Using Early Warning Score for vital signs analysis in *IoT* healthcare environment.

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Abstract

The ability to monitor vital signs in a hospital environment can be improved by information technology, specifically by IoT for healthcare. This technology allows services ranging from monitoring and analysis of vital signs in various environments and times of everyday life. This paper presents patient scenarios associated with data on heart rate, respiratory rate, blood pressure and peripheral oxygen saturation. By monitoring these data it is possible to calculate the risk score using the EWS (Early Warning Score), assisting health teams, reducing intervention times and improving data accuracy. The results obtained in this study demonstrate that individual monitoring and risk analysis, in hospital or other settings, besides improving the quality of care, can reduce the time to identify which patients are at risk, increasing the accuracy of the monitored signals.

1 Introduction

he Internet of Things (IoT) is an emerging technology that can modify the way we know the industry, can be applied in several areas and help solve various problems [15]. To reinforce the emergence of this technology, forecasts predict that by 2020 there will be more than 40 billion connected devices, [8, 11].

This transformation is caused by the constant technological development of this area. According to [10] mobile health technologies can modify clinical intervention especially in the care of the elderly with chronic diseases and in the monitoring of NCDs such as cancer, diabetes, cardiovascular diseases and respiratory [14]. The WHO (World Health Organization) stands for 2025 the elderly population will be 14.8% of the world's population. This problem, along with NCDs, will be challenges to health development in the 21st century [14]. The growth of IoT applications is a real demand. Healthcare devices for monitoring vital signs based on conventional IoT have primary tasks such as gateways for receiving and transmitting data, reinforcing the perception of the possibility of Fog Computing. The results presented by [2] demonstrate that automated monitoring of individuals improves the accuracy of the data and the earlier one perceives the deterioration of individuals, the shorter the time for activation of the Rapid Response Team (RRT). This activation is based on risk values calculated through the pre-defined EWS scale (early warning score). In [2] it is verified, due to the computerization, that there are improvements in the accuracy and the time of perception of deterioration of the individual. Already [12] presents a team dedicated to improve without automation the accuracy of data and vital signs. Thus, supporting the results of [2] in the work of [12], it is perceived that it is very difficult to maintain the precision in the acquisition of these signals, since the qualitative factors are those that most affect the work of the team. An IoT-based system can provide a monitoring service and alerts can be efficient when using protocols such as EWS and/or EPFC (Escalation Protocol Flow Chart), which describes the procedures to be performed. The objective of this work is to use the use of these two health protocols and apply them in simulations to save energy and transmissions to the cloud.

In section two, presents concepts of healthcare alerts (EWS and EPFC). Section three will show concepts and scenarios of patients in attendment. Section four presents methodology, database, and software used. Section five shows related works and relevance of the proposed here. Section six presents the results, at section seven discussion and section eight conclusion and future works.

2 Healthcare alerts

EWS is a system that calculates values of vital signs measured and recorded by the nursing team. The objective is to identify the deterioration of the individual from the following vital signs: Pulse, Blood Pressure, Respiratory Rate and Temperature [1].

Another approach to the EWS is the ViEWS which, in addition to all of the vital signs mentioned above, includes observation of the whole and verifies the individual's breathing with the help of artificial oxygen and voice response alert information, pain response and/or lack of response. Table 1 shows the signal boundaries and their score.

Score	3	2	1	0	1	2	3
`Respiratory rate (breaths/min)`	<=8		9–11	12–20		21–24	>=25
`SpO2(%)`	<=91	92–93	94–95	>=96			
`Temperature (C)`	<=35		35.1–36	36.1–38	38.1–39	>=39	
`Systolic BP(mmHg)`	<=90	91–100	101–110	111–249	>=250		
`Heart rate(bpm)`		<=40	41–45	51–90	91–110	111–130	>=131
`AVPU`							Verbal(V) Pain(P) Unresponsive(U)
`Inspired O2 FiO2`				Air			Any O2

Table 1: Risk scale EWS/ViEWS - Adapted from [1].

