c shows that for all age ranges and for a PA speed varying from 8 Km/h to 14 Km/h, most of the PAs were judged as vigorous with some exceptions. For instance, the PA was judged as light if a person, whose age is less than 30 years old, is running at a speed of 8 Km/h. Whereas, it was judged as moderate for a person, whose age is between 30 and 45, is running at a speed of 8Km/h. Moreover, if a person, whose age is less than 45, is running at a speed of 10 Km/h the PA was also judged as moderate. Thus, the following conclusions can be drawn:

- The higher the speed of the PA is, the closer the PA is to vigorous and thus the higher the intensity value is.
- For a same PA, the older the person is, the greater the effort to perform it is and thus the higher the intensity value is.

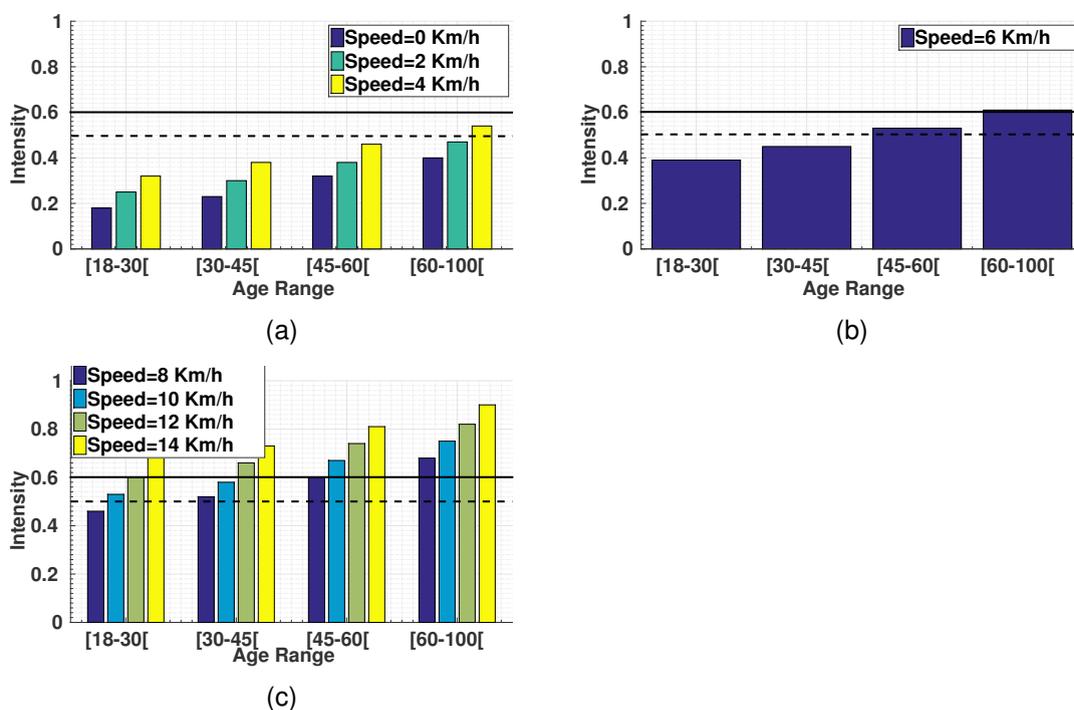


Figure 6.6: Intensity evaluation of different PAs ranging from light intensity (a) to moderate intensity (b) to vigorous intensity (c) for different age ranges and different speeds.

Figure 6.7 shows the results obtained for a fixed age of 18 indicating that the person is young and a varying BMI. As shown in Figure 6.7a, for all BMI ranges and for a speed less than 4 Km/h, the proposed PA intensity evaluation model assessed the PA as light except for a person who is obese. If the latter is walking at a speed of 4Km/h, then our proposal judged his/her PA as moderate. Whereas, walking at a speed of 6 Km/h was only judged as moderate for a person who is under weight or over weight. However, it was judged as light for a normal person and vigorous for an obese person (cf. Figure 6.7b). Finally, Figure 6.7c shows that for all age ranges and for a PA speed varying from 8 Km/h to 14 Km/h, most of the PAs were judged as vigorous with some exceptions. For instance, the PA was judged as light if a normal person is running at a speed of 8 Km/h. Whereas, it was judged as moderate for an over weight or under weight person running

at a speed of 8 Km/h as well as for a normal person running at a speed of 10 Km/h. Thus, the following conclusion can be also drawn:

- For a same PA, the farther the person's BMI is from the normal range, the greater the effort to perform it is and thus the higher the intensity value is.

