Multisensor Data Fusion for Patient Risk Level Determination and Decision-support in Wireless Body Sensor Networks

Carol Habib
Univ. Bourgogne
Franche-Comté (UBFC)
FEMTO-ST Institute
Belfort, France
carol.habib@univ-fcomte.fr

Abdallah Makhoul
Univ. Bourgogne
Franche-Comté (UBFC)
FEMTO-ST Institute
Belfort, France
abdallah.makhoul@univ-fcomte.fr

Rony Darazi
Antonine University
TICKET Lab
Hadat-Baabda, Lebanon
rony.darazi@ua.edu.lb

Raphaël Couturier
Univ. Bourgogne
Franche-Comté (UBFC)
FEMTO-ST Institute
Belfort, France
raphael.couturier@univ-fcomte.fr

ABSTRACT

Wireless Body Sensor Networks (WBSNs) are a low-cost solution for healthcare applications allowing continuous and remote monitoring. However, many challenges are addressed in WBSNs such as limited energy resources, early detection of emergencies and fusion of large amount of heterogeneous data in order to take decisions. In this paper, we propose a multisensor data fusion approach enabling one to determine the patient risk level based on vital signs scores. Consequently, a corresponding decision is taken routinely and each time an emergency is detected. This approach is based on early warning score systems, a fuzzy inference system and a technique determining the score of a vital sign given its past and current value. We evaluate our approach on real healthcare datasets.

Keywords

WBSN; multisensor data fusion; fuzzy theory; early warning system; patient risk level; decision-making

1. INTRODUCTION

WBSNs are a subset of wireless sensor networks used for healthcare applications allowing to remotely and continuously monitor a patient's health condition, thus reducing healthcare expenditures [7]. Some monitoring scenarios include the surveillance of elderly in nursing homes and home monitoring of chronic or acutely ill patients. Many applications have been addressed in the literature so far such as gait analysis, monitoring vital signs, daily activities [6], fall detection systems and stress evaluation systems [4]. Such a network consists of wearable sensor nodes called biosensor nodes and a coordinator. The biosensor nodes are placed on the body of the patient or can be implanted inside the body. They sense continuously and periodically physiological signals and vital signs. The collected data are communicated to the coordinator which can be a smartphone, a pda or any other portable device. The data aggregation and fusion are performed at the coordinator level in order to take decisions routinely and when emergencies or critical events are detected such as an abnormal variation in the heart rate. The coordinator alerts the patient and sends the collected data as well as the decision to the healthcare center or any other destination [3]. Many challenges arise in WBSNs. One of the most important ones is the energy consumption at the biosensor node level due to periodic transmission and sensing. Another challenge, is the fusion of the large amount of heterogeneous data collected by several biosensor nodes in order to represent the global situation of the patient and take consequently the corresponding decision. Several approaches for the data management and processing in WBSNs have been proposed in the literature so far. To the best of our knowledge, no one has so far tackled the problem of monitoring and fusing the vital signs of a patient while taking into consideration data reduction for energy consumption requirements as well as limited computational resources. In this paper, we propose a new multisensor data fusion approach enabling the determination of the patient's risk level. The main purpose is to obtain information of greater quality by taking decisions corresponding to the patient's situation determined by the collected data. The decisions are taken routinely and when emergencies are detected, based on an early warning score system. The proposed approach, uses fuzzy sets to deal with

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uncertainties and a fuzzy inference system to map the aggregate score of vital signs to the patient's risk level. We also propose a technique for keeping the information about a vital sign up-to-date while taking into consideration its past and current score. The following of the paper is organized as follows. Section 2 presents the background and related work. In section 3, the proposed data fusion model is described. In section 4, the experimental results are shown. Section 5 concludes the paper with some directions and future work.

2. BACKGROUND AND RELATED WORK

2.1 Context and WBSN Architecture

In this paper we propose a data fusion model to be implemented at the coordinator level of a WBSN. This model allows continuous monitoring of a patient's vital signs subject to acute illness. An acute disease requires immediate medical attention due to life-threatening possibilities and continuous assessment. Our proposed approach allows the early detection of emergencies, deterioration and improving condition of the patient regardless his location. The patient is equipped with biosensor nodes and a coordinator, usually being his smartphone. A biosensor node is defined as a traditional sensor node equipped with sensors that monitor vital signs. We suppose that each biosensor node senses only one vital sign and that 5 vital signs are monitored: Heart Rate (HR), Respiration Rate (RESP), Blood Temperature (BLOODT), Oxygen Saturation (SpO2) and Systolic Blood Pressure (ABP Sys). Therefore, the WBSN is composed of 5 biosensor nodes and one coordinator communicating under a star topology.

