Enhancing the Early Warning Score System Using Data Confidence

Maximilian Götzinger[1], Nima Taherinejad[2], Amir M. Rahmani[1], Pasi Liljeberg[1], Axel Jantsch[2], and Hannu Tenhunen[1]

[1] Department of Information Technology, University of Turku, Finland
{maxgot,amirah,pakrli,hannu.tenhunen}@utu.fi,
[2] Institute of Computer Technology, TU Wien, Austria
{nima.taherinejad,axel.jantsch}@tuwien.ac.at,

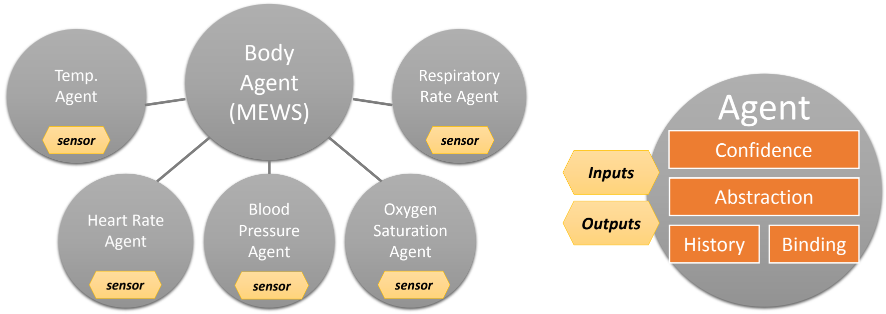
Abstract. Early Warning Score (EWS) systems are utilized in hospitals by health-care professionals to interpret vital signals of patients. These scores are used to measure and predict amelioration or deterioration of patients' health status to intervene in an appropriate manner when needed. Based on an earlier work presenting an automated Internet-of-Things based EWS system, we propose an architecture to analyze and enhance data reliability and consistency. In particular, we present a hierarchical agent-based data confidence evaluation system to detect erroneous or irrelevant vital signal measurements. In our extensive experiments, we demonstrate how our system offers a more robust EWS monitoring system.

Key words: Early Warning Score, Self-awareness, Data Confidence, Consistency, Plausibility, Hierarchical Agent-Based System

1 Introduction

Early Warning Score (EWS) systems are common practice in hospitals with the goal of detecting and predicting patients' health deterioration. In 1997, Morgen *et al.* proposed this system for the first time [1], covering vital signals such as heart rate, respiratory rate, body temperature, blood pressure, and blood's oxygen saturation. These signals are monitored and added up to derive the EWS. However, not everyone whose condition is deteriorating is already in the hospital. Therefore, portable devices and ubiquitous systems utilizing Internet-of-Things are needed for monitoring vital signals and calculating the EWS [2].

It is of key importance to provide these systems with an acceptable level of reliability. In other words, EWS systems always need to monitor vital signals accurately. Azimi *et al.* propose a system that calculates a self-aware EWS through changing the classification of the various vital signals based on the patient's activities [2]. This self-aware property is essential because the values of vital signals change when a patient is sleeping or running. Knowledge of different situations and circumstances improves the decision-making ability of the system [3]. However, they assume that the measured data is always correct and relevant. Noisy or erroneous vital signals can lead to a wrong calculation of the



(a) System Architecture (b) Agent Architecture

Fig. 1. System Architecture; (a) Constituting agents (modules) of the system, and (b) Constituting units of the agents.

EWS, which can result in false or missing alarms. Hence, EWS systems need to be robust and aware of the reliability of input data.

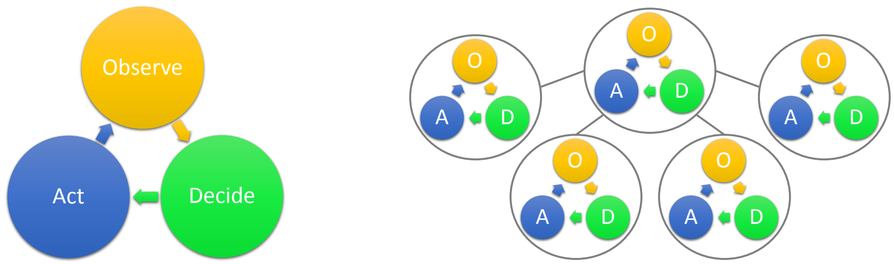
In this paper, we propose a modified EWS (MEWS) system by exploiting a customized data confidence enhancement technique. Our method is inspired by the concept of self-awareness enabling the system to - adaptively - correct the sensory data in case of faulty readings.