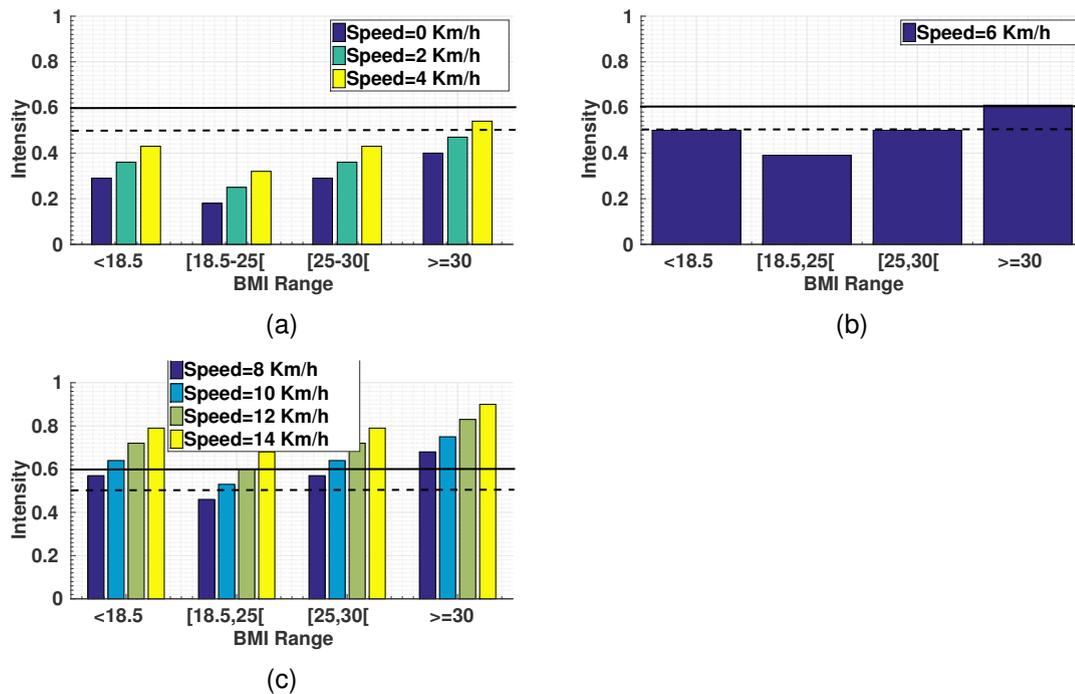
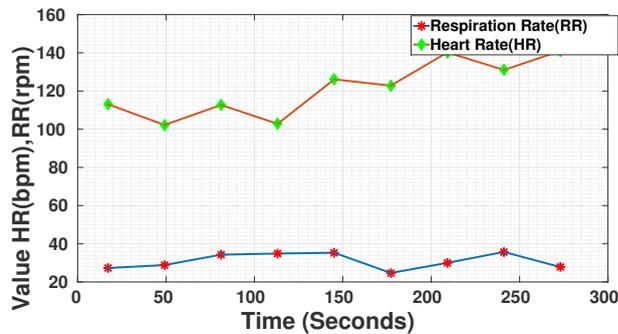


Figure 6.7: Intensity evaluation of different PAs ranging from light intensity (a) to moderate intensity (b) to vigorous intensity (c) for different BMI ranges and different speeds.

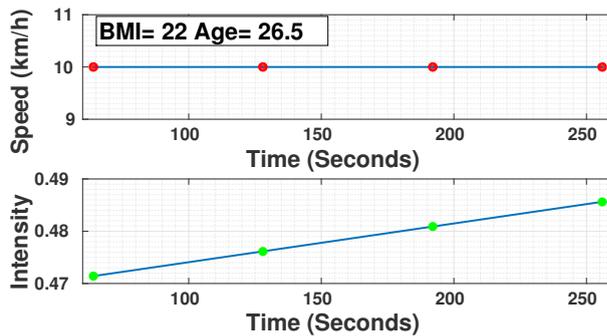
In comparison to [127], the proposed PA intensity evaluation model takes into consideration multiple PA characteristics other than the speed at which it is performed as well as the person's attributes which affect the effort required to perform it. As shown in the results, instead of having theoretically fixed PA intensity categories, the proposed approach dynamically and subjectively evaluates the intensity of PAs based on contextual information. Finally, Table 6.5 shows the intensity of walking at a speed of 6 Km/h for 20 min for two different profiles, as per the proposed PA intensity evaluation model. As shown, the PA intensity is assessed to a value of 0.44 for Profile 1 compared to 0.64 for Profile 2. Noting that the first profile represents a healthy person who regularly exercises whereas the second profile represents an overweight person who do not exercise. Thus, based on the person's profile, the same PA is judged to be light in one case and somewhat vigorous in the another case.

6.5.2/ CONTEXT-AWARE HEALTH ASSESSMENT

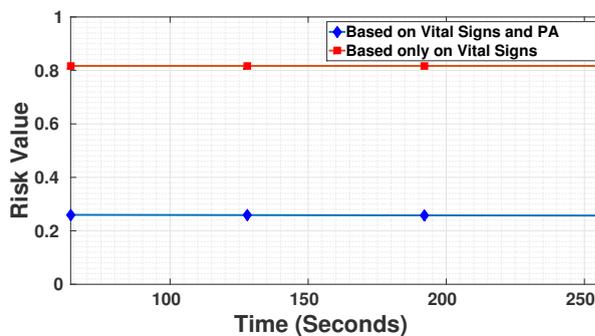
In this section the proposed context-aware health assessment model is compared to the health assessment model presented in Chapter 5. The records of the PPG During Exer-



(a)



(b)



(c)

Figure 6.8: (a) Heart Rate (HR) and Respiration (RR) of a 26 years old person, whose BMI is normal (b) Speed of PA and intensity evaluation over time (c) Proposed context-aware health assessment model vs health assessment based only on vital signs.

cise database correspond to healthy subjects (average age is 26.5) who are performing for a short period of time (between 4 to 6 min), one or more of the following activities: walk, run, pedal on an exercise bike set at a low resistance and pedal on an exercise bike set at a higher resistance [125]. We supposed that all subjects have a BMI in the normal range since no other indication was given in the database.