2.2 Early Warning Score System

An early warning score system (EWS) is a guide used by emergency medical services staff in hospitals to determine the severity of a patient's illness and thus, the degree of criticality of his or her situation. Once measured and recorded, the vital signs are weighed and aggregated. For each vital sign, a normal healthy range is defined ($score = 0$). Measured values outside of this range are allocated a score ranging from 1 to 3 according to the magnitude of deviation from the normal range. The 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 send only the important changes in vital signs to the coordinator. In our work, we have used the National EWS (NEWS) used in hospitals in the UK [1] as a scoring system.

3. MULTISENSOR DATA FUSION MODEL

The coordinator receives the measurements sent by different biosensor nodes running $Modified\ LED^*$ algorithm [5]. Its role is to perform the multisensor data fusion in order to obtain meaningful information about the patient's health condition represented by a computed patient's risk level. Depending on the computed risk, an advice or decision is given to the patient. In this paper, we propose to use a Fuzzy Inference System (FIS) which uses fuzzy set-theory in order to map inputs to outputs. Having information about how critical is the patient's health condition, a fuzzy logic system can determine the patient's risk level. Fuzzy logic is widely used as a method for representing uncertainty particularly for high-level data fusion tasks. When dealing with medical data, these can be uncertain, ambiguous, and are interpreted in a human reasoning way.

3.1 Aggregate Score and Patient Risk Level

For health experts and doctors, it is interesting to find the aggregate score of the monitored vital signs of a given patient. This total score represents the early warning score. It allows them to determine the criticality level of the patient as well as the intervention mode that should be adopted [1]. In our work, we use the aggregate score as an input into our FIS in order to get as an output the patient's risk level. According to $Modified\ LED^*$ [5], the biosensor nodes keep the coordinator updated with changes in vital signs. At the beginning of each period p, they send the first captured measurement. Then using NEWS, each time there is a change in the score of the vital sign, the corresponding measurement is sent. Therefore, the coordinator receives several measurements for each vital sign during one round R where $R = m \times p$, $m \in \mathbb{N}^*$. In order to compute the aggregate score at instant t, the coordinator calculates first the up-to-date score s_t for each vital sign at instant t as follows:

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

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 current score at time t and s_{t-1} is the score calculated at time $t-1$. Therefore, the current score $score_t$ and the score s_{t-1}, representing the history of the vital sign, are given equal weights. Second, the aggregrate score is calculated as follows:

$$AggScore = \sum_{i=1}^{N} s_i \tag{2}$$

where s_i is the up-to-date score (equation 1) of the i^{th} vital sign during a round R and N is the number of vital signs (biosensors). Since the analysis and the interpretation of medical data, more specifically the aggregate score of vital signs varies from one subject to another, we believe that the evaluation of the patient's health condition should be done using fuzzy theory. The aggregate score $AggScore$ is the input of the FIS. Firstly, the $AggScore$ is fuzzified, using for this purpose 3 fuzzy membership functions: Low, Medium and High as shown in Figure 1. Then, the patient's risk level determination is carried out using a set of fuzzy logic rules.

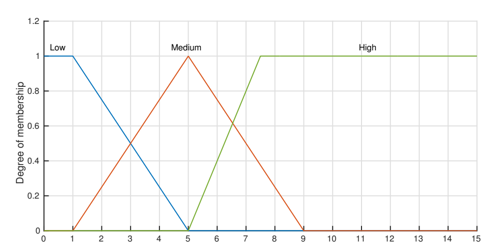

Figure 1: Aggregate Score Membership Functions

As it has already been mentioned, the objective of the proposed FIS is to determine the patient's risk level according to the received measurements of the vital signs. For this

Table 1: Fuzzy Rule Base

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

purpose, 3 fuzzy membership functions for the evaluation of the risk are defined: Low-Risk, Medium-Risk and High-Risk as shown in Figure 2. The patient's risk level r is expressed using a quantitative variable and can range from 0 up to 1.