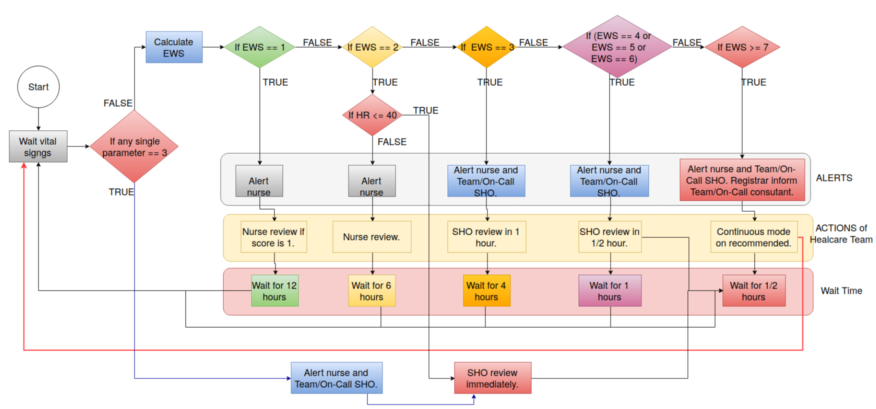

Figure 1: Flow chart of Escalation protocol EWS - Adapted from [1].

3 Monitoring scenarios

The purpose of the scenarios in this work is to organize/contextualize the use of day-to-day sensors of people who need some care, collecting, measuring, storing, inferring intelligence and analyzing risks to promote the health of the individual [10]. Thus, in all these scenarios people previously use in their day-to-day some kind of sensor of the type bracelet capturing some vital signs, similarly as in [9], which suggests capturing pulse in beats per minute, spo2 (oxygen saturation) and temperature.

Individual on the street: in this scenario the patient can be monitored as he presented the work [9]: It shows through a bracelet the capture of the pulse, spo2 and temperature. The mobile application sends the vital signs to the cloud, where an emergency service can be triggered in the event of a person's accident, fall, or malaise. In this scenario, there is a stand-alone concept. Therefore, it is necessary to use dew computing and intelligence on the context so that unimportant messages are not transmitted to the cloud. At an opportune moment, the individual's historical information is sent to the cloud or at a relevant moment as in an accident or fall event.

Individual in ready care: prompt care is the case where the patient has a complaint and goes to a doctor on call who evaluates it. The physician can access the information of the last days reported by the individual, verify if their complaints are related to the monitored vital signs, medicines and electronic medical record. In this scenario, the stored data is characterized by centrality and an intelligence can analyze the data and show possible indications of diagnoses. It can be said that artificial intelligence, ontologies and data mining would help as in the study [5] and can infer more information.

Individual in the observation room during emergency care: in the observation room the person may be connected to more sensors and have more vital signs observed for evaluation and follow-up by the health team [9]. In this case, personal data and vital signs can be placed in a context above the location and below the cloud, a fog context. The person begins to be monitored and evaluated by his/her vital signs through a context that concentrates the data before sending to the cloud. Although a context of intelligence, datamining or ontologies is again similar to the work of [5], the EWS analysis can also be taken into account.

Individual hospitalized in a hospital bed: hospital admission chart requires a lot of care and procedures already in the hospital. The use of sensors at this time is almost mandatory, however, there are several levels of monitoring [10]. In this case, Dew, Fog and Cloud computing approaches may be required, in addition to the risk analysis approach using the EWS.

Individual at home: in this scenario, the patient may have several situations, here they were divided into 3: **total individual dependent on caregivers, restricted to bed and monitored** - this case resembles that of the individual in the ward or hospitalized; **individual not bedridden and partially dependent on the caregiver for support in the necessities of daily living** - here, the scenario may be similar to that of the individual who moves but needs support from a second person to carry out their activities of daily living; **independent person** - in this scenario, the individual can be compared to the individual on the street.