Figure 6.8 shows the results obtained for record s4_run. The latter subject is running at a speed of 10 Km/h during approximately 5 min. Figure 6.8a shows his/her HR and RR which are respectively extracted from the ECG and the PPG signals each 32 sec. Both vital signs are outside the normal range (51-90 bpm for HR and 12-20 rpm for RR c.f. Figure 4.1 in Chapter 4). Each 64 sec, a PA intensity evaluation as well as a

Table 6.5: Intensity of walking at a speed of 6 km/h for 20 min for two different profiles.

Profile	Age	BMI	Fitness Level (min/week)	Intensity
1	25	20	450	0.44
2	25	28	0	0.64

health assessment are performed. Figure 6.8b shows that, given the person's profile, the proposed PA intensity evaluation model considered running at a speed of 10 Km/h during 5 min as moderate. An intensity value of approx 0.48 was assigned to the PA. Based on the person's vital signs and the performed PA, the proposed context-aware health assessment model assessed the situation as a low risk (0.36) compared to a high risk (0.82) as per the health assessment model presented in Chapter 5. This is due to the fact that our model takes into consideration not only the vital signs but also the information available about the PA that is being performed by the person. Thus, the proposed approach has correctly classified the record whereas the other model, which only takes into consideration the person's vital signs, has wrongly classified the record. All the records were classified as low risk by the proposed context-aware health assessment model. We would like to emphasize that the records that included moderate to vigorous activities such as running and pedaling on an exercise bike set to a high resistance (level 6 to 8) were correctly assessed by the proposed approach and were classified as low risk resulting in the absence of false alarms.

6.6/ CONCLUSION

In this Chapter, a context-aware health assessment model was proposed. It is composed of two modules: PA intensity evaluation and health assessment. Contextual information such as the person's profile and the physical activity being performed were taken into consideration for the health assessment. We proposed to subjectively assess physical activities based on the person's profile using hesitant fuzzy sets. The results show that the PA intensity evaluation model subjectively assessed activities compared to another approach in the literature which considers fixed classifications. Moreover, the results showed that there were no false alarms when assessing the health condition of people that are performing moderate or vigorous activities.

REAL APPLICATION: REAL-TIME STRESS DETECTION & EVALUATION

Stress is a physical, mental or emotional factor that causes bodily or mental tension. It is generally recognized as one of the major factors leading to a spectrum of health problems. Therefore, people with high risks of getting stressed should be continuously monitored in order to detect any stress signs before it causes health problems. Wireless body sensor networks (WBSNs) provide opportunities to monitor stress and can provide initial treatment. In this chapter, we propose an energy-efficient stress detection and evaluation framework by adapting the previously presented techniques to the application of interest.

7.1/ INTRODUCTION

Stress is your body's way of responding to any kind of demand. It can be caused by emotional, mental or physical situations. It is a common problem that affects almost all of us at some point in our lives. Stress detection and monitoring technology have the potential to help people better understand and release stress by increasing their awareness of higher levels of stress that would otherwise go undetected. Stress and physiological signs are correlated. For example when a person is in a stress situation, his/her body releases hormones like adrenaline and cortisol which causes an increase of the heart rate and stronger contractions of the heart muscle. Stress can be monitored by using a Wireless Body Sensor Network (WBSN) which is a self-configuring network composed of small biosensor nodes, communicating using radio signals.

Many existing approaches have been proposed to detect stress levels using the human being's physiological signals. In these approaches, authors have used neural networks (NN), which firstly need to be trained, to determine the stress level using as input the captured physiological signals. In these approaches, stress is calculated offline using physiological signals data which are previously collected by biosensor nodes, and only after several hours or even days the person is able to know his/her stress level. Most of the existing approaches, require a huge amount of data to train the system in order to calculate stress levels. However, nowadays, there exists no medically verified data sets that prove and determine accurately stress level based on human physiological signals. This means that in these works, unverified data has been used for the training phase of the system, therefore we cannot confirm that these approaches have yielded

accurate stress detection and evaluation. Another challenge directly related to WBSNs is the energy consumption due to the continuous transmission of data. In a WBSN, data transmission consumes the most power, consequently the sensors' lifetime is reduced. Therefore, data transmission should be then taken into consideration.

In this chapter, we propose a real-time stress detection framework using a wireless biosensor node and a fuzzy inference system (FIS). First, the skin conductance (SC) is analyzed. If stress signs are detected, then stress level is evaluated via the FIS based on the monitored person's vital signs. These vital signs are: the Heart Rate (HR), the Respiration Rate (RR) and the Systolic Blood Pressure (ABPSys). Our method requires analyzing the SC signal on the coordinator to detect stress signs. The chosen vital signs are the most affected by stress when it occurs. In our proposed approach, the stress level evaluation process is only triggered when the coordinator detects stress signs, therefore data transmission is reduced and the biosensor nodes' energy resources last longer.

