Health Risk Assessment and Decision-Making for Patient Monitoring and Decision-support using Wireless Body Sensor Networks

Carol Habib[a,b,*], Abdallah Makhoul[a], Rony Darazi[b], Raphaël Couturier[a]

[a] *Univ. Bourgogne Franche-Comté, Femto-st institute, Belfort, France*
[b] *Antonine University, TICKET Lab, Hadat-Baabda, Lebanon*

Abstract

This paper proposes a generalized multi-sensor fusion approach and a Health Risk Assessment and Decision-Making (Health-RAD) algorithm for continuous and remote patient monitoring purposes using a Wireless Body Sensor Network (WBSN). Health-RAD determines the patient's health condition severity level routinely and each time a critical issue is detected based on vital signs scores. Hence, a continous health assessment and a monitoring of the improvement or the deterioration of the state of the patient is ensured. The severity level is represented by a risk variable whose values range between 0 and 1. The higher the risk value, the more critical the patient's health condition is and the more it requires medical attention. Moreover, we calculate the score of a vital sign using its past and current value, thus assessing its status based on its evolution during a period of time and not only on sudden deviations. We propose a generalized multi-sensor data fusion approach regardless of the number of monitored vital signs. The latter is employed by Health-RAD to find the severity level of the patient's health condition based on his/her vital signs scores. It is based on a fuzzy inference system (FIS) and early warning score systems (EWS). This approach is tested with a previously proposed energy-efficient data collection approach, thus forming a complete framework. The proposed approach is evaluated on real healthcare datasets and the results are compared with another approach from the litera-

*Corresponding author

Email addresses: carol.habib@univ-fcomte.fr (Carol Habib), abdallah.makhoul@univ-fcomte.fr (Abdallah Makhoul), rony.darazi@ua.edu.lb (Rony Darazi), raphael.couturier@univ-fcomte.fr (Raphaël Couturier)

ture in terms of data reduction, energy consumption, risk assessment of vital signs, the patient's health risk level determination and accuracy. The results show that both approaches have coherently assessed the health condition of different Intensive Care Unit (ICU) patients. Yet, our proposed approach overcomes the other approach in terms of energy consumption (around 86% less energy consumption) and data reduction (around 70% for sensing and more than 90% for transmission). Additionally, contrary to our proposed framework, the approach taken from the literature requires an offline model building and depends on available patient datasets.

Keywords:
WBSN, multi-sensor data fusion, fuzzy theory, patient's health risk level, EWS, decision-making

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1. Introduction

According to the World Health Organization (WHO), the number of people aged 65 or older is projected to grow from an estimated 524 million in 2010 to nearly 1.5 billion in 2050, with most of the increase in developing countries. Moreover, wearable health monitoring systems (WHMS) are expected to become more available and have a larger impact on people's life, thus promoting a better quality of life (QOL). In the last decade, Wireless Body Sensor Networks (WBSNs), a subset of wireless sensor networks (WSNs), drew the attention of researchers due to their attractive low cost and diverse healthcare application potential. This technology ensures a remote and continuous monitoring of the patient's health condition, therefore reducing healthcare expenditures [1]. Most popular and needed monitoring scenarios include the surveillance of the elderly in nursing homes and in-home monitoring of chronic or acutely ill patients, especially after a surgical intervention. Many applications have been addressed in the literature so far such as gait analysis, monitoring vital signs [2], daily activities [3], fall detection systems and stress evaluation systems [4, 5].

In our approach, the WBSN consists of biosensor nodes and a coordinator. First, the nodes are placed on the patient's body and they continuously sense vital signs such as the oxygen saturation, the respiration rate, the skin temperature, etc [6, 7]. We suppose that each biosensor node only senses one vital sign. Second, the coordinator can be the patient's smartphone, pda or any other portable devices [8]. It receives the collected physiological data in order to perform the multi-sensor data fusion and routinely takes decisions and when emergencies occur. Such emergencies are called critical events since they are triggered when abnormal variations, such as an increase in the heart rate indicating a tachycardia or a decrease in the heart rate indicating a bradycardia, of the vital signs are detected. Moreover, the coordinator alerts the patient when critical events are detected and sends the collected data and the taken decisions to the medical center or any other destination for storage and further analysis [9].

However, 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 [10]. 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 take the corresponding decision. Several data analysis and processing approaches in WBSNs for anomaly detection, prediction and decision making [11, 12] 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.

In a previous work [13], a specific 5 vital signs multi-sensor data fusion model, based on a FIS and EWSs, was introduced. The major contributions of this paper 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 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 wireless body sensor 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.
3. Further experiments are performed to validate the proposed multi-sensor data fusion approach, combine it with a previously proposed energy-efficient data collection technique [14], thus forming a complete framework (from data collection to fusion), and compare it with an existing approach [15] 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 paper is organized as follows. Section 2 presents the related work. Section 3 presents some background work related to our proposed approach and the complete framework. The multi-sensor data fusion model is explained in section 4. Then, Health-RAD is presented in section 5. Experimental results are shown and discussed in section 6. Finally section 7 concludes the paper with some directions and future work.

