Intelligent and Real Time Data Acquisition and Evaluation to Determine Critical Events in Intensive Medicine

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Abstract

Using the information regarding critical events to support decision making in Intensive Care Units would be useful. However it is seldom used in real settings as the information regarding those critical events is difficult to gather and make available in real time. The most usual procedures record only those events that are related to errors. This paper presents a solution to obtain critical events from clinical data. From data collected using an automatic and real-time data acquisition system it is possible to calculate the critical events regarding five variables that are usually monitored in an ICU. These results are presented to the medical and nursing staff in a friendly and intuitive mode. Using a color code our system provides visual warnings related to the evolution of the monitored variables values. Actually, a quick glance allows doctors to get a high level overview of the patient's condition

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1. Introduction

Intensive Care Units (ICU) are flooded with devices aiming at giving doctors better information regarding their patient’s condition. For example, bedside monitors continuously show blood pressure, oxygen saturation, heart rate together with the values of other variables.

When working with such data we are faced with a wealth of data streams instead of the more usual static data table [1]. Indeed, for each monitored variable in the ICU one has a data stream and, to further complicate matters, it is often the case that data from different sensors are gathered at different time intervals. For example, real time data, acquired from the bedside monitors must be merged together with analysis data, which comes in only once or twice a day. Thus, while traditionally one would have one or two records per patient per day, entered manually by the nursing and/or medical staff, automated data acquisition gives us an almost infinite amount of data. In fact, in the ICU we can now collect data for 16 different variables (when applied) with a 10 second interval between observations. This scenario makes us face a potentially high number of information per patient, per day. And, as already stated, this data arrives at different times and with different time intervals.

For automatic data acquisition to be possible and efficient in such a scenario, data pre-processing is of paramount importance assuring that important information is kept and that irrelevant one is filtered out. For example, one does not need to store the same amount of data for a stable patient that is needed for another that is having more problems. Also, doctors seldom need the exact values, they would rather reason in terms of change (e.g. “did the blood pressure rise much in the last hour?”) than in terms of the exact values each variable had.

One very important pre-processing activity in such a context is that of identifying those situations that are potentially medically relevant as there is a huge number of value changes and only a small subset is potentially medically relevant. Models used for outcome and organ failure prediction depend on information regarding Critical Events (CE). In order to use those models in a real setting it was necessary to define the procedures to automatically compute CE for five variables: Diuresis, Blood Pressure, Heart Rate, Respiratory and Temperature.

This paper is divided in seven chapters, the first (this one) introduced the paper, the second frames the problem, then the data acquisition process and data analysis will be described. Chapter five will present the CE tracking system and the sixth will present the results obtained so far and the system interface. Finally some concluding considerations will be made.

2. Background

2.1. INTCare

The work we are presenting is part of a research project called INTCare. The algorithms in use in INTCare’s prediction module require information regarding the critical events that have occurred during the stay of the patient in the ICU. In order to be able to use INTCare with real time data one must have some means of extracting the CE also in real time.

INTCare includes an Electronic Nursing Record (ENR) module that is responsible for data collection [2]. It maintains the patients daily clinical records and other information relevant to the decision making process. Data collected includes the patient’s vital signs, medical procedures, therapeutic plans, medical scores, information regarding ventilation and others. There is a touch screen workstation near each ICU bed. Medical and nursing staff may use them to record, validate and visualize all clinical information about each patient.
INTCare [3, 4] is implemented in the Intensive Care Unit of Hospital Santo António, Centro Hospitalar do Porto.

2.2. Intensive Care

Intensive care is a critical area of medicine, where the patients are in too weak conditions and/or in serious life-risk [5]. Intensive Care units are the place where this type of medicine is applied. Usually, during the stay of these patients is possible to verify a set of adverse events. These events can influence the future outcome and can occur various times a day [6]. The ability to calculate the events automatically and in real-time is an important support to the decision making process. In addition, the development of an Intelligent Decision Support System, like INTCare, which uses these variables to predict the patient condition, can help the doctors to maintain a pro-active action that will benefits the patients.