The remainder of this chapter consists of a state of the art in relation with stress detection presented in Section 7.2. The system's architecture is presented in Section 7.3. The stress detection system is described in detail in Section 7.4. An evaluation of the system is provided in Section 7.5. Section 7.6 shows and discusses some preliminary results. Finally, Section 7.7 concludes the chapter.

7.2/ RELATED WORK

Different existing approaches and techniques have been proposed and developed to study a subject's stress level. In [99], a real-time personalized stress detection algorithm using the heart rate and the body temperature as inputs to a fuzzy logic system is proposed. In [30], the authors have developed a fuzzy logic system to detect stress in real-time. However, only two physiological signs have been used and no further analysis or assessment of the stress level is provided. Nonetheless, it is not common to focus only on one or two physiological signals but to focus on many of them in order to obtain further and more precise information about the stress level. Considering this multimodal approach, there are several articles which study a variety of parameters and signals, as well as the combination of them [26, 68]. Most of these approaches use deep learning or support vector machine (SVM) [27, 89] to determine the stress level of an individual. However, no explanation about the used data in the training phase of these intelligent systems is provided neither the data that is used are provided. In modern days, there exists no medically verified data for stress that can be used to train a deep learning system to correctly calculate the stress level. Therefore, the existing approaches have been trained using proprietary stress related data making the algorithms imprecise and not generalized. While in other approaches, a limited number of physiological signs have been used to detect stress, thus decreasing their robustness and accuracy. Most of the previously mentioned approaches do not operate in real-time, but rather operate in two phases: first the data is collected then it is analyzed offline to get the results. To the best of our knowledge, none of the stress detection approaches in the literature have given any concern about the energy consumption that reduces the sensors' lifetime.

In this chapter, a real-time stress detection and evaluation approach is proposed. It uses multiple vital signs as input and determines the stress level using a FIS. It also takes into consideration the data transmission to maximize the sensor nodes' lifetime.

We develop a system composed of a Shimmer3 GSR+ sensor node and by extracting the HR, the ABPSys and the RR, the stress level is calculated. An android application is developed to test the proposed approach and the whole system.

7.3/ SYSTEM ARCHITECTURE

Figure 7.1 shows the system architecture of the proposed stress monitoring application. The two main components of the network are the biosensor node and the coordinator. The former is attached to the person's wrist and has a PPG sensor and a GSR sensor. The latter is the person's smartphone. The two devices communicate wirelessly via bluetooth. The coordinator performs both the detection and the evaluation of the stress. The former is done based on the person's average skin conductance (SC) over a time period, such that the SC is extracted from the GSR signal. The latter is done based on the person's vital signs (HR, RR and ABPSys) which are extracted from the Photoplethysmogram (PPG) signal. The stress evaluation process is triggered only when the coordinator detects stress signs. In the following sections, the stress detection and evaluation processes as well as the extraction of the SC and the vital signs are explained.

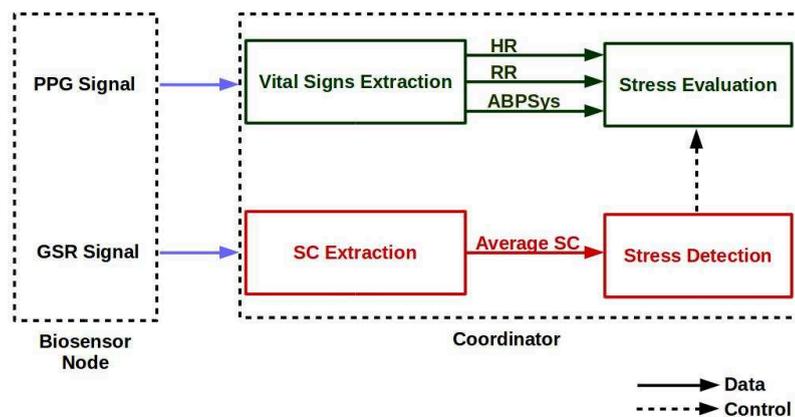


Figure 7.1: System Architecture

7.4/ STRESS DETECTION

In our proposed method, the coordinator continuously receives skin conductance (SC) measurements from the GSR sensor node. In order to reduce the transmission of data, we propose to use the lowest sampling frequency possible (1 Hz [169]) indicated by the constructor of the sensor node. The Stress Detection Algorithm *StressD* operates as follows (cf. Algorithm 3). A window size of 10 minutes is required to detect stress, thus the coordinator must record the received SC measurements. Stress detection can be made by calculating the average of the SC measurements over a time window of 10 minutes. If the average is above the normal range (greater than 1 MOhm [169]), then the person is going through a stress episode and stress should be evaluated to determine its level. If the average is within the normal range, then the person has not reached

a stress episode yet. In both cases, we use a sliding time window of 10 minutes to recalculate the SC average after a time period T of two minutes. The SC average should only be considered when the person is not doing some physical efforts. During sports, the person skin glands produce a lot of sweat to keep his/her body cooled down, therefore, the SC measurements exceed the normal range. In our work, we suppose that the WBSN can detect physical activity using the accelerometer feature in the used sensors and only evaluates the stress level when the person's high SC is not related to physical effort. T is a time period that allows the coordinator to calculate the stress level frequently. Its value is updated depending on the evaluated stress level.