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, inconsistancy 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 [16]. Assessing the health condition of a patient suffering from a particular disease or an acutely-ill patient, such as in our scenario, requires a continous 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 [17, 18, 19]. For instance, Shoaib et al. [20] have 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: Begum et al. [2] have proposed a physiological signal classification technique based on multisensor data fusion and case-based reasoning in order to asses the stress level of the individual being monitored. The matching between cases is done using fuzzy logic [5]. Lee and Chung [21] have 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: Wang et al. [22] have 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. Pantelopoulos and Bourbakis [23] have proposed a physiological data fusion model for multisensor WHMS called Prognosis. The proposed model generates the prognoses of the patient's health conditions using fuzzy regular language and fuzzy finite-state machine. Apiletti et al. [15] have 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 [15] 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 [15] to demonstrate the effect of data reduction on the fusion and the energy consumption in the WBSN.

3. Background

In this section, early warning score systems are presented and the data collection technique which we have adopted in the proposed framework. The former is used by the sensor nodes and the coordinator to assess vital signs [24]. The latter is a previously proposed approach [14] which reduces the amount of sensed and transmitted data to the coordinator, thus extending the network's lifetime.

3.1. Early Warning Score System

An early warning score system (EWS) is a chart used by emergency medical services staff in hospitals to determine the severity level of a specific illness that patients are suffering from or more generally to ascertain their heath status. It is used as a systematic protocol for the measurement and recording of the vital signs. Afterwards, the vital signs are weighed and aggregated in order to allow an early recognition of patients who are subject to an acute illness or those whose health condition is deteriorating [25]. For each vital sign, a normal healthy range is defined. Values outside of this range are allocated a score according to the magnitude of the deviation from the normal range. The score weighing reflects the severity of the physiological disturbance. Since our approach aims at early detecting emergencies, such scoring systems can give the biosensor nodes the ability to locally detect criticalities and only send the important changes in vital signs to the coordinator by computing their scores.

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.

Royal College of Physicians

NHS Training for Innovation

Figure 1: Early Warning System

Figure 1 shows the National EWS (NEWS) which has been used in our work. NEWS is standarized and employed in hospitals in the United Kingdom (UK) for the assessment of acute-illness severity [26]. For example, as shown in Figure 1, if the respiration rate is between 12 bpm and 20 bpm then the measurement is given a score of 0 indicating that it is in the normal range. However, if the measurement is outside of this range a score of 1, 2 or 3 is given to it according to its level of severity/criticality. For example, if the respiration rate is between 21 bpm and 24 bpm then a score of 2 is given to it. In our work, we have used the measurement ranges defined by NEWS to compute the scores of any of the following vital signs: the respiration rate, oxygen saturation, temperature, systolic blood pressure and heart rate.

Next, the data collection algorithm, which is proposed in a previous work [14], running on the biosensor node level, is briefly discussed.

3.2. Data Collection

In a previous work [14], we have proposed a local emergency detection and adaptive sampling algorithm (*Modified LED**) at the biosensor node's level. WBSNs are periodic sensor networks in which huge amounts of data such as vital signs are collected for monitoring needs. Our goal is to reduce the amount of sensed data by the biosensor node as well as the transmitted measurements to the coordinator. On the one hand, *Modified LED** adapts the sampling rate of the biosensor node in accordance to the dynamic evolution

Algorithm 1 Modified Local Emergency Detection with Adaptive Sampling Algorithm *Modified LED**

Require: m (1 Round = m periods), R_{max} (maximum sampling rate), r^0, α

Ensure: R_t (instantaneous sampling rate), N Number of sensed measurements.

```
R_t ← R_max
while Energy > 0 do
    for each round do
        for each period do
            takes and sends first measurement r_0
            gets score S of r_0
            takes measurements r_i at Rate R_t
            gets score S_i of measure r_i
            if S_i != S then
                sends measurement r_i
                S = S_i
            end if
        end for
        compute SR, SF and F.
        if N < m then
            R_t ← R_max
        else
            find F_t given α such that F_t = F_α(m − 1, N − m)
            if F < F_t then
                R_t ← BV(F, F_t, r^0, R_max)
            else
                R_t ← R_max
            end if
        end if
    end for
end while
```

of the monitored vital sign and its monitoring importance. This is done using the Fisher Test with One-way ANOVA to study the inter-variances (SF) and the intra-variances (SR) of the collected measurements in m consecutive periods. The result F of the Fisher Test is calculated as follows:

$$F = \frac{SF/(m-1)}{SR/(N-m)} \tag{1}$$

where N is the total of measurements. We define the variable r^0 as the risk level of a vital sign. It represents the monitoring importance given to the vital sign regarding to the patient's health condition such that $r^0 \in [0, 1]$. The greater the value of r^0 is , the more the vital sign is considered critical and the lower its value is, the less the vital sign is considered critical. Having the Fisher Test result F and the risk level r^0, a Quadratic Bezier curve is used as a Behavior Function (BV) to assign the appropriate sampling rate for the following period [27]. On the other hand, our proposed algorithm reduces the transmission by reducing the amount of measurements sent to the coordinator. The biosensor node uses an EWS to detect changes in the state of the monitored vital sign. These changes can indicate a normal state or different levels of criticality. Therefore, the biosensor node sends a measurement each time there is a change in the score indicating an increase or a decrease in the level of criticality.

