Mining intensive care vitals for leading indicators of adverse health events

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Objective

To present a statistical data mining approach designed to: (1) Identify change points in vital signs, which may be indicative of impending critical health events in intensive care unit (ICU) patients and (2) Identify utility of these change points in predicting the critical events.

Introduction

The status of each ICU patient is routinely monitored, and a number of vital signs are recorded at subsecond frequencies (1), which results in large amounts of data. We propose an approach to transform this stream of raw vital measurements into a sparse sequence of discrete events. Each such event represents significant departure of an observed vital sequence from the null distribution learned from reference data. Any substantial departure may be indicative of an upcoming adverse health episode. Our method searches the space of such events for correlations with near-future changes in health status. Automatically extracted events with significant correlations can be used to predict impending undesirable changes in the patient's health. The ultimate goal is to equip ICU physicians with a surveillance tool that will issue probabilistic alerts of upcoming patient status escalations in sufficient advance to take preventative actions before undesirable conditions actually set in.

Methods

To generate potentially informative events from vital signs, we first segment each data channel into sequences of k consecutive measurements. We then perform Fourier transformation to obtain spectral profiles of each segment of raw signal. Multiple spectral profiles, extracted from periods of observation that are considered medically benign, are then assembled to form a k-dimensional flat table. We apply principal component analysis to this, and the top p components are considered further. These p components form a null space model of the expected normal behavior of the given vital sign. We build one null space model for each channel separately; this concludes the learning stage of the process.

Each newly observed set of k consecutive measurements is then processed through Fourier transform and projected onto the p principal components of the corresponding null space models. Over time of observation, these projections produce p time series per measurement channel. We apply a cumulative sum (CuSum) control chart to each of these time series and mark the time stamps at which CuSum alerts are raised. These moments correspond to circumstances in which the observed spectral decomposition of a vital sign does not match what is expected. We consider each such event as potentially informative of near-future deteriorations in the patient's health status. We quantify the predictive utility of each type of these automatically extracted events using training data, which contain actual health alerts, in addition to the vital signs data. To accomplish the task, we perform an exhaustive search across all pairs of CuSum event types (inputs) and alert types (outputs) and identify pairs with high values of the lift statistic (2). Input-output pairs with lifts significantly greater than 1.0 can be expected to enable prediction of health status alerts.

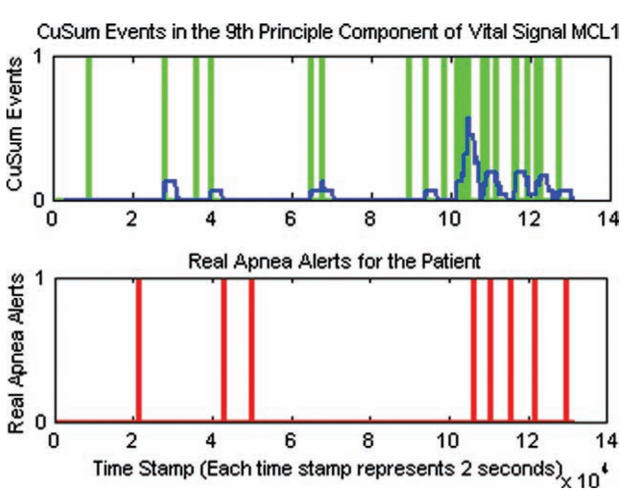

Fig. 1. Increased frequency of CuSum events (top) typically precedes the real apnea alerts (bottom).

Results

Fig. 1 depicts an example result obtained with the presented method. The CuSum Events (green spikes) obtained for the 9th principal component of Modified Chest Lead 1 (MCL1) signal, and the alerts (red spikes) are critical apnea conditions. We can see that, for this patient, the CuSum events most of the time precede apnea alerts, and they can potentially be used to predict an upcoming apneas.

Conclusions

We have outlined a method of processing vitals collected routinely at the bed side of ICU patients. It identifies signals that can be predictive of upcoming adverse health events.

Keywords

Critical care; event detection; data mining

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