2 System Architecture

In an agent-based modular architecture (Fig. 1(a)), each sensor is connected to a dedicated module which we call an “Agent” [4]. It processes the sensory data and reports to a higher level agent, which is the “Body Agent”. Each agent consists of an Abstraction-, a History-, a Confidence Validator-, and a Binding Module. The role of each module in an agent is as follows:

- *Abstraction*: To change the representation of the input data to the appropriate format of the output. The purpose is to provide the higher level agents with more compact and only relevant information [5].
- *History*: To save recent data, track changes, and establish a stable baseline for the data when possible. This unit also smooths the data via weighted averaging to eliminate the noise in the signal.
- *Confidence*: To assess the trustability of the input data and provide the output data with a confidence tag, that allows the higher levels to have a better understanding of the data and their validity. This topic is discussed in more details in Section 3.
- *Binding*: To bind several input data, relate or compare them, and perform necessary operations on them. This module is specifically useful when an agent has multiple inputs, as is the case with the Body Agent. We note that this process is more complicated than a simple mapping of the values as done in the Abstraction module.

To enhance the functionality of our system, we have incorporated some of the concepts of self-awareness. Self-awareness is a well-known concept which can be traced back to 1960s in psychology [6] and late 1990s in computing [7]. It provides several advantages to the system such as the ability to cope with changing



(a) ODA (b) Modular ODA

Fig. 2. Observe-Decide-Act (ODA) loops implemented in (a) overall system, and (b) each module.

environments [6] or changing goals [8], and to optimize resource utilization [9]. As the basis for our self-aware system design, we use an Observe-Decide-Act (ODA) loop [8, 7] as illustrated in Fig. 2(a). For better modularity and simpler implementation we use a mini ODA loop inside each agent, as shown in Fig. 2(b). That is, each agent monitors its own behavior, decides about certain actions, and acts accordingly. Self-awareness covers a wide range of aspects in the system design under each of the chains of the ODA loop. All of which could provide the system with certain abilities and advantages. In this work, we specifically concentrate on the role of the confidence aspect of observation as elaborated in [5]. We then analyze its effect on the overall performance of our EWS system.

3 Data Confidence Concepts

Data Confidence is meta-data and builds on Data Reliability (which consists of accuracy and precision of sensory data [5]). It provides another level of understanding regarding the validity of the data which is beyond that of the sensors. For example, in the context of the EWS, if the sensor is not attached to the body of the subject, the temperature data provided by the sensor may still be accurate and precise. However, it is not valid in the context of the application. Therefore, although the data is reliable, the system should not consider such a value. Assessing Data Confidence based on the context and the application can be very challenging [5]. Among the identified potential solutions are consistency and plausibility control as well as redundant verification [5]. Since the latter requires redundant hardware and implies additional costs and our objectives include cost as well as energy efficiency, in this work we focus on the two former aspects: consistency and plausibility.

Consistency: Anomalies are - at some level of analysis - inconsistent with the normal trend of data, which could indicate a problem[1]. Hence, Consistency is an aspect that can provide insight into how confident the system can be about its observation. In the context of our EWS system, we consider temperature continuity as an indicator for data consistency. Body temperature has very small and slow changes; a change of 0.16°C during one minute can be normal. However,

[1] We note that the consequence of an anomaly detection should be/is decided by higher levels of the system. Regardless, the observation unit needs to alert the higher levels.

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

a change of several degrees per minute is inconsistent with the nature of the subject of measurements (body temperature) [10]. This may be caused by a sensor failure or a detachment of the sensor from the body. Regardless of the reason, this should not affect the warning score. After performing consistency analysis and finding an inconsistent behavior, by reducing the confidence tag of the incoming data, the EWS system knows that it should not take this number into consideration. We note that in some other parameters, such as respiratory rate, for example, some discontinuities might be acceptable and should not be marked as an inconsistency or decrease the confidence of the system in the incoming data. Hence comes forward the next aspect of confidence, which is the plausibility.

Plausibility: One aspect of plausibility which goes hand in hand with consistency is the plausibility of changes in the data, e.g. body temperature change. Another aspect is the plausibility of the absolute value. For example, a body temperature of 85 or 95°C is not plausible and regardless of the cause, it should not be considered for score evaluation of the EWS. The same goes for negative temperatures of this magnitude, or in the case of oxygen saturation, for values outside 0 to 100.