Algorithm 3 Stress Detection Algorithm

Require: Time period T , SC Threshold $threshold = 1M\Omega$

```

repeat
  Store the received SC data
until  $ReceivingTime > 600000$  ms
  Initialize  $T$  to 5 mins
  Set  $calcStress = True$ 
  Calculate  $avgSC$  average of received SC data
repeat
  if  $avgSC > threshold$  then
    Evaluate  $StressLevel$ 
    if  $StressLevel > 3$  then
      repeat
        Re-Evaluate  $StressLevel$  after time period  $T$ 
        Update  $T$ 
      until  $StressLevel \leq 3$ 
       $calcStress = false$ 
    else
       $calcStress = false$ 
    end if
  else
    Re-calculate  $avgSC$  each  $T = 2$  mins over a sliding window of 10 mins.
  end if
until  $calcStress = false$ 

```

When stress is detected from the SC data, the coordinator will first ask to receive PPG signal to determine vital signs values and then calculate the stress level immediately, then after each time period T , the stress level will be re-calculated until its value is within the normal range, then in this case the stress detection algorithm will stop.

7.5/ STRESS EVALUATION

Stress evaluation is done using a FIS and the following vital signs: the HR, the RR and the ABPSys. In the following, we show the correlation between each of the vital signs and stress and we explain the methods used to extract them from physiological signals. Then, we present the components of the FIS. Vital signs and stress are highly correlated. Indeed the HR, RR and ABPSys vary and exceed the normal range when a person is experiencing acute stress due to an increase of the amounts of hormones in his/her body.

- *The Heart Rate:* When a person is under a stressful situation, the body increases

the production of stress-hormones known as adrenaline, noradrenaline and cortisol. During this moment, the blood vessels dilate which leads to an increase in the HR.

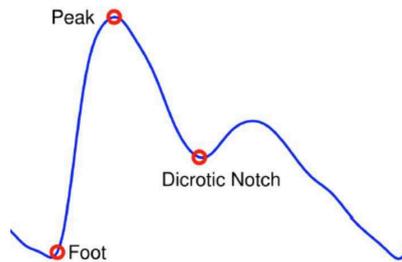


Figure 7.2: PPG Waveform

The HR can be calculated from the PPG signal (shown in figure 7.2) using the following equation:

$$\frac{60 * x}{TimeToDetect(s)} \quad (7.1)$$

x (number of peaks) is specified in the setup phase of the coordinator. The higher x is, the more accurate the HR value is. However, the extraction will require more processing time. In this chapter, we set x to a default value of 3.

- *The Blood Pressure:* Acute stress is accompanied by an increase of the ABPSys. Short-term stress-related spikes in the blood pressure added up over time may put the person at risk of developing long-term high blood pressure. ABPSys can be predicted from the PPG signal. According to [1], ABPSys, for an adult aged 18 and above, is calculated using the following equation:

$$ABPSys(mmHg) = (-0.6881 * PTT) + 210.94 \quad (7.2)$$

where PTT represents the pulse transit time in milli-seconds (ms). To calculate PTT, the time interval between a waves peak of the PPG signal and the Dicrotic notch of the same waveform is determined (c.f. Figure 7.2).

- *The Respiration Rate:* When a person is under acute stress, the RR increases to distribute oxygen and blood quickly to the body core. If the stress level is very high, it may lead to Tachypnea having severe consequences on people with breathing or heart disease problems. To calculate the RR, there exists an algorithm called "Multi-parameter Respiratory Rate Estimation From the Photoplethysmogram" [57] which consists of studying the variations of the PPG signal values (frequency, intensity, and amplitude) over a fixed time window to calculate the RR.

We have chosen to use a FIS because it is an intelligent decision system that uses several variables as input to determine the output and it is easy to implement and configure in a mobile application. Also, in a FIS the training phase can be skipped, as long as we know the domain we are modelling and its reaction/behaviour rules. Moreover, the readings of medical data such as the vital signs can be vague and imprecise as well as the evaluation of the stress level follows a human-reasoning logic, thus the FIS is appropriate to the type of data and reasoning since it uses fuzzy logic. According to the universal pain assessment tool [139], stress is measured in a scale of 1 to 10, 10 being the highest level. Table 7.1 shows the average range of each vital sign with its corresponding stress level.

Table 7.1: Stress categories

	Low Stress	Medium Stress	High Stress
HR (Bpm)	40-70	70-90	>90
RR (Rpm)	8-16	16-20	>20
ABPSys (mmHg)	80-120	120-139	139
Stress Level	0-3	3-7	7-10

The FIS has three inputs: the HR, the RR and the ABPSys and has one output: the stress level. For this purpose, membership functions are defined for the three inputs as well as for the output. The membership are in a ramp shapes which are built according to Table 7.1. In the proposed approach, the FIS rules are defined manually based on national health organization reports on stress and its effect on a person's vital signs.

