Enhancing the Self-Aware Early Warning Score System Through Fuzzified Data Reliability Assessment

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Abstract. Early Warning Score (EWS) systems are a common practice in hospitals. Health-care professionals use them to measure and predict amelioration or deterioration of patients' health status. However, it is desired to monitor EWS of many patients in everyday settings and outside the hospitals as well. For portable EWS devices, which monitor patients outside a hospital, it is important to have an acceptable level of reliability. In an earlier work, we presented a self-aware modified EWS system that adaptively corrects the EWS in the case of faulty or noisy input data. In this paper, we propose an enhancement of such data reliability validation through deploying a hierarchical agent-based system that classifies data reliability but using Fuzzy logic instead of conventional Boolean values. In our experiments, we demonstrate how our reliability enhancement method can offer a more accurate and more robust EWS monitoring system.

Keywords: Early Warning Score · Modified early warning score
Self-awareness · Data reliability · Consistency · Plausibility
Fuzzy logic · Hierarchical agent-based system

1 Introduction

Chronic diseases such as cardiovascular diseases are the leading cause of death in the world [1]. Such diseases put patients at the risk of sudden health deterioration, which is reflected in patient's vital signs up to 24 h in advance. Early enough health deterioration detection effectively increases the chance of patient's survival [2].

In hospitals, particularly in intensive care units, the Early Warning Score (EWS) is a prevalent manual tool, by which patient's vital signs are periodically recorded and the emergency level is interpreted [3]. To this end, a score

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(0 for a perfect condition and 3 for the worst condition) is allocated to each vital sign according to its value and the predefined limits (see Table 1). The summation of the obtained scores indicates the degree of health deterioration of the patient (the higher the EWS, the worse the patient's health condition). However, there are two major restrictions in this manual tool. First, unreliable interpretation might be made due to the presence of inaccuracy and latency in the manual data collection. Secondly, and the more important restriction from a practical point of view, this manual tool is not applicable to out-of-hospital situations where no professional caregiver is available to perform the measurements. Recent advancements in Internet of Things (IoT) technologies can mitigate these restrictions by providing 24/7 remote health monitoring. In EWS systems based on IoT devices, patients' vital signs along with context data are continuously monitored via mobile/wearable sensors, while cloud server performs data analysis and decision making algorithms for the score determination [4,5].

Data reliability of such IoT-based EWS systems in remote health monitoring is of paramount importance. In our previous work [6], we proposed an architecture which exploits self-awareness techniques to adaptively adjust the EWS in the case of faulty readings from the sensor. We indicated a binary decision-making technique to determine whether the sensory data is reliable, and if needed we accordingly adjusted the EWS. However, like many other natural phenomena, data reliability of the sensory data is a continuous value and treating it in a binary manner, although simplifying the analysis, can lead to loss of information. For example, many somewhat reliable sensory data can lead to an unreliable assessment whereas in a binary assessment they may be interpreted as reliable (since they may fall closer to a reliable value in the spectrum) and thus create a wrong assessment.

In this paper, we propose a data reliability validation technique that is based on Fuzzy logic. The usage of Fuzzy logic instead of Boolean logic to classify input data as reliable or faulty covers the unsharp (fuzzy) ranges in which vital signs can indeed be correct or incorrect. In our extensive experiments, we show how our Self-Aware Early Warning Score (SA-EWS) method can be leveraged to enhance the reliability and robustness of health monitoring systems.

Table 1. Score classification table of a set of vital signals

Vital signal score	3	2	1	0	1	2	3
Heart rate (beats/min)	<40	40–51	51–60	60–100	100–110	110–129	>129
Systolic blood pressure (mmHg)	<70	70–81	81–101	101–149	149–169	169–179	>179
Respiratory rate (breaths/min)		<9		9–14	14–20	20–29	>29
Oxygen saturation (%)	<85	85–90	90–95	>95			
Body temperature (°C)	<28	28–32	32–35	35–38		38–39.5	>39.5

2 Data Reliability Concepts

Data reliability is an additional meta-data which describes the quality of the measured data. The reliability consists of accuracy and precision of sensory data [7] and grants a higher level of comprehension on the validity of the input data. If a sensor is broken, the monitored vital sign will be most probably inaccurate and not precise. Whereas the data provided by the sensor can still be accurate and precise when the sensor is detached from the patient's body. However, in both of these cases, an EWS calculated based on their values is invalid and therefore, unreliable in the given context. Hence, determining the reliability of the input data can be very challenging, but there exist potential solutions; consistency and plausibility controls, as well as cross validation are among them [7]. While the calculation of the EWS is based on the absolute values of the vital signs, the reliability of the EWS uses additional information about slopes and inter-correlations of the vital signs.

