Predictability of Unplanned Extubations

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***Abstract*— Acute life threatening events such as cardiac/respiratory arrests are often predictable in adults and children. However critical events such as unplanned extubations are considered as not predictable. This paper seeks to evaluate the ability of automated prediction systems based on feature space embedding and time series methods to predict unplanned extubations in paediatric intensive care patients. We try to exploit the trends in the physiological signals such as Heart Rate, Respiratory Rate, Systolic Blood Pressure and Oxygen saturation levels in the blood using signal processing aspects of a frame-based approach of expanding signals using a nonorthogonal basis derived from the data. We investigate the significance of the trends in a computerised prediction system. The results are compared with clinical observations of predictability. We will conclude by investigating whether the prediction capability of the system could be exploited to prevent future unplanned extubations.**

I. Introduction

An Unplanned Extubation (UE) is a clinically unexpected dislodgement or removal of the endotracheal tube (ETT) from the trachea of an intubated patient. Tracheal intubation in children in intensive care is widely used to support respiration, maintain their airway open and remove secretions. In the study presented by Kapadia et al [1] 36 unplanned extubations occurred during 9,289 intubated patient days. A review presented by Lucas da Silva and de Carvalho [2] showed that unplanned extubations occur at a rate of 0.11 to 2.27 events per 100 intubation days.

An UE is a potential acute life threatening event which is usually not predictable or preventable. An UE could result in respiratory failure, increased length of ICU and hospital stay and higher probability of adverse effects of reintubation [3], [4]. The risks associated with reintubation include laryngeal or tracheal injury, aspiration, hypoxia and death [5]. It is especially frequent in neonates and small children due to their small tracheal length and bigger impact of head and neck movement on ETT position. As the age of 48% of paediatric intensive care population is less than 12 months [6], the incidence of UEs and the associated risks is a significant problem. Rachman et. al. [7] found that some of the most commonly indicated reasons for an UE in their hospital included inadequate patient sedation and not securing the tracheal tube to the face of the patient. Other studies have found that the rate of unplanned extubations is higher in neonates and small children (less than three years of age) compared with older children [7].

One of the UE preventive measures includes the implementation of standardised sedation practices by clinicians using protocols based on the COMFORT scale. The COMFORT scale [8] derives a score of patient status based on eight parameters. A value of one to five is assigned to the eight parameters including alertness, calmness, agitation, physical movement, muscle tone, facial tension, mean arterial blood pressure, heart rate and respiratory response. A score of eight or minimum on the COMFORT scale represents 'deeply sedated' and the maximum score of 40 represents 'alert and distressed'. Large scale clinical studies have shown that critical deterioration in patients are preceded by deteriorating trends in the recorded physiological parameters of the patients. In this paper we investigate the significance of the trends of four physiological parameters heart rate, respiratory rate, systolic blood pressure and oxygen saturation. We will evaluate if a computerised prediction system utilising these four parameters will result in a successful prediction of an UE. The results are compared with clinical observations of predictability.

II. Data acquisition

The data used for the research was recorded in the Paediatric Intensive Care Unit, Birmingham Children's Hospital over a 12 months period from November 2012 to October 2013. This data was collected as a part of a larger study (not blind) which intended to evaluate the efficacy of real time data analysis algorithms in predicting life threatening events such as cardiac/respiratory arrests. All the patients admitted to intensive care were screened for suitability for the trial. Ethical approval from Medical Ethics Committees was obtained for 'opt out' consent and parents were approached by research or bedside nurses and informed about the study. Patients whose parents/carers consented for their data to be used were included in the trial.

The project involved the installation of real-time data recording, processing and analysis software on a data server on the BCH computer network. The software comprised McLaren's [9] SQLRace Application Processing Interface and Microsoft SQL Server database for storing data from individual patients, McLaren's vTAG Server software for running pattern processing algorithms in real-time and McLaren's ATLAS software. ATLAS is a software package which is used to obtain, display and analyse data from control systems such as those used within motorsport. The SQLRace application interfaces between the data server and ATLAS.

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Vital physiological data were recorded from all the patients continuously from the time they were admitted till they were discharged. All the physiological parameters of the patient that are being monitored are recorded in the database. The parametric data is recorded at 5s intervals. However for the study and the research presented in this paper only four parameters are utilised. The four parameters are Heart Rate (HR), Respiratory Rate (RR), Oxygen Saturation levels in the blood (SpO2) and Systolic Blood Pressure (SBP). These four parametric values help the clinicians to assess the cardiopulmonary stability of the patient which is an important objective in intensive care. Though clinical parameters such as "work of breathing" are considered as vital in assessing the level of respiratory distress, this parameter is not available in the electronic database. To our knowledge there does not exist a robust sensor which can measure this parameter effectively.

