



On line extraction of temporal episodes from ICU high-frequency data: A visual support for signal interpretation

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Summary This paper presents a method to extract on line temporal episodes from high-frequency physiological parameters monitored in ICU, as a visual support for signal interpretation. Temporal episodes are expressions such as: "systolic blood pressure is steady at 120mmHg from time t_0 until time t_1 ; it increases from 120 to 160mmHg from time t_1 to time t_2 ...". Three words are used to describe the data evolution: {steady, increasing, decreasing}. The method deals with noisy data and missing values. It uses a segmentation algorithm that was developed previously and a classification of the segments into temporal patterns. The results obtained on simulated data are quite satisfactory. They show that the method is able to detect rapid variations as well as slow trends. Episodes extracted from real S_pO_2 data recorded over a period of 44h from 10 different adult patients are analysed. The visual representation of the temporal episodes is a powerful tool to help the physicians analyse in a glance the evolution in time of the variables monitored. It can help carer personnel to make quicker decisions in alarm situations.

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1. Introduction

Intensive Care Units receive patients in critical condition, whose state requires considerable attention from personnel. To help them in their surveillance task, patients are equipped with monitoring systems recording on line physiological parameters describing the patient's state. The

number of these variables recorded at a high frequency rate is constantly increasing thanks to technological advances, and the personnel is often overwhelmed by this continuous data flow. Cognitive overload is a problem frequently suffered by operators supervising a complex process, yet, in Intensive Care Units, it is aggravated by the fact that the personnel has to take care of several patients, suffering from various pathologies. The important false alarms rate, due to limit alarm systems, worsens the situation by diminishing the personnel vigilance [1–3]. Intensive Care Units are

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in a great need of tools able to help the personnel analyse the huge amount of data recorded and to support the personnel in his decision making task.

Some work has been carried out in the past decade to develop intelligent alarm and monitoring systems for ICU. The purpose of this work is to assist clinicians in the interpretation of an alarm situation [4,5]. The earliest systems analysed the situation of a patient through various current physiological measurements, often converted into symbolic values. Current systems analyse the data monitored through a temporal dimension, using trend extraction procedures and temporal pattern abstractions [6,7]. For these systems, “the abstraction of primary data into intervals over which a specified predicate holds is a central task” [8–11].

Numerous methods to extract temporal patterns, such as trends or level shifts, from physiological data can be found in the literature. In the following, we will only report methods developed for or applied to ICU high-frequency physiological parameters.

Avent and Charlton [12] present a complete review of the trend detection techniques used in the 1980s. Many of these techniques are provided by the automatic control community and are able to detect quite early on whether the process is deviating from a trend. For example, we can quote the Cumulative Sum of errors (CUSUM) and the Exponential Weighting Moving Average (EWMA) charts. However, these techniques require a reference value, known a priori or calculated from the past values, which are very difficult to obtain in practice in the context of ICU patient monitoring.

Time series analysis methods were also applied on ICU physiological parameters. Among these methods, Imhoff et al. [13] propose to recognise on line an artefact, a step level change or a trend using autoregressive models or phase space models. These techniques, applied to real ICU data, are able to detect an artefact or a level change but have problems detecting a trend. Moreover, they cannot quantify it.

Makivirta et al. [14] calculate qualitative trends on data, after applying a median filter, by calculating the sign of the slope using the best fit least squares method on a fixed time window, associated with a step detector. The length of the time window is a choice, which is made a priori. For hemodynamic data, the trends are calculated on the last 30 min.

To avoid the problem of choosing a priori the adequate time window to calculate the trend, Calvelo et al. [15,16] developed a methodology to extract the underlying temporal trends in a physiological signal by determining, during a training pe-

riod, the width of the time window during which the approximation by a linear function is statistically acceptable on the signal. They calculate the parameters of the linear function that best fit the data on the moving window. This time window is named the characteristic span. The qualitative trend, increasing, decreasing or steady, is given by the value of the slope at each sample time. They add a fourth category, unsteady, when the variance of the signal is superior to a given threshold. This category corresponds to important variations affecting the signal or to rapid transients.

Hau and Coiera [17] developed a front end and segmentor units to process data so as to build qualitative models. In the front end unit, the signal is removed from its artefact, filtered using a median filter then smoothed with a gaussian filter, then its derivative is calculated by a FIR filter. Temporal intervals are then constructed by segmenting the signal at zero crossings of its derivative calculated previously. The sign of the derivative determines the kind of interval: increasing, decreasing or steady if the derivative remains between tolerance bounds.

To fit a linear curve on a fixed size moving window or to smooth a signal with a low pass filter distorts the rapid variations of the signal that may be important to report, such as a step-like variation. It can be noted that this problem is partly solved by Calvelo et al. by adding the unsteady class that classifies rapid variations into instability. It also introduces a constant delay that depends on the length of the time window or the filter.

Moreover, the methods using the value of the slope of a linear function to detect qualitative trends may be very insensitive to slow trends, the characteristic of which is a very small value of the slope. These are the main drawbacks of the methods listed above.

Hunter and McIntosh [18] used the bottom up segmentation algorithm developed by Keogh [19] to extract temporal intervals from ICU physiological time series. The bottom up segmentation algorithm creates intervals by merging existing intervals into larger ones. The algorithm first converts a sequence of time points into a sequence of elementary intervals, then iterates by merging two adjacent intervals into a larger interval until a halting condition is satisfied. The slopes of each of the intervals can then be calculated. However, this algorithm cannot work on line.

Haimowitz et al. developed a computer program called *TrenDx* that detects significant trends in time-ordered patient data by matching data to patterns they call trend templates [9,20]. A trend

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