In the following, we assume that all the biosensor nodes run the *Modified* LED^* algorithm (cf. Algorithm 1). All of them have one common period p, at the beginning of which the 1^{st} sensed measurement is sent to the coordinator. During p, a biosensor node senses a measurement at a rate R_t and only sends it if its score is different from the last measurement sent to the coordinator. At the end of each round $R = m \times p$ where m $\in \mathbb{N}^*$, the sampling rate of the biosensor is adapted using the BV function. The latter takes as parameters the maximum sampling rate R_{max} (corresponding to the total of samples in a period), the risk level r^0, the result of the Fisher Test F and the critical F-value F_t as defined by the Fisher Test table for a given Fisher risk α. Noting that R_{max} and r^0 are parameters to be medically judged by the healthcare experts based on the monitoring requirements for a given patient. Further details concerning the energy-efficient data collection technique can be found in [14].

4. 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. The proposed model can be classified under the cooperative sensor fusion techniques forasmuch as 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 [16].

Figure 2 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 (cf. Figure 2) 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 [28, 29]. 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 paper, 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. Then, we discuss the input of the FIS being the aggregate score and its fuzzification as well as 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.

4.1. Up-to-date Score

The biosensors running the $Modified\ LED^*$ algorithm keep the coordinator updated with changes in vital signs (cf. Algorithm 1). 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 as follows:

$$s_t = \frac{s_{t-1} + score_t}{2} \tag{2}$$

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

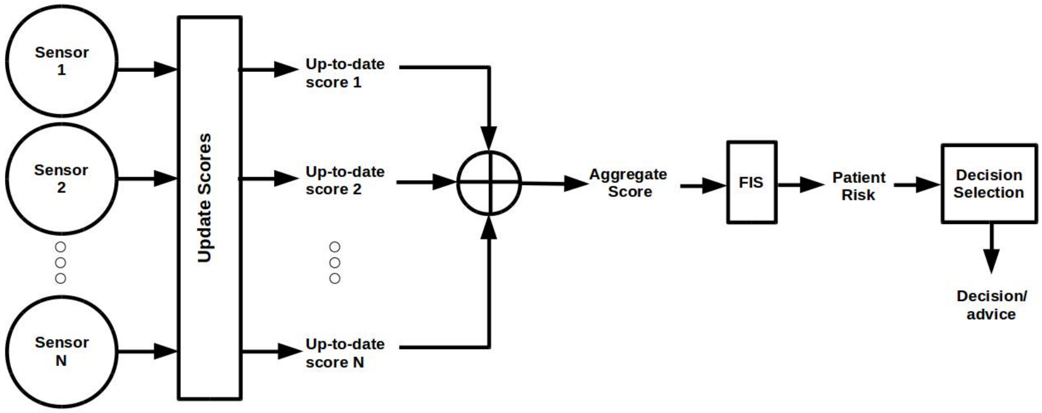


Figure 2: Architecture of the Multi-sensor Data Fusion Model

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 (2). 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:

$$\lim_{s_{t-1}\to b} s_t = \lim_{s_{t-1}\to b} \frac{s_{t-1} + b}{2} = b \tag{3}$$

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.

4.2. 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 [26]. 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:

$$AggScore = \sum_{i=1}^{N} s_i \tag{4}$$

where s_i is the up-to-date score (see equation 2) 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 4). 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.

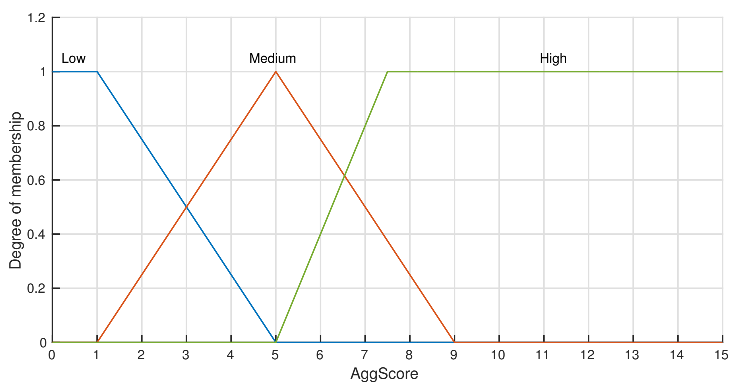


Figure 3: Aggregate Score Membership Functions

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

$$f_1(x) = \begin{cases} 1, & x \leq 1 \\ \frac{1}{1-N}x + \frac{N}{N-1}, & 1 \leq x \leq N \\ 0, & otherwise \end{cases} \tag{5}$$

$$f_2(x) = \begin{cases} \frac{1}{N-1}(x-1), & 1 \leq x \leq N \\ \frac{1}{1-N}(x+1-2\times N), & N \leq x \leq 2N-1 \\ 0, & otherwise \end{cases} \tag{6}$$

$$f_3(x) = \begin{cases} 2(\frac{x}{N} - 1), & N \leq x \leq \frac{3}{2}N \\ 1, & x \geq \frac{3}{2}N \\ 0, & otherwise \end{cases} \tag{7}$$

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 3 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 $AggScore > 5$.

4.3. 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 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 4. 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 $0.5 < r < 1$.