Consistency: Signals often have some limits such as maximum rate of change, these limits can be exploited to assess the reliability of a signal. Consistency is an aspect that can provide information on whether an observed input signal is reliable or not based on its history. A signal with a physically impossible slope indicates a problem which can be evoked by a sensor failure or a detachment of the sensor from the body. Regardless of the reason, a faulty monitored vital sign affects the calculation of the EWS negatively and should be avoided. For example, a change of the body temperature of several degrees per minute is impossible [8]. Therefore, in such a case the gathered sensory data should be classified as unreliable and treated accordingly.

Plausibility and Correlation: One aspect of plausibility is the absolute value of an input signal. For example, the oxygen saturation can only be between 0% and 100%. An input data that shows values of the oxygen saturation outside of this boundary must be classified as unreliable.

Another aspect of plausibility is the cross-reliability or co-existence plausibility. Various efforts have been conducted to indicate correlations between different vital signs [9–11]. For instance, considering the possible effect of the body temperature on the heart rate value, the probability of an increase in heart rate is high in the case of elevated body temperature [10]. As a second example, we can consider that a body temperature of $-30\,^{\circ}\mathrm{C}$ is implausible in the case of a living patient, although a deceased person lying in a very cold area can have such a low body temperature.

3 Fuzzified Reliability Assessment

In contrast to our previous work [6] where the data reliability validation was based on Boolean logic, we propose here the use of Fuzzy logic. Because of the lack of complete knowledge of all body functions, determining whether a vital sign is monitored correctly is a hard task. Fuzzy logic brings the significant advantage of covering unsharp (fuzzy) ranges in which vital signs cannot be easily tagged as correctly monitored or not. Thus, a vital sign can have a reliability value between 0 and 1 (0% and 100%), instead of just being reliable or unreliable.

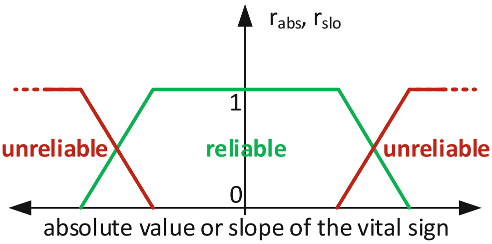


Fig. 1. Example for a fuzzy membership function.

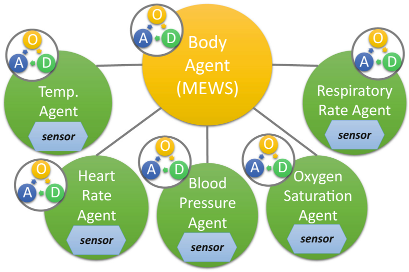


Fig. 2. System architecture.

In the proposed system, the first task of reliability module is to analyze two metrics of a vital sign, the absolute value of the signal and its slope. For this analysis, fuzzy membership functions (shown in Fig. 1) are needed, each of which is configured to match the properties of the assigned signal. The result of this analysis is given by two parameters, the reliability of the absolute value r_{abs} and that of the signal slope r_{slo}. Subsequently, the reliability of an input signal r_{sig} is calculated with

$$r_{sig} = r_{abs} \wedge r_{slo} \tag{1}$$

where the fuzzy "and" ($\wedge$) is equal to a minimum function [12]. The parameter r_{sig} gives information about the reliability of each signal considered separately and omits the correlation of the different vital signs (reviewed in Sect. 2). To consider the correlation, more highly abstracted information is needed on how one vital sign can impact another. The cross-validated reliability, r_{cro}, which exists for each pair of signals is given by

$$r_{cro} = \begin{cases} 1 & \text{if } S_{vs1} = S_{vs2} \\ \frac{1}{p_{cro}|S_{vs1} - S_{vs2}|} & \text{if } S_{vs1} \neq S_{vs2} \end{cases} \tag{2}$$

where $p_{cro} \in (0, \infty)$ denotes a coefficient of the strength of the correlation[1] between vital signs vs_1 and vs_2, and S_{vs1} as well as S_{vs2} are the abstracted scores of these two vital signs.