4 Methodology

4.1 Data and software used

A risk comparison was performed using vital signs values from the maximum and minimum limits, according to the literature, in comparison to the calculation of the EWS risk score.

According to [4], when the temperature of an adult is above 37.5 ° C, the individual is considered to have a fever, and below 35 ° C, characterizes hypothermia. For the data of cardiac arrhythmia problems, the following interval was used: values above 100 bpm and below 60 bpm.

For blood oxygen saturation levels, it should be equal to or above 95%, so any value below should be alarming [4]. For systolic blood pressure, normal values should be 80 to 120 mmHg and diastolic values of 60 to 80 mmHg. For the respiratory rate, the values are between 14 and 20 breaths per minute. In this work the physionet/MIMIC database was used, which has several monitored vital signs of individuals in the Intensive Care Unit (ICU). Only subjects with the following vital signs were used for a period of approximately 12 hours per second: respiratory rate, heart rate, SpO2, and systolic blood pressure. The number of individuals on this basis with these vital signs totaled 36.

The Octave version 4.2.2 was used to compare the data and to initially perceive the differences or similarities between the monitoring of the patients using the parameters of the literature and using the EWS scale. Thus, three functions have been created: The first (normalClassification), returns true or false for each signal presented if it were with parameters outside of normal. The second (ewsClassification) returns true for any of the risk scores above or equal to 1, or false for risk 0. The third (riskLevel) calculates the risk rating of each displayed signal that returns values from 0 to 5, where 0 represents the Patient without risk and from 1 to 5 represents the risk classified according to the EWS system.

To reduce the number of transmissions of the signals to the cloud and to decrease the signals that can be measured by some type of fault or discrepant values, the calculation of the arithmetic mean of risk was used for a period of 60 samples, in this case, for 60 seconds. Since EWS scale times allow monitoring ranging from 30 minutes to 12 hours, this period has been adopted here.

4.2 Network simulation

To simulate the data that travels in the network, the CORE (Common Open Research Emulator) software and Wireshark were used to verify/measure the traffic statistics of this simulation.

In the simulation, to reduce the simulation time the data were transmitted every 0.1 seconds. Thus, each sensor node carries vital sign data (respiratory rate, spo2, systolic blood pressure, and heart rate) of each person in the MIMIC database. Then each node processes the risk and transmits it to the centralizing node. This stores 60 samples of each person, calculates the arithmetic mean and transmits the risk to the cloud. The following messages are set to send the individual's signals and their risks respectively.

Message of vital signs: {"bmp":"valor (max 10 bytes)", "spo2":"valor (max 10 bytes)", "rr":"valor (max 10 bytes)", "systo":"valor (max 10 bytes)", "id":"valor (max 10 bytes)"}.

Message of risk: {"id": "valor (max 10 bytes)", "risk": "value (max 2 bytes)"}

5 Related work and motivation

Work [7] used a mesh topology network for communication between devices to send the monitored temperature. While this work will use a TCP/IP network and a client-server architecture.

A Fog architecture is proposed to process signals through FPGA with a mesh layer to aggregate data before processing them in the Fog layer. In this research the idea of Fog will also be used to try to reduce the flow of data transmitted based on the risk of the patient.

The use of NEWS (National Early Warning Score) was proposed in the work of [6] to assess the patient's risk situation, together with a proposal of evaluation using the Fuzzy Inference

System (FIS). However, signaling thresholds and health procedures using EWS are already defined and documented in consolidated health monitoring procedures, so it is proposed here to use this health protocol to determine the patient's degree of risk.

In the work of [15], a service-oriented IoT architecture proposal is presented and compared to SOA, SOA-IoT, with arguments that both SOA and IoT would be to promote network and service heterogeneity. The proposal of heterogeneity here is to use the EWS to redefine what data will be transmitted and what data will be marked to decrease the flow, addressing the quality of service of the network.

A system was proposed and tested to monitor the vital signs of patients, their requests for care, and the moment the health team responds to the request for care. Thus, in the continuation of this work, as mentioned previously, a risk classification of EWS vital signs will be used.