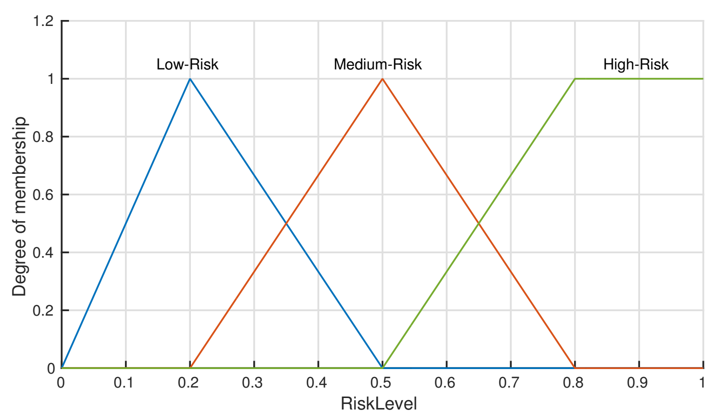


Figure 4: Patient Risk Level Membership Functions

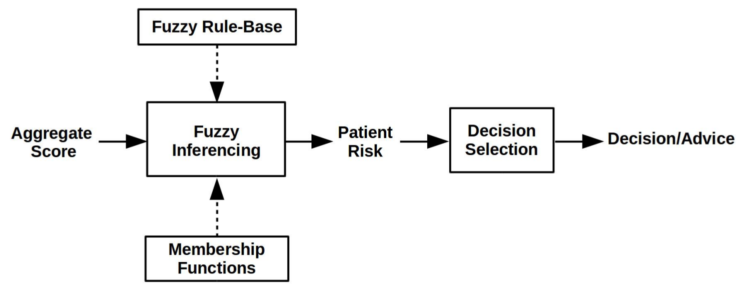


Figure 5: Fuzzy Inference System and Decision Selection Blocks

4.4. Fuzzy Inference System and Decision-Making

Figure 5 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 4.2). Its output is the patient's risk level. It uses the fuzzy membership functions described in section 4.2 and the fuzzy rule base given by health experts or doctors to map the input to the output.

Table 1: Fuzzy Rule Base

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

Table 2: Example of an Association Table between patient risk values and decisions

Decisions	**Risk value range**
d1	$r < 0.25$
d2	$0.25 \leq r < 0.4$
d3	$0.4 \leq r < 0.6$
d4	$0.6 \leq r < 0.8$
d5	$r \geq 0.8$

The fuzzy rule base is shown in Table 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. A decision, some advice or even an action is selected based on the value of r. It is selected from an association table between the patient's risk values and the decisions (c.f. Table 2). Such a table is set by healthcare experts. The decisions/advices 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. Health Risk Assessment and Decision-Making Algorithm

A Health Risk Assessment and Decision-Making (Health-RAD) algorithm at the coordinator level (cf. Figure 6) 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. Depending on the value of r, 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. section 3.2) and $m \in \mathbb{N}^*$.

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

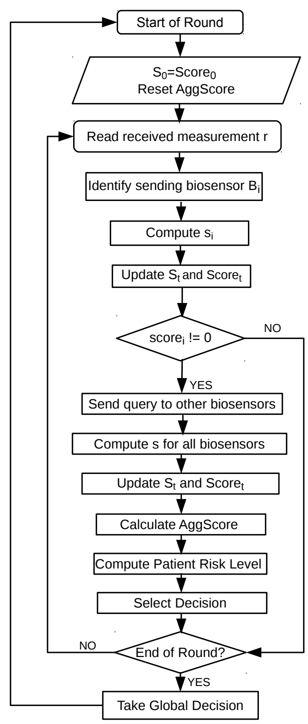


Figure 6: Health Risk Assessment and Decision-Making Algorithm Flowchart

(cf. equation 2) and calculates the aggregate score $AggScore$ (cf. equation 4). The 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.

6. Experimental Results

Experiments are conducted on real medical datasets using a cutom-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 [30]. 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 1) is implemented on the biosensor nodes and NEWS (cf. Figure 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 $\alpha = 0.05$.
- Patient risk $r^0 = 0.9$. 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 [15] 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 [31]. 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 [15].
- k coefficients and h weights for the risk components are found in [31].
- 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 paper, we refer to the existing approach [15] 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 [15]). 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.

6.1. Data Reduction

The signals of the original dataset of a given patient are shown in Figure 7. 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 8 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 7), for example, to the sent signal by the HR biosensor (Figure 8), it is remarkable to see that the number of small oscillations is considerably reduced while maintaining the general shape and progession of the HR curve over time. This is due to $Modified\ LED^*$, where only the 1^{st} measurement and changes in the vital sign's score are sent to the coordinator in a period 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

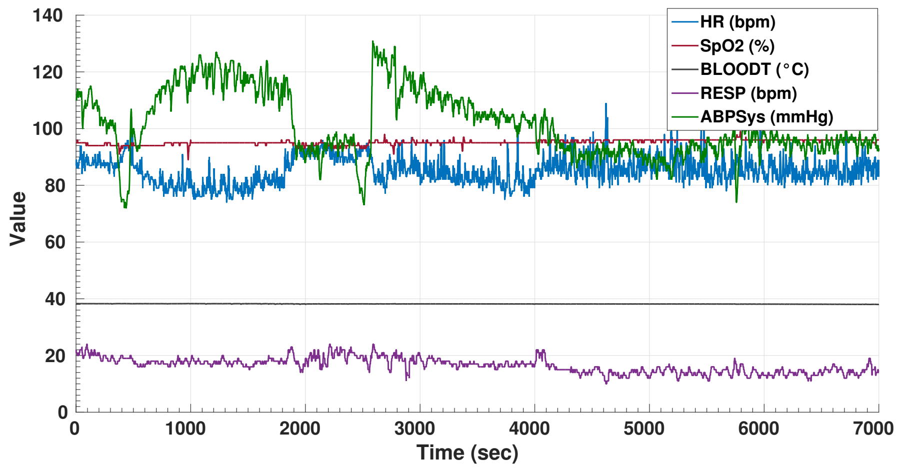


Figure 7: Original dataset showing the variation of the 5 vital signs of interest over 2 hours.