[1] The reliability module in our implementation limits the cross-reliability r_{cro} to a value between 0 to 1, although theoretically, a coefficient less than 1 can lead to a r_{cro} higher that 1.

When all reliability and cross-reliability values are available, the reliability of the calculated EWS is given by

$$r = (r_{sig_1} \wedge \cdots \wedge r_{sig_n}) \wedge (r_{cro_{12}} \wedge r_{cro_{13}} \wedge \cdots \wedge r_{cro_{mn}}) \quad (3)$$

where the first term conjugates all reliabilities of the various vital signs, and the second term contains the conjunction of all combinations of cross-reliabilities.

4 Experiments

4.1 Implemented System Architecture

As in our last work [6], a hierarchical agent-based model, implemented in C++, constitutes the base of the SA-EWS system (Fig. 2). Such an agent-based approach combined with the usage of mini ODA loops enable a good modularity and simple implementation. Every agent works according to an ODA loop; which means that every single agent monitors certain inputs, decides what to do, and acts accordingly.

Beside its modularity, such hierarchical agent-based architecture has another essential advantage. The input data with all its semantic content and contextual information can be abstracted in different layers [13]. As shown in Fig. 2, each agent of the lower hierarchical level is connected to a sensor. Due to the agent-based design, the scoring of vital signs and the calculation of the EWS are performed independently in different locations.

4.2 Functional Description of the System

First, each low-level agent reads the actual value of the vital sign the sensor attached to it provides. Subsequently, it abstracts the raw input data to a vital sign score S (Table 1) and validates the reliability of the signal, r_{sig} (Eq. 1). Finally, the low-level agent sends both values (score S and the signal reliability r_{sig}) to the agent of the higher hierarchical level; the "Body Agent".

Similar to the low-level agents, the body agent starts its task with reading the input values, although these are coming from the low-level agents and not from sensors. This high-level agent is responsible for the calculation of the EWS as well as the reliability of the calculated EWS. While the agent's binding module sums up all gathered scores to calculate the EWS, the reliability module calculates the cross-reliability, r_{cro}, for each pair of vital signs (Eq. 2) followed by the reliability, r, of the overall EWS (Eq. 3). As the last step and before the next data sets are read, the calculated EWS and its reliability, r, are outputted.

4.3 Experimental Data

All vital signs are collected from a 36 years old male subject with diastolic hypertension. Several sensors and devices are used for data collection. The Bioharness 3 [14] chest strap with a wearable Bluetooth sensor set is used to record the heart rate and the respiration rate. Blood pressure and blood Oxygen saturation are recorded using iHealth BP5 [15] arm blood pressure monitor and iHealth PO3 [16] finger grip pulse oximeter which both of them are Bluetooth-enabled monitoring devices. Body temperature sensor is a DS18b20 [17] digital temperature sensor connected to ATMEGA328P [18] microcontroller and nRF51822 [19] Bluetooth low energy module. We used an Android phone to collect data from all sensors during the experiments with the rate of one sample per second.

We conditioned the data collection phase to emulate certain faults and errors. These conditions are applied in order to show how the system is able to detect the changes from normal to the abnormal condition and back from abnormal to normal condition. To this end, a change has been applied for around 5 min in the middle of a 15-min data collection. We note that the conducted experiments are proof-of-concept experiments and more extensive tests with more patients are planned for the future. The applied abnormal conditions are: (i) The temperature sensor has been detached from the body and brought to contact with an object at room temperature, (ii) The temperature sensor has been detached from the body and brought to contact with a cold object, (iii) The temperature sensor has been detached from the body and brought to contact with a hot object, (iv) A biceps contraction has happened during the blood pressure measurements, and (v) The chest strap for the heart rate and respiration rate monitor has been loosened.