2.3. Critical Events

Studies done in the past reported that the most common adverse errors were due to wrong mechanical or human performance [7]. However, other points exist, that are difficult to analyze (eg. patient clinical events). This happens because it is very difficult to quantify the number of clinical errors due the lack of automatic data acquisition systems in the ICUs. Normally, these results are collected by some alerts provided from bedside monitors ([8]). This paper will explain an approach to obtain the number and the time of clinical adverse events to five variables (Heart Rate, Blood Pressure, Saturation of Oxygen, Diuresis and Temperature).

The adverse events in use were assigned in an electronic application at a continuous acquisition basis. To understand if an event is critic or not, two main criteria were used [9]:

- occurrence and duration should be registered by physiological changes;
- related physiological variables should be routinely registered at regular intervals.

An event is considered critical, when a longer event occurs or a more extreme physiologic measurement is found [9].

In this project we used two different definitions: critical values and critical events. Critical values are values that are out of a normal range. Critical event is defined as a label to signal that a variable had critical values for more than the admissible time span, as defined in Table 1. Also, a critical event may signal that the critical value was so out of range that it is considered serious regardless of the duration of that observation. For example, a critical event happens whenever the patient’s heart rate stays above 120 bpm for more than 1 hour. Also, a critical event happens every time the heart rate drops below 30 bpm or rises above 180 bpm.

Table 1. The protocol for the out of range physiologic measurements (adapted from [9])

<table>
<thead>
<tr>
<th>Normal range</th>
<th>BP</th>
<th>SpO2</th>
<th>HR</th>
<th>UR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>90 to 180 mmHg</td>
<td>&gt;= 90%</td>
<td>60 to 120 bpm</td>
<td>&gt;= 30 ml/h</td>
</tr>
<tr>
<td>Critical event</td>
<td>&gt;= 1h</td>
<td>&gt;= 1h</td>
<td>&gt;= 1h</td>
<td>&gt;= 2h</td>
</tr>
<tr>
<td>Critical event a</td>
<td>&lt; 60 mmHg</td>
<td>&lt; 80%</td>
<td>&lt; 30 bpm or &gt; 180 bpm</td>
<td>&lt;= 10 ml/h</td>
</tr>
</tbody>
</table>

a Defined when continuously out of range.
b Defined anytime.
3. Data acquisition process

To implement the system it is necessary to be able to gather the values for all variables automatically, continuously and in real-time. Initially, none of the variables was acquired automatically or/and in an electronic mode. Every hour these values were registered by hand in a paper based nursing record. After some changes [2, 4, 10] were made in the ICU acquisition system it became possible to automatically collect some data. Now, using these new data sources it is possible to make a calculation of the critical events. For the critical events system, the following data sources are being used:

- Bed Side Monitor - vital signs (VS);
- Electronic Nursing Record (ENR) – Hourly values (Diuresis);

To perform the tasks associated with data acquisition a set of agents have been implemented [11] to acquire and process the data from the different ICU data sources.

Firstly, the data are extracted from the ICU data sources by the agents; during the extraction some automatic procedures are executed. Then, all process of interpretation of values is executed by the pre-processing agent and finally, all data are loaded into a data warehouse that stores all critical values to be used by the Critical Events System. Fig. 1 summarizes the process of the data acquisition system which has been developed in order to collect data from bedside monitors and ENR.

![Fig. 1. ICU Critical Events – Data acquisition](image)

In the present we are concentrating on detecting the critical events that were deemed most important by the doctors we are working with. Automated data acquisition without human intervention is already in place for most of them. However, the urine output measurement is not automated at the ICU and the respective values have to be manually entered by the nursing staff. Table 2 explains, which are the variables collected in real-time, the correspondent data source and if they are acquired in an automatic or manual way. In this case, only one of the variables requires a manually operation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Data Source</th>
<th>Acquisition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blood Pressure (BP)</td>
<td>BM</td>
<td>Automatic</td>
</tr>
<tr>
<td>Temperature (TEMP)</td>
<td>BM</td>
<td>Automatic</td>
</tr>
<tr>
<td>Hearth Rate (HR)</td>
<td>BM</td>
<td>Automatic</td>
</tr>
<tr>
<td>Oxygen Saturation (O2)</td>
<td>BM</td>
<td>Automatic</td>
</tr>
<tr>
<td>Urine Output (UR)</td>
<td>ENR</td>
<td>Manual (hour)</td>
</tr>
</tbody>
</table>
4. Data Analysis