Figure 1 shows the number of UEs listed over a 12 month period from November 2012 to October 2013 in PICU, BCH. The number of UEs per calendar month falls within the range observed across multiple care centres.

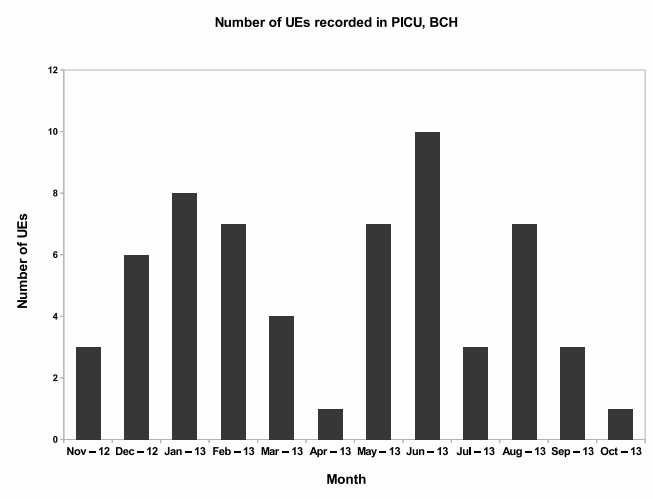

Fig. 1. Number of unplanned extubations recorded in PICU, BCH

III. Methodology

We take a dynamical systems perspective. The complex, coupled autonomic human system is regarded as a dynamical system with an unobservable, latent, state vector $\boldsymbol{y}_t$. The true system state vector (describing the dynamical evolution of the state of health of the individual patient) $\boldsymbol{y}_t \in \mathcal{A}$ evolves on an attracting subset $\mathcal{A}$ of a (low dimensional) manifold $\Gamma \in \mathbb{R}^D$ but is unobservable directly.

Physiologically, the state vector $\boldsymbol{y}$ represents the phase space evolution of the autonomic patient system, which therefore is a combination of several component physiological processes in the body, all interacting to maintain homeostasis. An observation function h maps the latent space variable $\boldsymbol{y}$ to the observation space: $x^k(t) = h^k(\boldsymbol{y}_t) + \eta_t$ including some observational noise η_t, for each separate sensor k. (So, $x^k(t)$ represents actual sensor measurements).

The aim is to extract knowledge of $\boldsymbol{y}_t$ given only knowledge of $\{x^k(t)\}$ and in particular, note when there are significant departures of $\boldsymbol{y}_t$ away from the manifold $\mathcal{A}$. We do this as follows.

The trajectory of delay vectors formed from the measurements

$$\boldsymbol{x}_i = (x_i, x_{i-1}, \ldots, x_{i-n+1}) \in \mathbb{R}^n$$

constitute a one-one mapping of $\boldsymbol{y}_i$ provided n is large enough.

In principle, several different types of sensors giving multiple time series $x^k(t)$ can be used to improve the insight which is what we do in this paper to effect the data fusion of the 4 sensors.

The delay embedding trajectory matrix $\boldsymbol{X}^k(t) \in \mathbb{R}^{N\times n}$ for sensor k whose rows are the set of N delay vectors $\{\boldsymbol{x}_i^k\}_{i=1}^N$ therefore captures all the informative characteristics of the patient's state of health (including all the various noise processes). ie the *delay embedding matrix* of size $N \times n$ obtained from a time series of $N + n$ data points should include all relevant information on the original manifold, and hence on the patient under the assumptions of the model. However the trajectory matrix is not in a useful form to extract and exploit this information. We now need to perform dimensionality reduction and feature extraction of this matrix to obtain meaningful representations of the underlying data dynamics.

We are interested in the signal components described by this delay embedding matrix $\boldsymbol{X}(t)$ since changes in the signal space indicate changes in the patient's state of health. A decomposition of $\boldsymbol{X}(t)$ into separate orthogonal signal and noise subspaces is traditionally obtained using the dominant d most significant right singular vectors of $\boldsymbol{X}$ forming a natural orthogonal spanning basis set for the signal subspace and the remaining $n - d$ singular vectors spanning the noise subspace. In terms of the right singular vectors, *any* embedding vector for sensor k $\tilde{\boldsymbol{x}}^k(t) \in \mathbb{R}^n$ can then be expressed in terms of its projections onto the fixed row space basis vectors $\boldsymbol{v}_j^k$, expanded as

$$\boldsymbol{x}^k(t) = \sum_{j=1}^{d} \alpha_j^k(t)\boldsymbol{v}_j^k$$

where we have selected the top d vectors defining the signal subspace.