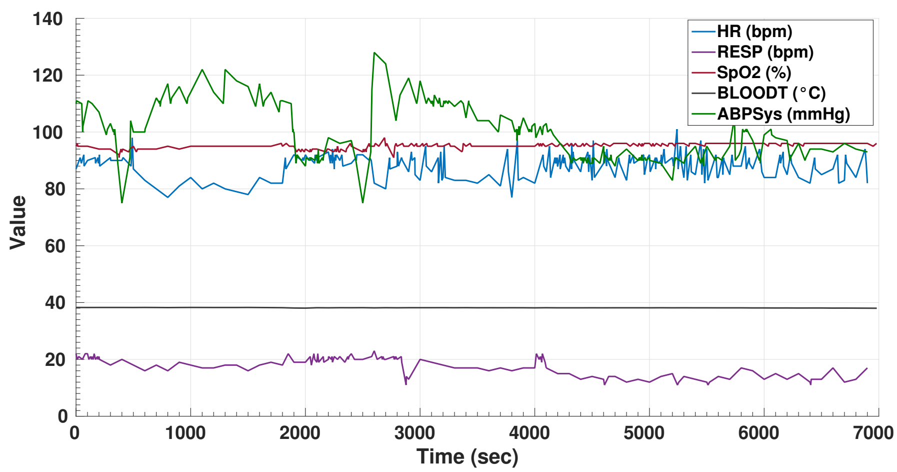


Figure 8: The received vital signs signals at the coordinator having been sent by 5 biosensor nodes running the $Modified\ LED^{*}$.

dataset, while maintaining information about changes in the 5 vital signs' score.

For different patient records and different number of monitored vital signs, Tables 3 and 4 show the percentages of data reduction performed at the sensing level and the transmitting level in our framework (biosensor nodes

Table 3: Data reduction performed for each monitored vital sign of record s01840-3454-10-24-18-46nm from MIMIC II compared to [15].

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

running *Modified LED**) compared to the existing approach [15] 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 ignored and not taken into consideration.

Table 4: Total data reduction of four patient records compared to [15].

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

6.2. 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 9 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) [32]. 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.

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.

6.3. 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

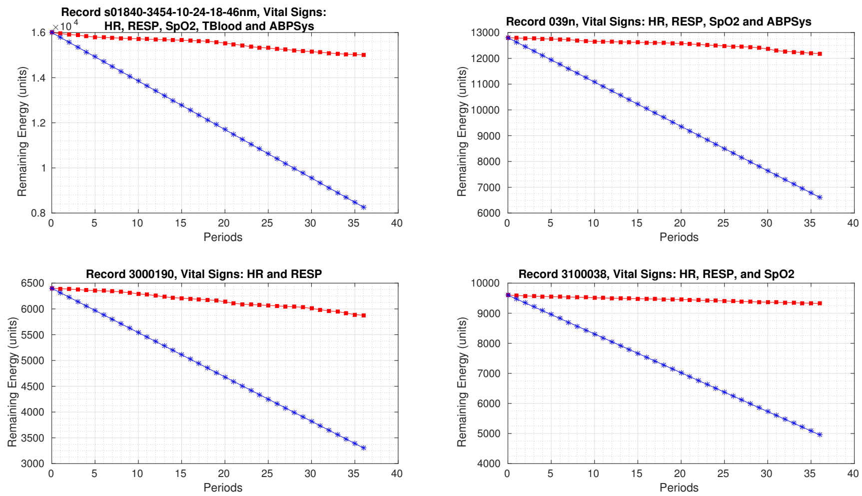
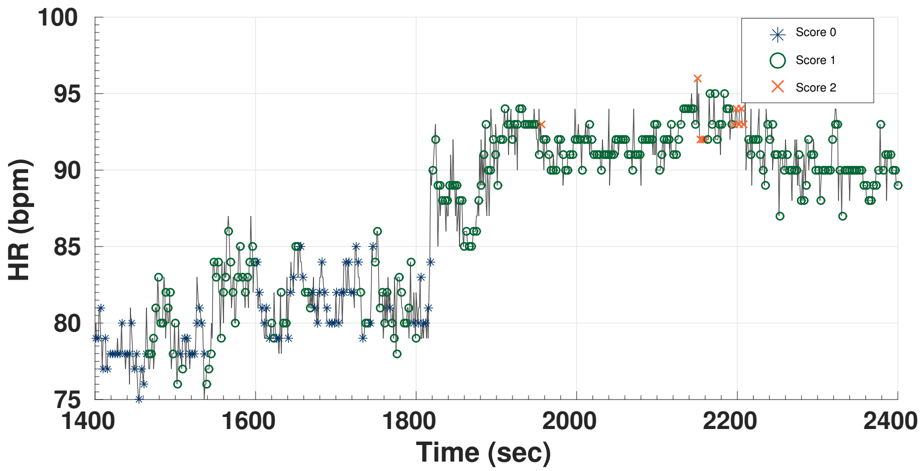
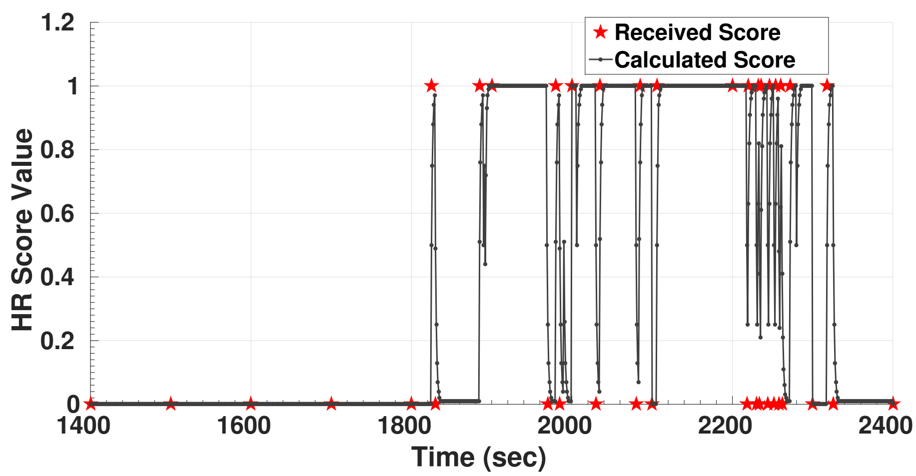