Another aspect of plausibility is the cross-validity or co-existence plausibility. That is, whether certain data could plausibly be valid given some other (complimentary) data and given certain conditions. For example, a body temperature of few degrees is valid only if the subject does not have any other vital signals (and is practically deceased), otherwise, it shows a discrepancy and the data cannot be trusted. Therefore, by adding such logical information regarding the co-existing situations and signals, the system can perform a cross-validity check and obtain another level of holistic awareness regarding the confidence it can invest in the observed data.

4 Impact Evaluation

In this section, we explain how we have taken advantage of the concepts discussed in previous sections to enhance the reliability of our EWS. The details of our experimental set-up and acquired results are as follows.

4.1 Experiments Set-up

EWS Table: Because human body functions have some variance from person to person, there exist several different EWS classification tables from various studies [2, 11, 12]. In this work, as shown in Table 1, we mainly use a similar table as

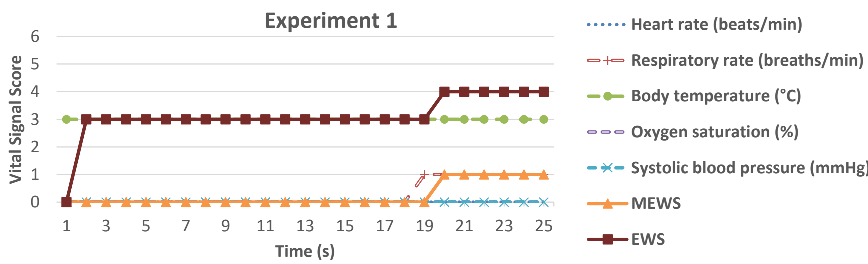


Fig. 3. Calculation of the MEWS and EWS with the same data set. Body temperature is manually set to $100°C$ which is out of the absolute bounds. CCVU deactivated for showing the difference.

in [2]. Whereas the original table showed only one possible score (= 2) for the hypothermia, Brown *et al.* introduced in their work [13] four different stages of an accidental hypothermia (called HT I to HT IV). Following that approach, we combined HT III and IV because HT III shows symptoms of weak- and HT IV of no vital signals.

Patients' Data: The vital signal data were obtained from the experiments carried out by Azimi *et al.* [2]. This dataset contained records of heart rate, systolic blood pressure, respiratory rate, and oxygen saturation of a 35 years old healthy male subject [2]. To evaluate the behavior of the system during a malfunction, instead of the measured temperature, we introduced faulty temperature data.

Analysis Environment: For the analysis of the EWS, we used our hierarchical agent-based model toolbox. It is developed in C++, and its agents can be configured in different ways based on the requirements.

4.2 Confidence Assessment and Results

Experiment 1: Absolute Bounds

The first validation step is to check if a measured value is in a plausible range. For temperature for example, according to Omics International[2], the temperature extremes in Europe are about $-58°C$ and $48°C$. Therefore, these values can be used to define the extreme lower and upper bounds of the temperature. The measured value will be classified as valid if it is in this range. Although this boundary allows us to evaluate the behavior of system regarding this parameter, we note that more accurate values will have to be chosen when the system is used to monitor a patient's condition in real life.

Figure 3 shows the results of the confidence validation's regarding the absolute bounds. The body temperature was manually set to $100°C$ which is out of the absolute bounds. Therefore, the score of the temperature is 3 for the whole time if it is not checked regarding its confidence and 0 if it is checked.

Experiment 2: Change Rate

Here, we concentrate on the consistency of the data based on the maximum plausible rates of change of an input signal. Regarding the body temperature, the

[2] http://research.omicsgroup.org/index.php/List_of_weather_records, accessed on July 2016

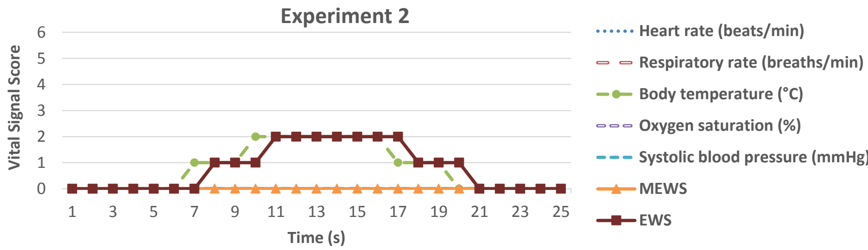


Fig. 4. Calculation of the MEWS and EWS with the same data set. Body temperature is manually set to $36°C$ (score 0) and then decreased faster as the maximum allowed rates of change is set. CCVU deactivated for showing the difference.

highest cooling rates obtained from persons that got completely buried under an avalanche are between $6°C/h$ to $9.4°C/h$ [10, 14, 15]. Assuming that temperature of a human body cannot increase faster than it can decrease, we set the maximum possible rate of change to $10°C/h$ $(= 0.17°C/min = 0.003°C/s)$. The body temperature will be considered as unconfident if the rate of change is higher than the maximum allowed limit set. The input signal has to have approximately the same value (previous value ± allowed rates of change) it had before it was unconfident to get the confident status back[3].