This process is the main process of the entire project. It is a first step through the data that allows for validation and for detection of values that may be part of CE. The data quality is fundamental to obtain the correct number of critical events. In this case, all values collected are being used, i.e., all values are necessary to be able to do a continuous calculation of events. In order to streamline the process it is necessary to have an automatic validation procedure. This procedure is activated whenever a new value arrives. Each value is checked to see if it is inside the valid range of values for the respective variable and then it is flagged as potentially critical or non-critical. This task is executed according to the values defined in Table 3. For example, a value of 25 for the temperature will be discarded as it is out of the valid range (25ºC is the room temperature and is sometimes recorded as the patient’s temperature if the sensor is not properly placed). A value of 39 for the same variable will be flagged as potentially critical.

<table>
<thead>
<tr>
<th>EV_ID</th>
<th>DESCRIPT</th>
<th>MIN_EC</th>
<th>MAX_EC</th>
<th>MIN_VAL_ICU</th>
<th>MAX_VAL_ICU</th>
<th>MIN_ANYTIME</th>
<th>MAX_ANYTIME</th>
</tr>
</thead>
<tbody>
<tr>
<td>3510</td>
<td>TEMP</td>
<td>36</td>
<td>38</td>
<td>34</td>
<td>45</td>
<td>35</td>
<td>40</td>
</tr>
<tr>
<td>1011</td>
<td>BP</td>
<td>90</td>
<td>180</td>
<td>0</td>
<td>300</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>3000</td>
<td>O2</td>
<td>60</td>
<td>120</td>
<td>0</td>
<td>300</td>
<td>30</td>
<td>180</td>
</tr>
<tr>
<td>2009</td>
<td>HR</td>
<td>30</td>
<td>1000</td>
<td>0</td>
<td>1000</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>DIU</td>
<td>UR</td>
<td>30</td>
<td>1000</td>
<td>0</td>
<td>1000</td>
<td>10</td>
<td></td>
</tr>
</tbody>
</table>

The procedure referred is applied only to the variables that are to be used in the calculation of the critical events. This procedure is executed through a trigger which is activated before the value is inserted in the table containing HL7 [12] data. For each value collected:

BEGIN
  IF CATEGORY IN (3000, 2009, 1011, 3510, ‘DIU’) THEN
    IF VALUE >= MIN_VALUE_ICU AND VALUE <= MAX_VALUE_ICU THEN
      IF (VALUE <= MIN_ANYTIME OR VALUE >= MAX_ANYTIME) THEN
        SET CRITIC TO 2
        SET VALID TO 1
      ELSIF VALUE <= MIN_EC OR VALUE >= MAX_EC THEN
        SET CRITIC TO 1
        SET VALID TO 1
      ELSE
        SET CRITIC TO 0
        SET VALID TO 1
      ENDIF
    ENDIF
  ENDIF
END

Immediately after this procedure is executed another trigger, which is responsible to calculate the time of these events, is activated.

5. Critical Events Tracking System

After having collected the critical values it is necessary to check if they originated a critical event. That requires some calculations. The base of the calculation is the Table 1. In order to help understand if the event
type collected is or is not the same which was before collected, a flag in the table will be used. The flag $\phi$ will identify the state of the event type collected, i.e., the flag value present in the table notifies if exist some event in the table with the same type and if that event is opened (1) or not (0). An “open” event is still in progress while a “closed” one has already finished.

When a value is collected and, immediately after it is validated and inserted in the HL7 table, the trigger will verify if there is some “open” record for this event category. If it doesn’t exist, a new row will be created. If there is a record for the same event type, nothing will be done, otherwise the event finish date will be defined according the collected date of the obtained value.

For each event type (0, 1, 2) some operations will be done according to the respective event state (open or not). Finally and after the event start and event finish date is filled, a procedure, which calculates the time of each event is executed. For each patient, event category and value collected (PEVID) and, after the values are correctly inserted in database, the trigger shown next will be executed:

```sql
BEGIN
    IF OPEN = 0 THEN
        SET DATE_START TO SYSDATE
        SET DATE_FINISH TO NULL
        SET OPEN TO 1
        SET CRITIC TO EVTYPE
    ENDIF
    IF OPEN = 1 THEN
        IF CRITIC <> EVTYPE THEN
            SET DATE_FINISH TO SYSDATE
            SET OPEN TO 0
            SET CRITIC TO EVTYPE
            SET TOTAL_TIME TO DATE_START - DATE_FINISH
        ELSE
            NULL
        ENDIF
    ENDIF
END
```

After the value is correctly identified and inserted into the database, with total time filled, another trigger will be executed. This other trigger is designed to verify if an event is critic or not.