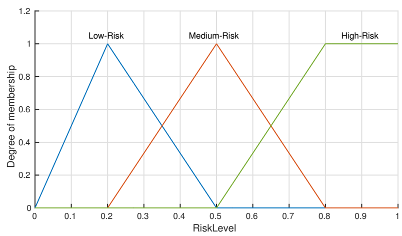

Figure 2: Patient Risk Level Membership Functions

3.2 Fuzzy Inference System

Figure 3 shows the proposed patient risk level determination block diagram. The coordinator, receiving the measurements from the m biosensors, calculates the patient's risk level in order to take a decision. This last is a predictive or corrective advice given to the patient. The input of our proposed system is the aggregate score $AggScore$ of the 5 monitored vital signs (cf. section 3.1). Using the fuzzy membership functions described in section 3.1 and the fuzzy rule base given by health experts or doctors, the FIS gives as an output the risk level of the patient. The fuzzy rule base is shown in Table 1. For example Rule 1 is: *if the aggregate score is Low then the patient risk level is Low-Risk*.

Finally, the risk level is defuzzified using the centroid method in order to obtain a crisp patient's risk level r. Depending on the value of r a decision or advice is selected.

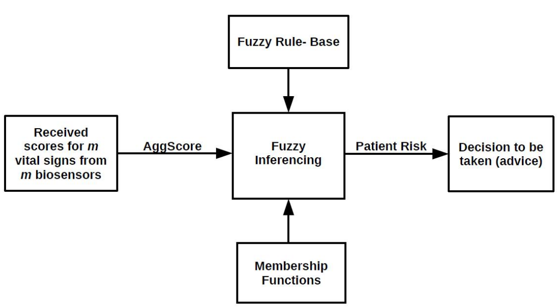

Figure 3: Patient risk level determination block diagram model

This is done using an association table between the decisions and the patient risk values as shown in Table 2. This table is set by experts or doctors. It contains simple decisions and advices such as: rest, take medicine, call the doctor etc.

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	$r \geq 0.8$

Table 3: Parameters settings for Modified LED^* and DFM

Modified LED^*	DFM
$p = 100$ sec $R = 2 \times p$ $\alpha = 0.05$ $r^0 = 0.9$ $SR_{max} = 50$ samples/period $SR_{min} = 10$ samples/period	$p = 100$ sec $R = 1 \times p$ $\delta_t = 1$ sec

4. EXPERIMENTAL RESULTS

Experiments are conducted on real medical datasets using a custom-based Java simulator and Matlab. In order to assess the performance of the proposed data fusion model, patient vital signs datasets are collected from Multiple Intelligent Monitoring in Intensive Care (MIMIC) II database of PhysioNet [2]. Five biosensors sense the HR, RESP, ABP Sys, BLOODT and the SpO2. The proposed data fusion model is tested based on the received measurements. Two ideas are highlighted: the score calculation for any vital sign and the patient risk level determination. $Modified\ LED^*$ is run on the biosensor nodes and the proposed data fusion model (DFM) is implemented on the coordinator. The simulation time is about 70 periods ($\approx$ 2 hours). The parameters settings for both algorithms are shown in table 3. Figure 4 shows the scores of the received measurements from the HR biosensor nodes. In addition, it shows the up-to-date score of the HR calculated by the coordinator over 10 rounds. At the beginning of each round R, the up-to-date score of each vital sign is assigned the score of the 1^{st} measurement sent by the corresponding biosensor nodes. Then, the up-to-date score is calculated each time a decision making process is triggered and at each refresh time δ_t. For example, at the beginning of the 1^{st} round ($t = 0$), the coordinator receives a measurement having a score equal to 0. Thus, the up-to-date score is set to 0. Then, at $t = 36$ sec, the coordinator receives a measurement from the HR biosensor node having a score equal to 1. The up-to-date score is calculated as follows : $\frac{0+1}{2} = 0.5$, thus giving equal importance to the history represented by the last claculated score and the current score. The up-to-date score is refreshed each $\delta_t = 1$ sec, hence according to figure 4, while the current score is stable it converges to 1. For $t > 500$ sec, the HR is stable, thus the up-to-date score does not change and is stable at 0. The up-to-date score is always bounded by the scores of the two last measurements received and converges to the last one depending on δ_t and the stability of the vital sign.