Figure 4 shows the results of the confidence validation's regarding the change rate. The body temperature was manually set to $36°C$ which is equivalent to score 0. After a short period, the temperature was decreased faster as the maximum allowed rate of change. We can see that in the absence of Confidence Validation Unit (CVU), we have false alarms which we do not observe in the enhanced system. If the CVU is deactivated, the body temperature score is unequal to zero when the associated input gets lower than $35°C$. On the other hand, the input signal is being considered as unconfident if the CVU is activated. Now to get the new data tagged as confident again, regardless of its change, its absolute value needs to go back to latest value tagged as confident ± allowed change. For example, we set the temperature signal to an unchanging value between the seconds 12 and 14 and although the input signal's rate of change is equal to zero, it is still classified as unconfident.

Experiment 3: Cross Confidence Validation

Humans' vital signals such as heart rate, blood pressure, and respiratory rate change with a body temperature when it is too high or too low [13, 16]. A mild hypothermia can come along with symptoms such as tachycardia and tachypnea, a medium hypothermia already shows signals of hypotonia and bradycardia. Henceforth, the lower the body temperature the weaker the vital signals get; until they finally stop [17]. Regarding hyperthermia, the changes of vital signals are not completely identical, but show a similar behavior; that is, general deterioration [16]. By implication, this means that body temperature cannot be injurious if all the other vital signals have a good value.

[3] We remark that to ascertain a signal's rate of change, a history is needed. As a preparatory work, history has to get smoothed before calculating the rates of change, otherwise, noise could affect this measurement.

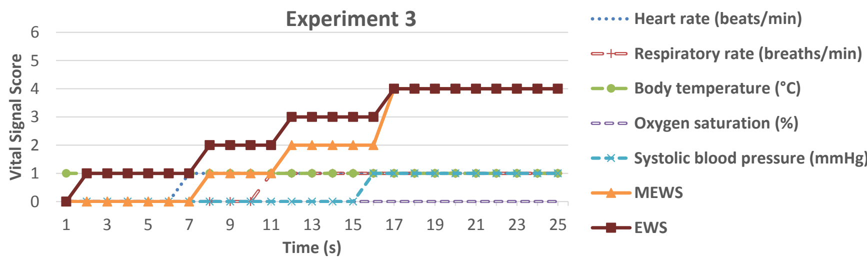


Fig. 5. Calculation of the MEWS and EWS with the same data set. Body temperature is manually set to $32°C$ (score 1) and the other input signals are time-displaced (one after the other) to values where there are no score 0 present.

In contrast to the two steps before, the Cross Confidence Validation Unit (CCVU) needs already abstracted knowledge from different sources. Therefore, this validation is only possible at a higher hierarchical level. In our case, that is the body agent which gets the abstracted data from the different agents. The CCVU was configured to consider the measured temperature as valid if more than 50% of the vital signals (body temperature excluded) have a non-zero score in accordance to that of the temperature.

Figure 5 shows results of the confidence validation test. The body temperature was manually set to $32°C$ (score 1). The other input signals are time-displaced to set their values to non-zero scores, one input after the other. It can be seen that at 17s the MEWS is changing when more than 50% (3 out of 4) of the input variables reach a non-zero score. We can see that if the temperature sensor is included in the EWS calculation - when the CCVU is deactivated - we have a higher EWS. Such a case, nonetheless, is physiologically not possible and hence, the EWS should not be affected.

5 Conclusion

It is vital that the Early Warning Score is computed correctly at all times, in spite of potential complications in the input data stream. Otherwise, there could be false or missed alarms. In this paper, we show that it is possible to check the confidence of the input data with our modular solution based on self-awareness. Using this concept, the reliability of EWS improved in all three cases we experimented with. Thus, we demonstrated that using the data confidence validation system, the quality, and robustness of the EWS assessment can be improved.

We used a hierarchical agent-based system which allows processing both the data and their meta-data, such as the confidence assessment. Due to its modularity and a good match of the data processing flow from lower to higher abstraction levels, it is a promising architecture for EWS or similar systems.