To identify if a set of collected results is or not a critical event it is necessary to analyze the table which contains all values collected with the respective time interval. By computing the length of that time interval, the procedure will identify which set of values are critical:

```sql
BEGIN
    READ ROW
    IF EV_TYPE = 2 THEN
        SET CRITICALEVENT TO 1
    ELSIF EV_TYPE = 1
        IF CATEGORY = 'DIU'
            IF TOTAL_TIME >= 7200 THEN
                SET CRITICALEVENT TO 1
            ELSE
                SET CRITICALEVENT TO 0
            ENDIF
        ENDIF
    ENDIF
END
```
ENDIF
ELSIF TOTAL_TIME >= 3600 THEN
    SET CRITICALEVENT TO 1
ELSE
    SET CRITICALEVENT TO 0
ENDIF
ENDIF
END

6. Results

As results, it is possible obtain a number of critical events for the patient by hour and category. The system is refreshed every 10 minutes. The results are obtained after know the importance of the values, i.e. critic or not, other procedure will start. This procedure will calculate the Accumulated Critical Events (ACE) – to reflect the patients’ clinical evolution/severity of illness by hour. The values obtained will be used to create some ratios. The next procedures will be in a regular execution, and have the objective to understand the number of events by type and hour, and the sum of them.

To count the number of events and sum of the time, grouping by type and hour:

    SET CATEGORY_HOUR_VALUE TO SUM(COUNT(CRITICALEVENTS) BY DATE_HOUR AND BY CATEGORY)

    SET CATEGORY_HOUR_TIME TO SUM(TOTAL_TIME) BY DATE_HOUR AND BY CATEGORY

The results obtained by the last procedures will be presented inside of Electronic Nursing Record in a grid designed to the effect. This system is composed by a traffic light system and a grid. The light system is an alert to the patient condition. For each variable, if some event is “open”, the event type (1 or 2) is checked. Then, for the event type = 1, it will calculate the time between the system date (sysdate) and the starting date. If the time in minutes is between 10 and 20 the label will be yellow. If this event is open more than 20 minutes the label will be red. In the cases of event type = 2 the label will be always red independent the time it is started. In the other cases the label will be green.

The critical event number and time results are presented in a grid. This grid shows: the number of critical events by hour, the number of accumulated events and the time in critical event by hour and the total time in critical event.

The grid has 13 columns. The first represents the hours of the day (1-24), the next four columns, contain the number of events for that hour for each event. Then, the next four columns contain the number of minutes of the event in this hour. The last two columns represent the number total of events and the ratio minutes by hour for all events.

In a context of proving the functionality of the system, Fig. 2 present the distribution of the values collected during the last six months. The values are grouped by variable, event type and hour. In the graph is possible to see the percentage of occurrence for three of the five variables (blood pressure (BP), SPo2, Heart Rate (HR) by hour (0-23) and event type (1 or 2).
From the graph some important conclusions can be made. The critical events of BP (59.85%) and HR (85.91%) are strongly associated to the events type 1. In the case of SpO2 the critical events are mostly of the type 2 (68.22%). The vast majority of the events (almost 20%) occurs between 9 and 11 am. This is most evident for the HR (critical event type 1) and SpO2 (critical event type 2). For the Blood Pressure, the 15th hour is the most critical (6.64% = 3.91% (1) + 2.73% (2) of the critical events occurred during this hour). This sort of analysis can help the doctors understand when each the event type normally occurs. The information obtained about the critical events combined with other variables can be used to alert the doctors in order to avoid critical events.

7. Conclusions & Future Work

The implementation of this new approach allows doctors, in ICU of Centro Hospital do Porto, to have a better understanding of the patient’s condition. The doctors can see, for each patient and in real time the number of events by hour and the time which the patient was in a critical event. In addition, they possess a traffic light system (green, yellow, red) to alert / show the actual situation for each event.

The output of the system developed will feed the DM models of the INTCare system in order to predict the organ failure and outcome. Due to the success of this implementation, in the future, further adverse events types will be explored and added to the system.

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References