When the coordinator detects stress signs based on the SC values, it orders the sensor node to stop streaming SC data and to start sending the PPG signal, and then it orders the sensor to stop when the vital signs are extracted. We propose to adapt the time period T at which the stress level is evaluated according to the evolution of the stress level value as follows:

- If the stress level is high, T decreases in order to evaluate the stress level more frequently.
- If the stress level is low, T increases in order to reduce the frequency at which the coordinator requests the PPG signal and evaluates the stress level and then it preserves its processing and energy resources.

When the stress level reaches the normal range (below 3), the stress detection process repeats from the beginning, where the system detects stress from the SC data.

7.6/ PRELIMINARY RESULTS

The coordinator is a smartphone running an Android application implementing the proposed stress detection and evaluation approach. It uses Bluetooth to communicate with the Shimmer3 GSR+ sensor node. The experiment was made on a person doing an oral presentation. The main outcome of the experiment is to test the coherence and accuracy of the proposed FIS and minor interest was given to the stress detection phase. The sensor node was configured to send the PPG signal to the coordinator for the vital signs extraction. The collection of the person's vital signs started before the beginning of his presentation in order to view how they change when he encounters stress.

Figures 7.3a, 7.3b and 7.3c show the variation of HR, ABPSys and RR respectively over time during the three following stages: before the presentation, during the presentation and after the presentation (during question time). Figure 7.3d shows the stress level variation during the three stages of the experiment. As shown in the figures, at the beginning the vital signs are in the normal. Then, they increase when the person starts his presentation to reach important levels during the presentation. This does not mean that stress is the only reason for this increase but could be a main one. We can see how the stress level is at a low level before the person has started the presentation. Then,

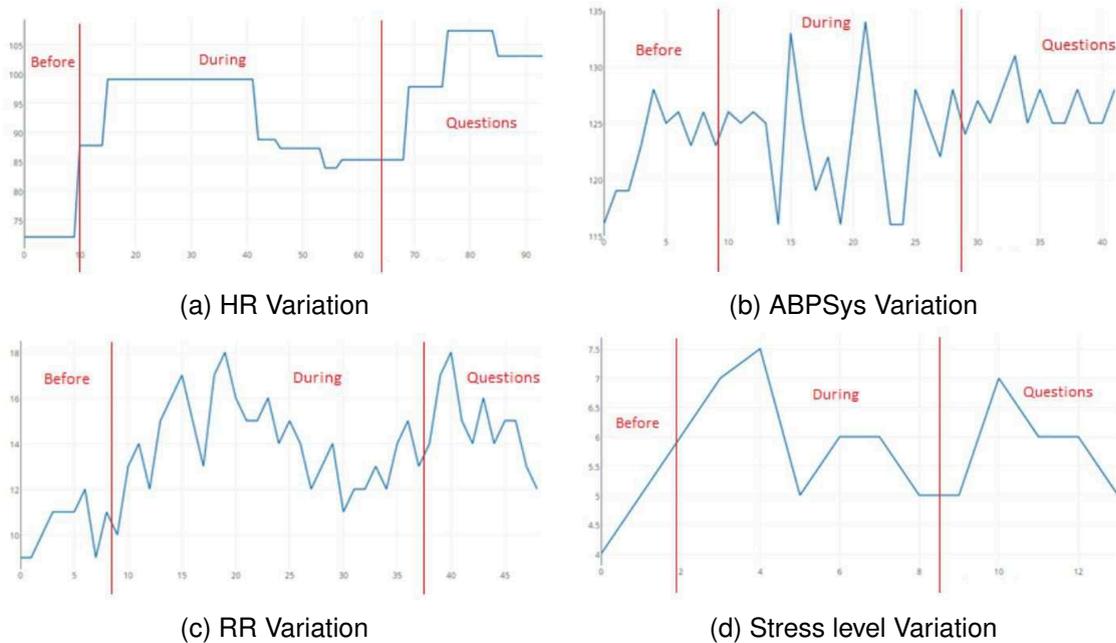


Figure 7.3: Vital signs and stress level variation along the oral presentation.

it reaches medium level and at some instants high level during the presentation and the question stages. In our experiment, stress level is evaluated based on the HR, ABPSys and RR. We cannot say that our approach gives precise results in stress level determination, because, there exists no medically proven method or data that can be used to accurately determine stress level using vital signs. However, based on these results, it is clear that vital signs are correlated with stress level. When a person is stressed, his/her vital signs exceed the normal range and when he/she is relaxed they are in the normal range. Moreover, the stress evaluation process yielded coherent results with the three different experiment stages of the oral presentation. Therefore, our approach is well designed and its implementation has given a good evaluation of the stress level.

7.7/ CONCLUSION

In this work, we have proposed a real-time stress detection and evaluation framework using WBSN. Our method consists of analyzing the SC signal transmitted by the GSR sensor node to the coordinator. When stress signs are detected the coordinator requests the PPG signal from the PPG sensor node to extract the vital signs and evaluate the stress level using the FIS. The results show that the proposed approach gave a good prediction of the stress level.