Figures 5 and 6 show the aggregate score and the patient risk level respectively over 70 periods. Each time a critical score is detected by the coordinator and at the end of each round, the decision making process is launched. A decision is chosen according to the patient's risk level. This last is the output of the proposed FIS and is based on the aggre-

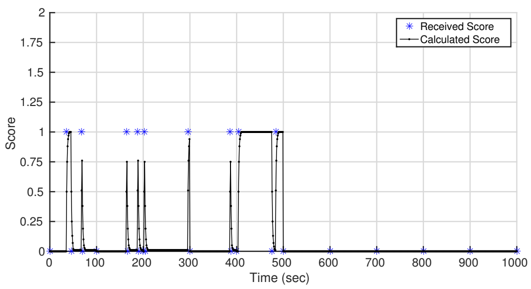

Figure 4: The scores of the received measurements from the Heart Rate biosensor node and the calculated up-to-date score by the coordinator over 10 **rounds.**

gate score (cf. section 3.2). Figure 5 shows the aggregate score over 70 periods. The values range between 1 and 8. The aggregate score is the sum of the up-to-date scores of the 5 vital signs. Using the rules defined in section 3.2, the patient's risk level is determined and is shown in figure 6. The higher the aggregate score, the more the patient's situation is critical. This last is characterized by the patient's risk level whose values, according to figure 6, range between 0.23 and 0.74.

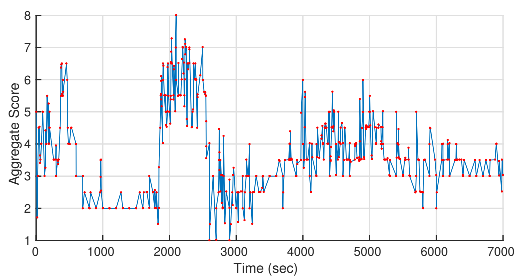

Figure 5: The aggregate score of the 5 **vital signs over** 70 **periods.**

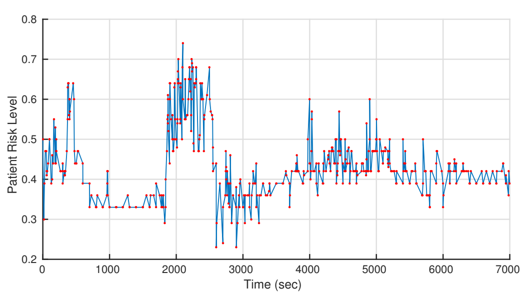

Figure 6: The patient risk level over 70 **periods obtained using the proposed FIS.**

Figure 7 shows the decisions that are taken each time the decision making process is triggered. Based on the patient's risk level (figure 6), a decision is selected using table 2. This table is predefined by doctors, where for each patient risk range, a decision is defined. As shown in figure 7, the decisions alternate between decision 1, 2, 3 and 4 depending on the patient's risk level at a given time t.

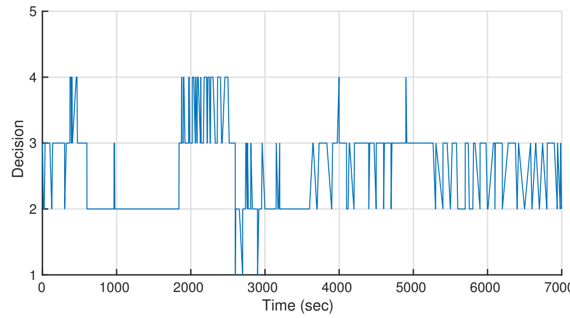

Figure 7: The decisions taken over 70 **periods based on the patient's risk level.**

5. CONCLUSION

In this paper, we have proposed a multisensor data fusion model allowing the coordinator of a WBSN to monitor continuously the health condition of an acutely ill patient. It takes a decision routinely and when emergencies are detected. The vital signs taken into consideration are the HR, RESP, BLOODT, SpO2 and ABP Sys. The approach takes into consideration the data reduction performed at the biosensor nodes level and uses a FIS to determine the patient's risk level. For future work, we intend to integrate other information for a better assesment of the patient's condition by adding environmental sensor nodes and motion detectors making the data fusion model context-aware.

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