In the future, we will extend our framework and add various features such as the ability of learning. We assume that a learning unit could help choosing better boundaries and values, based on the personalized behavior of the subject, for confidence evaluation and consequently the score calculation.

References

1. R. Morgan, F. Williams, and M. Wright, "An early warning scoring system for detecting developing critical illness," *Clin Intensive Care*, vol. 8, no. 2, p. 100, 1997.
2. I. Azimi, A. Anzanpour, A. M. Rahmani, P. Liljeberg, and H. Tenhunen, "Self-aware early warning score system for iot-based personalized healthcare," in *Proceedings of international conference on IoT and big data technologies for healthCare*, 2016.
3. A. Jantsch and K. Tammemäe, "A framework of awareness for artificial subjects," in *Hardware/Software Codesign and System Synthesis (CODES+ ISSS), 2014 International Conference on*. IEEE, 2014, pp. 1–3.
4. M. Götzinger, A. Rahmani, M. Pongratz, P. Liljeberg, A. Jantsch, and H. Tenhunen, "The role of self-awareness and hierarchical agents in resource management for many-core systems," in *Many-core Systems-on-Chip (MCSoC)*, 2016.
5. N. TaheriNejad, A. Jantsch, and D. Pollreisz, "Comprehensive observation and its role in self-awareness; an emotion recognition system example," in *the Federated Conference on Computer Science and Information Systems (FedCSIS)*, Sep. 2016.
6. B. Rinner, L. Esterle, J. Simonjan, G. Nebehay, R. Pflugfelder, G. Fernandez Dominguez, and P. R. Lewis, "Self-aware and self-expressive camera networks," *Computer*, vol. 48, no. 7, pp. 21–28, July 2015.
7. N. Dutt, A. Jantsch, and S. Sarma, "Toward smart embedded systems: A self-aware system-on-chip (SoC) perspective," *ACM Transactions on Embedded Computing Systems (TECS)*, vol. 15, no. 2, p. 22, 2016.
8. H. Hoffmann, M. Maggio, M. D. Santambrogio, A. Leva, and A. Agarwal, "SEEC: A framework for self-aware computing," MIT, Tech. Rep. MIT-CSAIL-TR-2010-049, October 2010.
9. J. Teich, J. Henkel, A. Herkersdorf, D. Schmitt-Landsiedel, W. Schröder-Preikschat, and G. Snelting, "Invasive computing: An overview," in *Multiprocessor System-on-Chip*. Springer, 2011, pp. 241–268.
10. M. Pasquier, P.-A. Moix, D. Delay, and O. Hugli, "Cooling rate of 9.4 °C in an hour in an avalanche victim ," *Resuscitation*, vol. 93, pp. e17 – e18, 2015.
11. R. W. Urban, M. Mumba, S. D. Martin, J. Glowicz, and D. J. Cipher, "Modified early warning system as a predictor for hospital admissions and previous visits in emergency departments," *Advanced emergency nursing journal*, vol. 37, no. 4, pp. 281–289, 2015.
12. J. Groarke, J. Gallagher, J. Stack, A. Aftab, C. Dwyer, R. McGovern, and G. Courtney, "Use of an admission early warning score to predict patient morbidity and mortality and treatment success," *Emergency Medicine Journal*, vol. 25, no. 12, pp. 803–806, 2008.
13. D. J. Brown, H. Brugger, J. Boyd, and P. Paal, "Accidental hypothermia," *New England Journal of Medicine*, vol. 367, no. 20, pp. 1930–1938, 2012.
14. G. Putzer, S. Schmid, P. Braun, H. Brugger, and P. Paal, "Cooling of six centigrades in an hour during avalanche burial," *Resuscitation*, vol. 81, pp. 1043 – 1044, 2010.
15. R. Oberhammer, W. Beikircher, C. Hörmann, I. Lorenz, R. Pycha, L. Adler-Kastner, and H. Brugger, "Full recovery of an avalanche victim with profound hypothermia and prolonged cardiac arrest treated by extracorporeal re-warming," *Resuscitation*, vol. 76, no. 3, pp. 474 – 480, 2008.
16. A. S. Fauci *et al.*, *Harrison's principles of internal medicine*. McGraw-Hill, Medical Publishing Division, 2008, vol. 2.
17. L. McCullough and S. Arora, "Diagnosis and treatment of hypothermia." *American family physician*, vol. 70, no. 12, pp. 2325–2332, 2004.