The essential point is that the delay embedding vectors are now described in terms of projections onto a spanning basis set, and so the dynamics have now been transferred into the projection coefficients $\boldsymbol{\alpha}^k(t) = \{\alpha_1^k(t), \ldots \alpha_d^k(t)\}$ since the spanning basis set is fixed. We model the dynamical evolution of these projection coefficients as separate linear autoregressive processes, ie for each sensor k and each projection coefficient direction j we assume models of the form

$$\alpha_j^k(t) = \sum_{\tau=1}^{T} \beta_\tau \alpha_j^k(t-\tau) + \epsilon_j^k(t)$$

where the residual error $\epsilon_j^k(t)$ is gaussian distributed:

$$p(\epsilon_j^k(t)) = \mathcal{N}[\alpha_j^k(t) - \sum_{\tau=1}^{T} \beta_\tau \alpha_j^k(t-\tau), \sigma_j^k]$$

Here σ_j^k is the standard deviation of the spread of residual errors, which will be different for each sensor, and each signal subspace projection direction and is estimated from the training data of 'acceptable' patients.

We use the same approach for each one of the k sensors. This approach gives great simplification for the data fusion process, since we can now assume that the joint distribution over all sensors can be decomposed into the product of individual distributions, and moreover, each individual distribution is assumed to be a gaussian (with different diagonal variance values) which therefore also decomposes into the product of individual one-dimensional gaussians, ie the joint distribution is :

$$p(\boldsymbol{\epsilon}^1, \boldsymbol{\epsilon}^2, \boldsymbol{\epsilon}^3, \boldsymbol{\epsilon}^4) = \prod_{k=1}^{4} p(\boldsymbol{\epsilon}^k)$$

and each single distribution is a simple product of 1-d gaussians: $p(\boldsymbol{\epsilon}^k) = \prod_{j=1}^{d} \mathcal{N}[0, \sigma_j^k]$.

This is an elegantly simple approach providing a preliminary baseline model to address the data fusion issue, but the above equation does suffer from the "Veto Effect", ie if any one of the sensor models breaks (due to incorrectly measured data, sensors becoming detached, or major departures from expected norms of behavour), then due to the exponential nature of the distributions, any (spurious) value of zero would destroy the noise model across all sensors, and not just the faulty one. Therefore we operate with a distance measure in negative log probability space of the noise model, so that one rogue sensor will not dominate the responses of the other sensors. Note that normality for the patient is tracked by measuring the consistency of the noise models to be jointly gaussian. In a distance space this becomes a simple weighted euclidean distance measure which can be checked against an a priori determined threshold based on training data of patients in acceptable bounds.

So our initial multivariate stochastic dynamical system is checked using a simple single scalar measure which takes into account all the sensors, and is patient-specific due to the projection of the patient's embedding vector onto the predetermined singular vectors spanning the signal subspace.

A. Stratification

The physiology of children varies with age. Hence paediatric data analysis has to factor in the changing physiological normality or the range of values that the physiological parameters can assume for the child to be considered healthy. Clinically children are separated into four groups, those less than 1 year; two to four years of age; five to 12 years of age and 13 to 16 years of age [10]. The physiology of children belonging to the same age group is considered to be similar. Hence in our study we designed four different automated prediction systems where each system was trained on signals recorded for 100 patients in each of the age groups. Each training set comprised of data segments of the HR, RR, SpO2 and SBP with no anomalies. The training data was used to obtain a patient-independent normality distribution model. The test set included data segments which were clinically classified as representative of UE.

The methodology implemented for all the systems being similar, the steps involved will be explained for one age group. Let $\mathcal{D}$ represent a set of parametric data recorded for a patient. $\mathbf{D} = [\mathcal{D}^1, \mathcal{D}^2, \ldots, \mathcal{D}^{100}]$ represents the data of 100 patients in an age group. A subset of $\mathcal{D}$, $\mathcal{X}$ consisting of one hour of data recording for only the four parameters of HR, RR, SpO2 and SBP is created. Each dataset $\mathcal{X}$ is manually selected to ensure that the values recorded for the four parameters are within the range considered to be acceptable for the age group.

Therefore the automated prediction system has four input sensor time series and one output parameter (the anomaly distance $\mathcal{I}$). This results in a data fusion system where multiple parameters are recorded from different sources.