6 Results

Figure 2, in blue, represents the percentage of vital signs that puts each individual at risk according to the following parameters and intervals: Respiratory rate: greater than 20 or less than 14 breaths per minute; Oxygen blood saturation - SpO2: less than 95%; Systolic blood pressure: less than 80 or greater than 120 mmHg; Heart rate: less than 60 or greater than 100 beats per minute. When the patient encounters all normal signs the risk is taken as zero, so the above result shows 12 initial monitoring hours using these intervals.

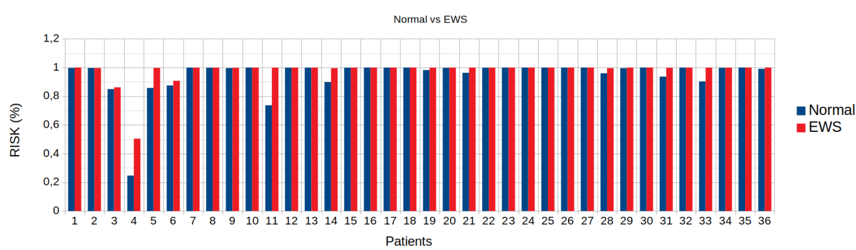

Figure 2: Classification of signs of patients evaluating the signs by "normal" classification and using EWS.

Figure 2, in red, represents the percentage of vital signs that put the individual at risk above 0. Individuals 3, 4 and 5 are those with the highest risk percentage with a value of 0, while the others are practically 100% risk. These results demonstrate that data from the MIMIC database, with or without the EWS scale, are mostly at critical levels above 0 and in this case confirm the critical state of those persons hospitalized in the ICU.

Figure 3 represents the percentage amount of vital signs for the risk rating ranging from 0 to 5 for each user. It is clear that when using this approach, because the EWS can evident urgent patients, health team can adopt monitoring periods and what level of risk should alert them by improving the quality of care since it is essential for the recovery of the individual [1].

In Figure 4 (left), represents the risk classification of users 1, 2, 3, 4 and 5 in the 12-hour interval or 43,200 seconds. Figure 4 (right) represents the average risk in the 60-second period. It can be seen that this average can represent the signal scores per second, reducing noisy points and discrepant signals.

Figure 5 shows the simulation of part of the data of the first 5 patients through the CORE simulation using the Dew and Fog computing paradigms. The sensor nodes calculate the EWS

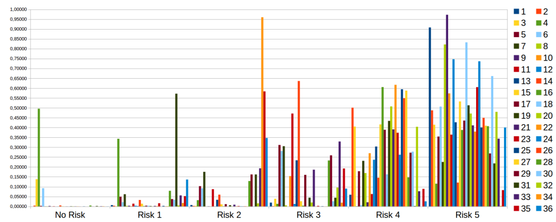

Figure 3: Risk classification according to each level for each individual.

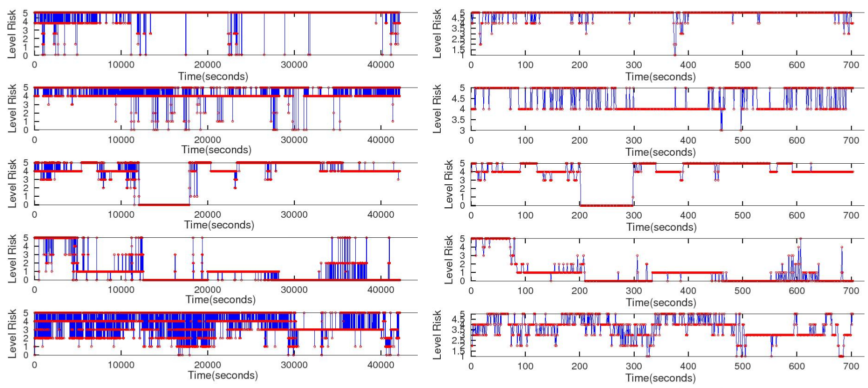

Figure 4: Left - EWS classification of users 1, 2, 3, 4 and 5 over time. Right - Risk classification by arithmetic mean at 60-second intervals.