IV

CONCLUSION & PERSPECTIVES

CONCLUSION & PERSPECTIVES

8.1/ CONCLUSION

In this thesis, data collection as well as data fusion approaches for wireless body sensor networks have been proposed in order to ensure continuous health monitoring. Several constraints have been taken into consideration while designing the models. Some constraints characterize WBSNs while others characterize the collected data. For instance, biosensor nodes are characterized by limited energy resources that rapidly get depleted due to periodic transmission as well as sensing and processing the acquired data. Moreover, the collected data is of huge amount, present redundant information, is heterogeneous, imprecise, ambiguous and sensitive. It includes vital signs, motion signals and other type of medical and personal data. Such data are interpreted in a human-reasoning logic in order to infer high-level information. Furthermore, important requirements of healthcare applications were taken into consideration such as accuracy and quality of service while designing the proposed approaches.

This dissertation is composed of two parts: the first part covers the scientific background of WBSNs, whereas the second one presents the contributions that have been made in this thesis. First, recent advances in WBSNs have been presented. A general overview about the architecture of WBSNs and the composition of biosensor nodes was given. The different types of the most commonly used biosensor nodes in WBSNs have been presented and some of the commercially available nodes on the market were listed. A special focus has been given to healthcare applications that are based on WBSNs. A classification of the latter was provided on the basis of the target monitoring task that is aimed. Finally, the requirements that any healthcare application must respect in order to ensure user as well as medical acceptance and satisfaction were highlighted.

Second, given that an energy-efficient data collection approach was proposed in this thesis, the most relevant energy-efficient data collection techniques, that are found in the literature, were covered. A classification of these techniques was provided on the basis of the targeted energy-consuming task: sensing, processing and communication. Then, energy-harvesting techniques were presented. This technology is promising but is still in its early stages. Furthermore, a discussion was provided about the trade-off between energy-efficient mechanisms and the requirements that healthcare applications should ensure. The requirements include: accuracy, delay, QoS, mobility, robustness, security and privacy. Moreover, a discussion about cross-layer approaches as well as about the potential of combining different energy-efficient mechanisms was made. Additionally, combining energy harvesting and energy-efficient mechanisms in order to ensure a self-

sustainable WBSN was discussed. Finally, we have concluded that any energy-efficient data collection technique must not compromise data accuracy especially that WBSNs collect medical and sensitive data. Furthermore, we have motivated the combination of different energy-efficient mechanisms in order to maximize the network's lifetime.

Third, data fusion is another challenge that was tackled in this thesis. Indeed, proposing multi-sensor fusion models for WBSNs was another objective in this thesis. Therefore, data fusion and multi-sensor fusion in WBSNs were defined. Multi-sensor based healthcare applications were motivated rather than single sensor based applications. Moreover, three classifications of multi-sensor fusion approaches were provided based on different aspects of the fusion. Then, the challenging aspects of the collected data in WBSNs were presented and discussed. Furthermore, high-level fusion challenges were briefly discussed. Finally, a discussion highlighting that data fusion in WBSNs is application-specific and that no single algorithm can solve all the data-related challenges was made. Furthermore, a focus is brought to the fact that data fusion approaches should not only take into consideration the energy and processing resources of biosensor nodes but also the resources of the coordinator of the network.

In the second part of the dissertation, the contributions were presented. First, a self-adaptive data collection approach is presented. It allows biosensor nodes to adapt their sampling rate in real-time and to locally detect emergencies. The proposed approach targets the energy consumption due to sensing and transmission by means of data reduction. The results show that more than 50% of data reduction is achieved at the level of sensing and more than 80% of data reduction is achieved at the level of transmission with a negligible loss of information (Mean Square Error ≈ 0.05) and the energy consumption is 10 times decreased over one hour of continuous monitoring.

Second, a multi-sensor data fusion model providing continuous health assessment is presented. Vital signs collected by different biosensor nodes are fused by the coordinator in order to infer a health assessment on a scale from 0 to 1. The higher the value, the more the monitored person is at risk and the lower the value, the less the monitored person is. The results show that compared to an existing data mining based approach, the proposed approach has coherently assessed vital signs as well as the patient's health condition. Furthermore, by combining the proposed data collection technique with the proposed multi-sensor data fusion model, the network's lifetime is increased without compromising information accuracy as compared to the other existing approach.

Given that vital signs are correlated to physical activity, performing health assessment in a context-aware setup increases the reliability of data fusion. Therefore, a context-aware multi-sensor data fusion model is thirdly presented. We have proposed to subjectively evaluate the intensity of physical activities by taking into account the person's profile and the characteristics of the physical activity. A physical activity intensity evaluation model based on hesitant fuzzy sets is proposed. The results show that for a same physical activity, its intensity classification varies from one subject to another. This is due to the fact that the proposed approach takes into account the persons' profile when evaluating his/her current physical activity. Moreover, the results show the proposed context-aware health assessment model reduces false alarms and enhances the health assessment.

Finally, a specific healthcare application was targeted by adapting our proposed approaches. A real-time stress detection and evaluation framework was presented. Real experiments were conducted by using Shimmer 3 GSR+ as a node to collect the data and an android mobile application was developed in order to process the collected data and

perform the data fusion. Preliminary results are promising.

8.2/ PERSPECTIVES

In this thesis, data collection and fusion models were proposed to ensure continuous health assessment and to detect emergencies when they occur. In fact, the perspectives to consider are numerous in a domain that continuously evolves and that has great potential in changing people's lives. Notwithstanding, specific perspectives, for each of the contributions that have been proposed, will be firstly discussed. Afterwards, general perspectives that target different lines of research will be provided.