Figure 9: Comparison of the remaining energy in the WBSN after 36 periods (1 hour) for different patient records and different number of monitored vital signs: proposed framework (in red) vs data mining based framework (in blue)

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 2, 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 10 and 11 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 randomnly. On the one hand, Figures 10a and 11a 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 10b and 11b show the scores assigned to the same vital signs during the same time interval, but when applying Health-RAD. In Figure 10b, 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. 10a) which corresponds to the normal range according to NEWS (cf. 1). However, Figure 10a 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.



(a)

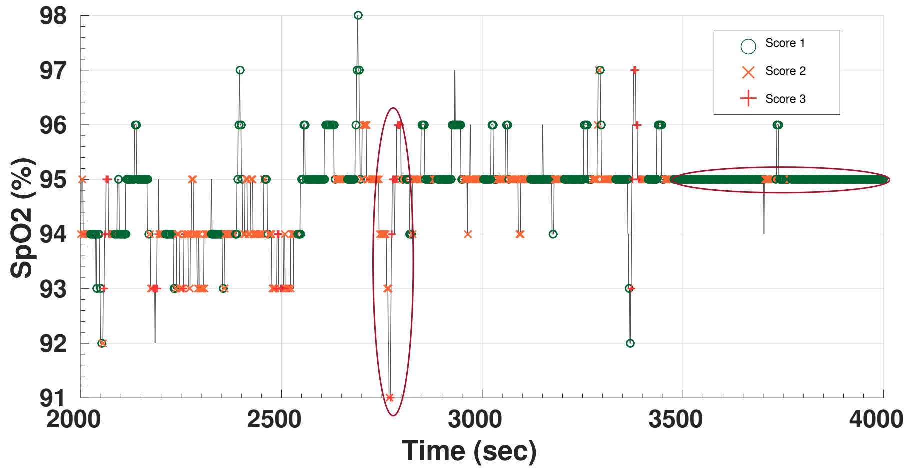


(b)

Figure 10: Severity level assessment of the HR of patient record s01840-3454-10-24-18-46nm using the data mining based framework [15] (a) and the proposed approach (b)

After $t_2 = 1800$ sec, Figure 10b 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 10a shows that the HR is assigned most of the time a score of 1, which is compatible to the resuts 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 11a and 11b 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 12 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).