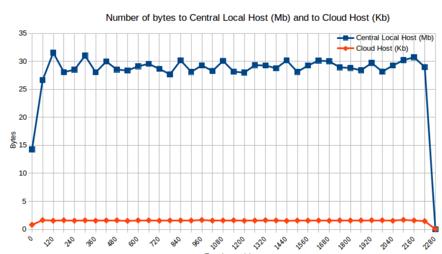

Figure 5: Simulation of traffic using CORE software

risk and send it to the central node in the local network. Lastly, it stores 60 of these values for each patient and then calculates the average for the period, sending the average risk to the cloud.

7 Discussion

It is relevant that using the individual risk classification according to the literature presented, even for non-ICU patients, differs from the EWS classification. In general terms, it is perceived that using only the classification, risk or risk-free, both for the first approach and for the second one generates a false interpretation of the risk of the individual [1]. Thus, when the

EWS risk classification is used through the various levels, the on-site observation period can be verified/alerted by the nursing team. However, through computer systems such as IoT, the health team can be warned, or can access at any time the data of the people monitored.

The individuals analyzed have risk levels practically at each of the six presented levels. This means that when monitoring the risk through the IoT/EWS architecture, the time of intervention by the health team can be efficiently reduced. It can also be determined the periods in which the team would need to intervene, optimizing the work of the team and improving the performance established in the protocol, or even the need to wait, but due to the real time service and the system inference. Therefore, the effectiveness of the health team, which [2] impacts on accuracy and quality of service, even with dedication and commitment, would not be a problem simply by automated monitoring [12], and by using information to improve clinical intervention [10].

In the Fog computing paradigm, where the data travels mainly in the local network, the data would be every second traveling in the network until the centralizing node, therefore, the bandwidth should be enough to be able to offer an efficient service of monitoring be it in real time or not, which should alert the health team to the states of individuals. In the Fog computing approach, as in [3], there are some network properties such as, bandwidth, availability, delay, losses that may be relevant, so network services can be affected. It is then understood that in the context Fog can be used to only send data to the cloud, or to a central of situation only the information relevant to the care of patients with a high degree of risk, thus, reducing the data flow on the network. And the other approach, as in this paper, may be to use the arithmetic mean of a given period that may well represent the individual's level of risk. It is noteworthy that using an arithmetic mean is an approach that reduces the number of transmissions per second and yet well characterizes the risk level of individuals (see Figure 4).

In the Dew computing paradigm, using the arithmetic mean at each node, it is possible to decrease packets trafficked in the local network, while the centralizing node only processes the level of risk that the health team will use to generate alerts in the cloud service [13]. This demonstrates that this approach unlike the previous approach can have an impact on data transmission, bandwidth usage, reduced data traffic to both the local network and the cloud. Therefore, monitoring the vital signs not only of the people in the ICU, but also in any of the scenarios described in section 3, is a way of seeking efficiency of the IoT services according to [15] and [10].

8 Conclusion

To use EWS risk scale in the decision to transmit individuals' data can reduce network traffic according to the level of risk that the health team selects and when calculating the arithmetic mean, a very significant reduction can be achieved, since the time periods of the EWS scale allow monitoring from 30 minutes to 12 hours. Therefore, through a computer system this can be monitored at any time, however, there is a need for containment, in several ways, in this case was decreased when transmitting this information. This is because Dew and/or Fog paradigms can be explored. It is therefore noticeable that the simplicity of this service and this architecture should be tested with more devices performing network performance tests. Another important observation is to also research on other risk protocols, making a comparison between them and finally in future works to provide QoS on the data using the risk levels to label the transmitted packets. This approach allows to define efficient periods of visit of the health team, allows to generate alerts at any moment, as well as to establish standards to define where the best moment for the team to act using artificial intelligence, data mining or ontology.

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