First, the proposed energy-efficient data collection is two-fold. It consists of an adaptive sampling rate model and of a local emergency detection model. The sampling rate of nodes is adapted using Quadratic Bezier curve as a behavior function and One-way ANOVA coupled with Fisher test to statistically study the collected measurements. Other statistical tests that can be applied on medical data could be exploited and compared to the used method. Moreover, other types of behavior functions could be proposed and compared to the performance of the proposed adaptive sampling rate scheme. In our proposal, the local detection of status changes and emergencies requires early warning score systems. Such scoring systems are available in the medical literature for vital signs and human behavioral aspects. The first question that comes to the mind is how can local detection be provided for other types of physiological parameters such as signals like the ECG, PPG and body acceleration? For these type of data, what is more energy-efficient: transmitting the sensed raw signals to the coordinator or performing some on-node processing to detect emergencies and send only informative data? Another issue that comes to the mind is that, when applying adaptive sampling, raw data showing the evolution of a specific physiological parameter over time is lost. This motivates reconstruction algorithms and techniques that can be applied to regenerate the pseudo-original data based on the received data. Finally, the proposed approach could be studied at the level of processing energy and resources it requires and compared to other emerging techniques such as compressive sensing.

Second, the proposed multi-sensor fusion approach employs the aggregate score of vital signs. Driven by the fact that the persistence of a vital sign in a given state is a reliable indicator of change, a smoothing technique was proposed in order to smooth sudden score changes that could be due to faulty measurements and to regularly update scores. However, other features could be taken into consideration in the multi-sensor fusion. For instance, the correlation between vital signs could be exploited to better detect emergencies, reduce false alarms and identify malfunctioning nodes. Indeed, the aggregate score can be affected by outliers and faulty measurements. Hence, the potential of combining the aggregate score with the knowledge of correlation that exists in vital signs on reducing false positives and identifying erroneous sensor nodes.

Third, the proposed context-aware multi-sensor fusion approach requires motion sensors attached to the patient body. Thus, a deeper study can be provided concerning their energy-efficient management and operation in the network. For instance, we have mentioned in our proposal that motion sensors only transmit data when the coordinator detects an abnormal aggregate score. However, no further study is provided concerning the context-based pull mechanism and its effect on the energy consumption of the network.

Moreover, the proposed physical activity intensity evaluation model employs quantitative variables to represent the person's profile such as age, BMI, average minutes of exercise per week etc. What if qualitative variables, which are essential in representing the person's profile are to be used? How can they be integrated? Some of these variables include sex and medical record (yes/no information regarding diseases, allergies, medicine intake etc.). Thus, another future work that can be considered is the integration of qualitative variables in assessing physical activities and vital signs.

Fourth, the proposed stress detection and evaluation framework is tested in a specific scenario. In fact, a PhD student will surely present some signs of stress when presenting his thesis in front of the audience. Clearly, the proposed framework identified stress episodes coherently with the steps of the thesis presentation. However, this work opens up many perspectives. What about if the stress detection was to be performed in everyday life? What sort of information should it integrate in order to accurately identify stress episodes? Facial expressions and body behavior are key elements in stress. Therefore, combining heterogeneous sources of information constitute a great challenge to achieve a reliable stress monitoring application. Recent advances in data science, suggest using deep learning as a mean to infer high level information from incomprehensible and complex data relationships.

Finally the works that have been done in this thesis open up limitless perspectives in different lines of research. For instance, context-awareness is mostly exploited in ambient assisted living solutions where the user is surrounded by connected objects. It enables context-aware services which can be proposed to the user. Such services include medical advice, reminders, rehabilitation follow-up and evaluation as well as suggestions. In the domain of healthcare applications, combining WBSNs with other sources of information such as ambient/environmental sensors and medical records allows to assess the patient's health condition in terms of its surroundings. Thus, a complete analysis and study of behavioral patterns can be made by studying specific diseases such as Alzheimer and predicting life-threatening diseases such as heart attacks. Multiple challenges arise in a heterogeneous network where massive amounts of data are periodically collected. On one hand, data management constitutes a domain apart. It encompasses data reduction, aggregation, processing, fusion, analysis and storage. With the emergence of edge computing, data analysis techniques and complex algorithms can be achieved close to the end user, thus ensuring timeliness. Delay is then taken into consideration by creating time-critical and powerful healthcare applications. At the level of WBSNs, specifically approaching the energy consumption requirement, the proposed data collection technique could be complemented by an energy-harvesting technology and tested in a real implementation setup to study the self-sustainability of such a network. Furthermore, context information can be used in order to provide energy management in the network. For instance, the proposed physical activity intensity assessment model could be used to manage the operation and the power-on time of accelerometers placed on the person's body. Two important aspects that have been not studied in this thesis are privacy and security. The proposed data collection technique can be complemented by a privacy mechanism that anonymizes the gathered data of different WBSNs existing in the same location (hospital, nursing home etc.). Furthermore lightweight encryption algorithms can be implemented at the level of the nodes to ensure secure data transmission. Finally, a real implementation of the proposed approaches is desirable in order to validate them and to study user and medical satisfaction.

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