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Real-time adaptive monitoring of vital signs for clinical alarm preemption

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Objective

To enable prediction of clinical alerts via joint monitoring of multiple vital signs, while enabling timely adaptation of the model to particulars of a given patient.

Introduction

Cardiovascular event prediction has long been of interest in the practice of intensive care. It has been approached using signal-processing of vital signs (1–4), including the use of graphical models (3, 4).

Our approach is novel in making data segmentation as well as hidden state segmentation an unsupervised process and in simultaneously tracking evolution of multiple vital signs. The proposed models are adaptable to the individual patient's vitals online and in real time, without requiring patient-specific training data if the patient-specific feedback signal is available. Additionally, they can incorporate expert interventions, produce explanations for alarm predictions and consider effects of medication on state changes to reduce false alert probability.

Methods

The proposed model represents distributions of patient data (vitals, state and treatment) as a dynamic Bayesian network. The state of the patient is observed only when an alarm is triggered. The arity of the state variable is estimated from data via E-M optimization. The state and another discrete observable, treatment (a vector of administered medications), influence the continuous output variables that represent the vital signs. The vitals are segmented adaptively using a Kalman filter to reflect a potentially nonstationary periodicity of signals. The segmented vitals are then represented with a continuous Semihidden Markov Model. The trained system is capable of predicting the patient's state on-the-fly from currently observed vitals. It can also learn on-the-fly whenever user feedback is available in the form of correct labels of the predicted states.

Results

We conducted evaluations using the MIMIC II data (5). We used ECG and respiratory rate as input vitals in an attempt to predict heart failure alarms. The results shown in Table 1 were obtained per-patient, by subsampling, using data from the patients held out of the training set. The proposed approach brings the AUC metric (area under the receiver operating characteristic diagram) to 0.66 on average, the patient-specific model offers an improvement, and the inclusion of treatment information provides further benefits.

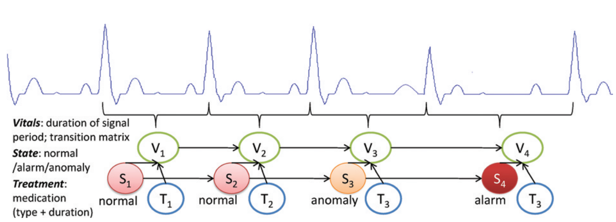

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Fig. 1.

Table 1.

Patient	AUC	Patient-adapted AUC	AUC with treatment info
1	0.67	0.68	0.70
2	0.61	0.63	0.65
3	0 71	0.72	0.72

Conclusions

We have outlined a probabilistic modeling system that is capable of predicting heart failure alarms using time series of vital signs. It is able to learn the key parameters from data (state and temporal resolution) and allows fast adaptation to personalized features of a specific patient. Tests involving a limited set of vital signs indicate improved predictability of heart failure events when compared to a model relying only on prior probabilities. The next steps involve adding more vital signs to the input space to realize improvements of predictive accuracy.

Keywords

Clinical alarm preemption; dynamic Bayesian networks; online learning; time series analysis

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