The process to output $\mathcal{I}$ is given below:

1) Four training sets across 100 patients for the four sensors are obtained.
2) A set of delay vectors representing 'stable values' for each parameter x_{HR}, x_{RR}, x_{SpO2} and x_{SBP} is obtained and concatenated into embedding matrices.
3) Spanning basis vectors are obtained which define the signal subspace of the embedding matrix for each sensor.
4) Density models representing 'clinically acceptable' characteristics for each parameter are obtained based on uncorrelated and gaussian assumptions.
5) Vectors representing the mean and variance of each density are calculated.
6) Delay vectors formed from each sensor are projected onto the signal subspace to determine the patient-specific coefficients, which are then used to compare normality expectations using the joint probability model.
7) Based on the auto regressive projection models, four-minute forward forecasts of the trajectory of the patient are evaluated for an early warning system.
8) An anomaly index for the test signal is calculated using the distance of the element from the centre of the normality region in negative log probability space.
9) If required, the posterior probability at time t, based on the fusion of decisions made by each system separately can be calculated.

IV. Results

Figure 2 shows how the four different sensors respond to an unplanned extubation and how the anomaly index $\mathcal{I}$ varies. As explained in section III the distance measure is a simple weighted euclidean distance. Individual thresholds ρ_k for each of the k sensors is obtained as the sum of the variances in the d dimensions defining the signal subspace of each sensor. The critical threshold of $\mathcal{I}$, $\mathcal{I}_c$ is the weighted

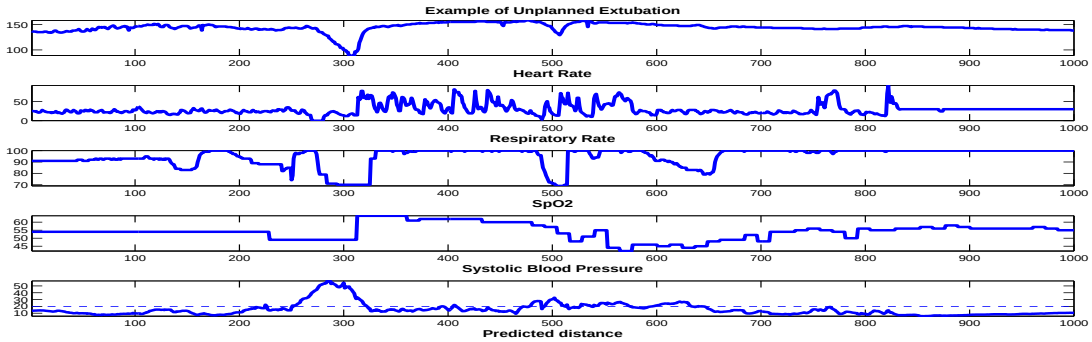

Fig. 2. The effect of an unplanned extubation on the four sensor responses.

sum of the individual thresholds ρ_k. The value of $\mathcal{I}(t)$ is compared against $\mathcal{I}_c$ to evaluate the status of the patient at time t. A value of $\mathcal{I}(t) \geq \mathcal{I}_c$ is an indicator of the deviation of the status from 'stable' to probable 'unstable'. It can be seen in figure 2 that $\mathcal{I}(t) \geq \mathcal{I}_c$ a few minutes before there are decreasing trends in the HR, SpO2 and rapid changes in the RR which are indicative of a critical event.

Table I shows the number of predicted unplanned extubations in a one year duration for both the automated system and by clinicians based on the age groups. All the critical events in the PICU are systematically reported and classified by the attending senior clinician into predictable or preventable categories as part of routine patient safety monitoring. The total number of UEs recorded (see Figure 1) is 60, only 24 of the UEs were analysed. The data for the 36 events that were not included had insufficient data, not useful data and data loss. Insufficient data refers to a patient experiencing a critical event within the first 15 mins of start of recording and therefore dynamic prediction was not possible. It can be seen from the results in table I that the trends in the data are so subtle that they can be captured by an automated system more efficiently compared with physical monitoring at the bedside.

Age (months)	UEs analysed	System predicted	Clinically predicted
≤ 12	19	11	3
≥ 13 & ≤ 48	3	2	0
≥ 49 & ≤ 144	0	0	0
≥ 145 & ≤ 216	2	2	0

TABLE I

NUMBER OF CLINICAL VERSUS SYSTEM PREDICTIONS OF UNPLANNED EXTUBATIONS

V. CONCLUSIONS

Preliminary results obtained from the analysis of multivariate biomedical time series have resulted in an efficient computer based early warning system. The prediction mechanism is a baseline decision support system which provides clinicians with the information to proactively prevent possible critical events. The system designed relies on the data recorded in the immediate past and an inference system built on the analysis of the characteristics of data recorded from multiple patients to predict future trends effectively ignoring noise. The combined metrics of clinical knowledge and experience, and a forecasted anomaly index based on the trends in the multi-parameter data set have been tested and have proven to be of immense help to clinicians. Future work will include the design and implementation of more complex data fusion models.

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