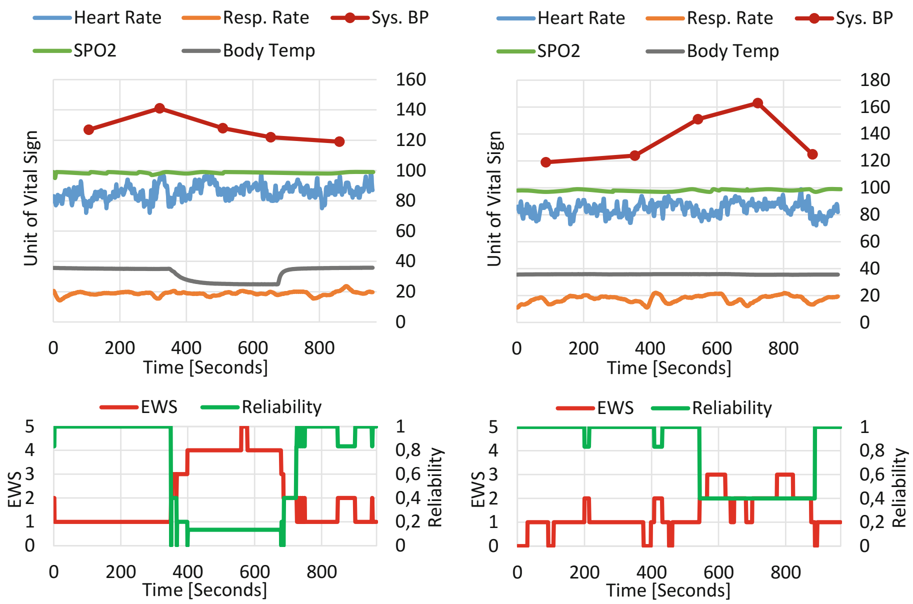
4.4 Configuration

Several factors influenced the setup of the fuzzy membership functions and the correlation coefficients. Besides the medical publications [8–11,20], expert's opinions from various physicians, the accuracy of the sensors used, and the medical condition of the patient were considered in configuring the system. To repeat the experiments with other sensors or patients, the setup should be reconfigured again to reflect such personalization. Although reconfiguration of these parameters is easy in our system, finding our the right values is a complex task which requires further research for enabling its automation.

5 Results

Our experiments show that the SA-EWS system works correctly, and the reliability of the calculated EWS coincides with the condition of the measurement setup. In other words, erroneous input data leads to a lower reliability. Due to the space limitation, only two of these cases are shown here in this section.

In the first experiment (shown in Fig. 3(a)) at around 350 s the body temperature sensor is detached and measures the room temperature until it is again attached (around 700 s). Over this period the reliability value decreases drastically. Whereas the validation of the slope causes the low reliability during the beginning and the ending phase of the period of detachment, the cross-plausibility validation does this for the rest of this period. Because of the medical condition (high respiration rate) of the test subject, the correlation between



(a) Detached temperature sensor (b) contraction of the biceps

Fig. 3. The monitored vital signs, the EWS and its reliability. (a) the body temperature sensor is detached from the patient and temporarily measures the room temperature (b) a contraction of the biceps interferes with the blood pressure measurement.

the respiration and the other vital signs was set to weak (decreased from the default value of 1.5 to 0.6). Nevertheless, during the moments when the respiration frequency reaches values greater than or equal to 20 (score 2), reliability level decreases even further.

For the second experiment shown here (Fig. 3(b)), we tampered with the measurement of the blood pressure. The gathered input data shows a high blood pressure value because the patient tensed his biceps during two of the samples (around 550 s and 700 s). Since there is a strong correlation between heart rate and blood pressure [9], the correlation coefficient p_{cro} was increased from 1.5 to 2.5. As the heart rate was more or less constant while the blood pressure was increased, the cross-reliability led to a low reliability. As in the first experiment, the temporary breathing rate with a score of 2 or higher leads to short periods of slightly reduced reliability at around 200 s and 400 s.

6 Conclusion and Future Work

In this paper, we presented an SA-EWS system with a fuzzified reliability validation which recognizes erroneous vital signs caused by various measurement artifacts such as loose sensors, detached sensors or other interferences. In our experiments, the proposed system was successful in detecting such events and decreased the data reliability during such events. This observation shows that self-awareness techniques such as the one proposed and used here can provide more robust EWS calculations. We note that deciding the value of parameters such as possible absolute values, signal slopes, and correlations among various vital signs demands domain knowledge. As the human body is an extremely complex system, not every phenomenon is already known. Therefore, although domain knowledge can be helpful for general cases, it does not replace personalized assessment which experts can provide each patient with. For this reason, we plan to add a learning module to the SA-EWS system which should learn about the patient's body functions and its basic health condition. In addition, more metrics should be generated and used, such as the derivation or the variability of a vital sign.

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