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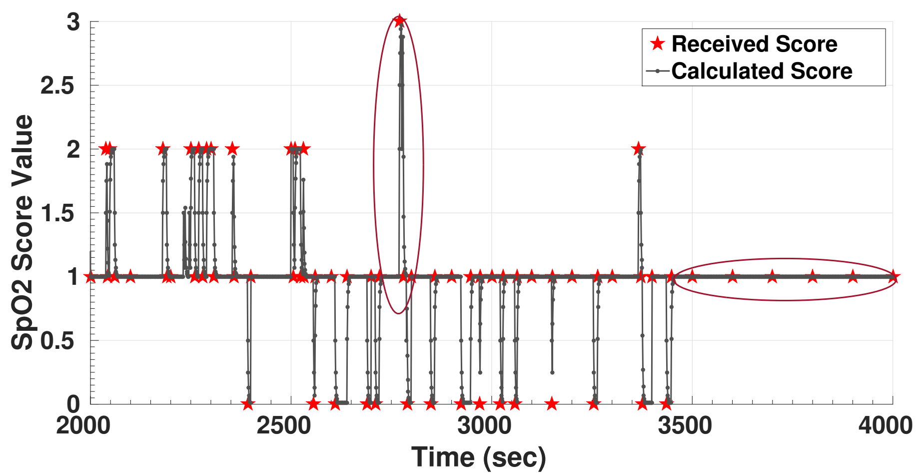
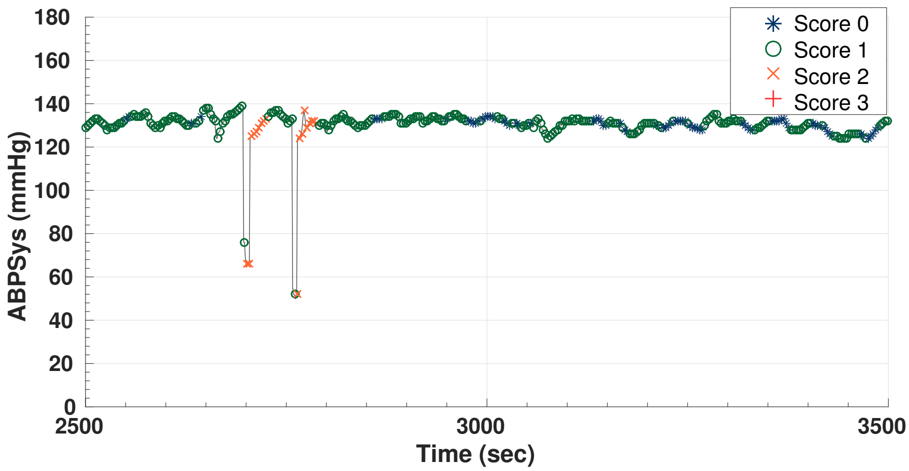
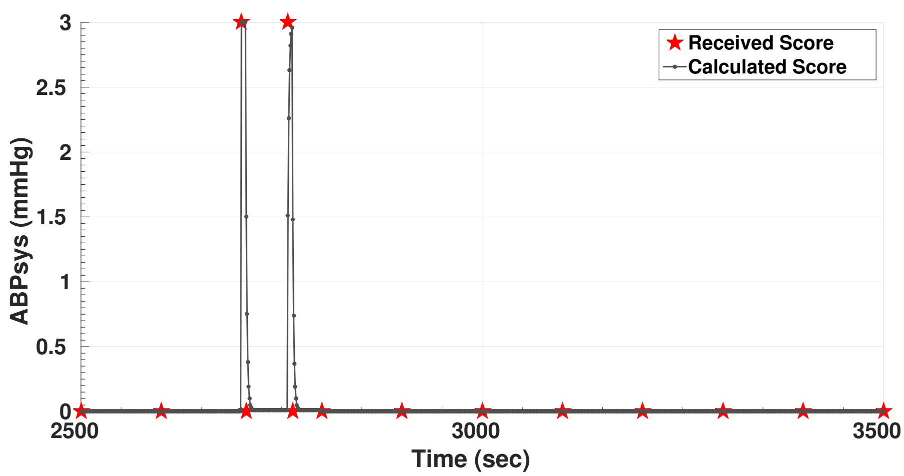


(b)

Figure 11: Severity level assessment of the SpO2 of patient record s01840-3454-10-24-18-46nm using the data mining based framework [15] (a) and the proposed approach (b)



(a)



(b)

Figure 12: Severity level assessment of ABPsys of patient record 267n using the data mining based framework [15] (a) and the proposed approach (b)

6.4. 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 13 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 ion Section 6.2).

In order to compare the risk value of the proposed approach to the global risk of the data mining approach, Table 5 is used. The average risk per period for each record based on the proposed approach is 0.36 (record 3000190), 0.26 (record 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 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 1 hour (absence of $risk < 0.2$ 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 unstability on short time periods and that the data mining based framework is more sensitive to single deviating vital signs.

Tables 6 and 7 show respectively the average 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 approaches. The results show that 50% of the 2 vital signs monitoring

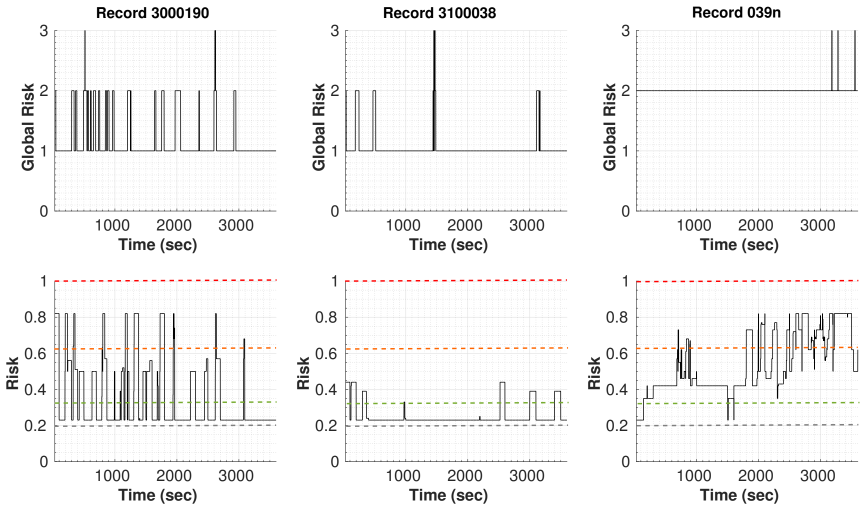


Figure 13: Comparison of health assessment during 36 periods (1 hour) for different patient records and different number of monitored vital signs: data mining based framework (second row) vs proposed multi-sensor fusion (second row)

Table 5: Equivalence Table between Risk of proposed approach and Global Risk of data mining based approach.

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

records (cf. Table 6) have been similarly assessed by both approaches whereas 90% of the 3 vital signs monitoring records (cf. Table 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).

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 [15]: 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, RESP, ABPsys,

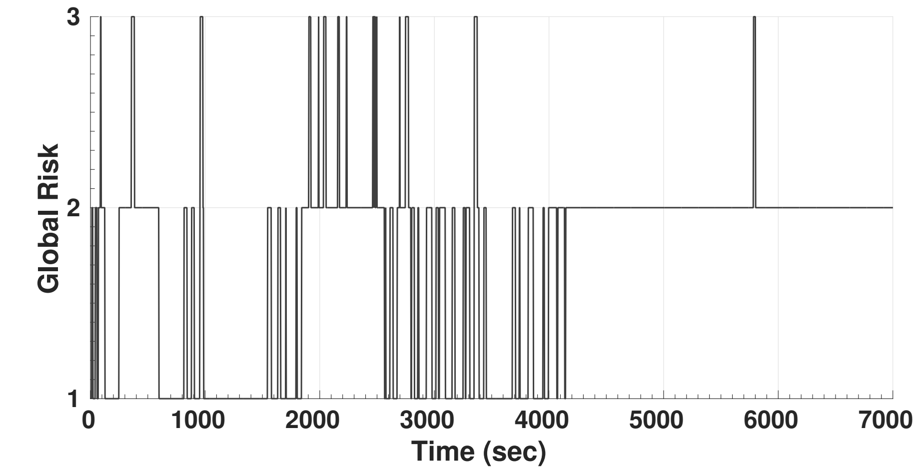
Table 6: Average Risk per period based on the proposed approach and Average Global Risk per period based on the data mining based framework for 10 patient records such as the vital signs of interest are the HR and RESP.

Record	**Average 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

Table 7: Average 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 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

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.



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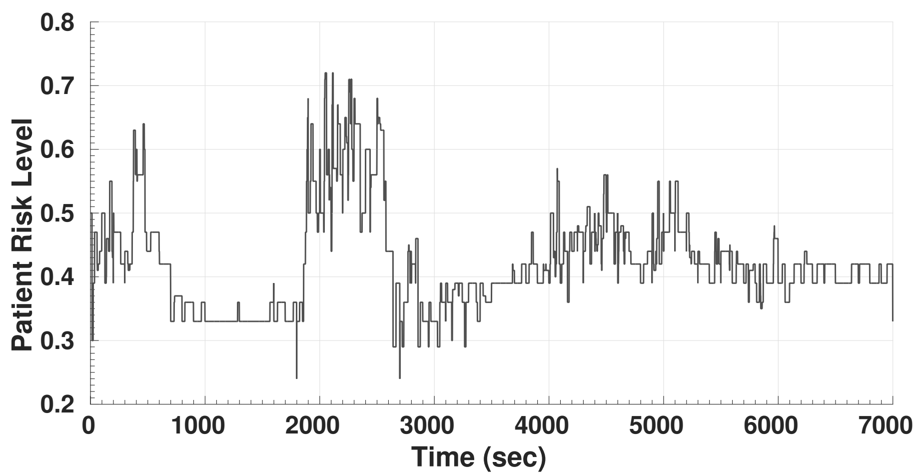

(b)

Figure 14: The health assessment of patient record s01840-3454-10-24-18-46nm using the data mining based framework [15] (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 14 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.

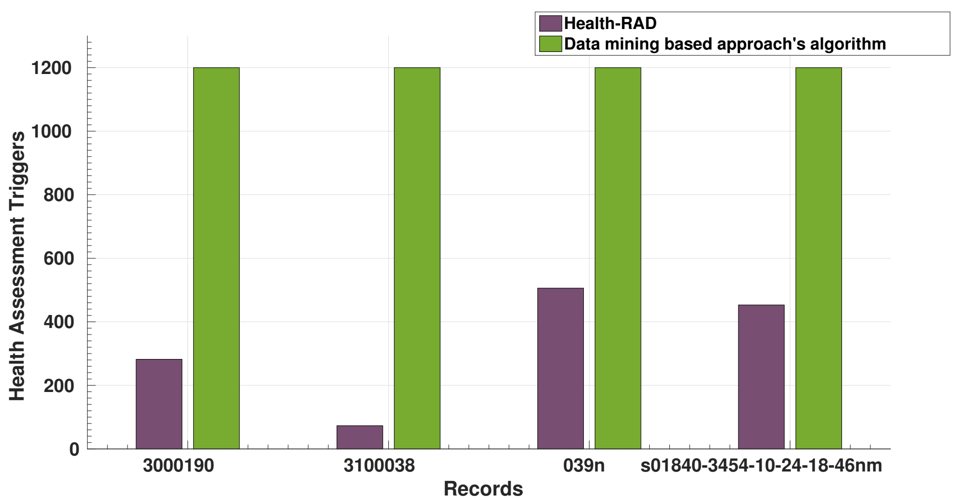

Figure 15: Comparison of the total of health assessment triggers over 1 hour between Health-RAD and the real-time assessment algorithm of the data mining based framework.

Finally, Figure 15 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). 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 ressources 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.

6.5. 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 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 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.

Table 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

7. Conclusion

In this paper, a health risk assessment and decision-making algorithm has been proposed whithin a complete acute illness monitoring system using a WBSN deployed on the patient's body. A generalization of the multi-sensor data fusion model has been proposed in order to make it more flexible and to allow its usage regardless of the number of vital signs being monitored. A comparison wih 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. As a future work, a real implementation of the complete framework is to be achieved in order to validate its performance on real-case scenarios. Additional information regarding the context of the patient are to be added into the data fusion process for more specificity and more robustness.

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