TITLE

Artifact in physiological data collected from brain injured patients: quantifying the problem and providing a solution through a factorial switching linear dynamical systems approach.

AUTHORS

Konstantinos Georgatzis, School of Informatics, University of Edinburgh

Partha Lal, School of Informatics, University of Edinburgh

Christopher Hawthorne, Academic Unit of Anaesthesia, University of Glasgow

Martin Shaw, Department of Clinical Physics, NHS Greater Glasgow and Clyde

Ian Piper, Department of Clinical Physics, NHS Greater Glasgow and Clyde

Claire Tarbert, Department of Clinical Physics, NHS Greater Glasgow and Clyde

Rob Donald, School of Mathematics and Statistics, University of Glasgow

Christopher KI Williams, School of Informatics, University of Edinburgh

For correspondence:

Christopher Hawthorne

Academic Unit of Anaesthesia, Pain and Critical Care Medicine, University of Glasgow

Level 4, Walton Building

Glasgow Royal Infirmary

84 Castle Street

Glasgow, G4 0SF

Email: Christopher.Hawthorne@glasgow.ac.uk

Tel: +44 (0)141 211 9703

Fax: +44 (0)141 331 2798

SUMMARY

Introduction: High resolution, artifact free and accurately annotated physiological data is desirable in brain-injured patients both to inform clinical decision making and for intelligent analysis of the data in applications such as predictive modelling. We have quantified the quality of annotation surrounding artifactual events and propose a factorial switching linear dynamical systems (FSLDS) approach to automatically detect artifact in physiological data collected in the neurological intensive care unit (NICU).

Methods: Retrospective analysis of the BrainIT dataset to discover potential hypotensive events corrupted with artifact and identify annotation of associated clinical interventions. Training of an FSLDS model on clinician annotated artifactual events in five patients with severe traumatic brain injury.

Results: In a subset of 187 patients in the BrainIT database, 26.5% of potential hypotensive events were abandoned due to artifactual data. Only 30% of these episodes could be attributed to an annotated clinical intervention. As assessed by the area under the receiver operating characteristic curve metric, FSLDS model performance to automatically identify the events of blood sampling, arterial line damping and patient handling was 0.978, 0.987 and 0.765 respectively.

Discussion: The influence of artifact on physiological data collected in NICU is a significant problem. This pilot study using an FSLDS approach shows real promise and is under further development.

KEY WORDS

Brain Injury, Critical Care, Physiologic Monitoring, Information Science

INTRODUCTION

Arterial hypotension and raised intracranial pressure (ICP) are secondary insults that are associated with poor outcome in patients suffering traumatic brain injury (TBI) [4, 3]. Through the acquisition of high frequency physiological data and using predictive modelling techniques there is now potential to predict these secondary insults with the possibility of intervening prior to the event [1, 2]. However, physiological data is subject to artifacts that reduce the available information and thus limit predictive capacity. This paper aims to firstly quantify the influence of artifact upon hypotensive events recorded in the neurological intensive care unit (NICU) and secondly present a possible solution.

To achieve the first aim we have performed an analysis of The BrainIT database (www.brainit.org) [5]. This contains validated data on 262 patients who suffered traumatic brain injury (TBI) and were admitted to one of 22 NICUs in 11 European countries between March 2003 and July 2005. The database has detailed physiological monitoring and ICU management data. It is thus an excellent resource to study the incidence of hypotensive events as well as the number of these events that are subject to artifact.

To address the second aim, we have used the machine learning technique of factorial switching linear dynamical systems (FSLDS), which has been previously applied to detect artifact in physiological data collected on the neonatal intensive care unit [6]. We describe a pilot project using FSLDS to automatically detect artifact in the monitoring signals from adult patients with TBI.

METHODS

Quantification of the influence of artifact on hypotensive events

The BrainIT dataset contains patients' arterial blood pressure (ABP) measurements recorded every minute for the duration of their NICU admission. Hypotensive events were classified as either mean ABP (ABPm) less than 70 mmHg or systolic ABP (ABPs) less than 90 mmHg. For an event to be valid it had to remain below the threshold for at least five minutes. The hypotensive event ended when both ABPm and ABPs rise above threshold and remained so for five minutes. Hypotension events were rejected due to missing data or extreme values during either of these five-minute periods (Figure 1).

FIGURE 1 - Schematics of different types of rejected event. Events are categorized as i) *Abandoned* (non-physiological data before, during or after a hypotension secondary insult defined as BPm <= 70 mmHg or BPs <= 90mmHg present for 5 sequential minute samples) or ii) *Invalid* as for *Abandoned* but with missing data values.

Also included in the BrainIT dataset are a series of annotations of nursing and medical interventions such as "blood-sampling", "transducer-calibration", "endotracheal suction" and "patient turning". For each of the rejected hypotensive events identified, an attempt was made to correlate the event with an annotated intervention by comparing the time-stamps of the two. The artifact was attributed to the annotation if the annotation occurred within six minutes of the event start.

Automatic detection of artifact

The FSLDS belongs to the class of hybrid state space models, which can be thought of as Switching Linear Dynamical Systems (also known as Switching Kalman filters) where the hidden state is a hybrid of both continuous and discrete variables. At each time step (i.e. every second) we can identify three types of random variables.

- First, there are the continuous observations, which correspond to the monitoring signals (heart rate, ABP, ICP) and constitute the input of our system. Secondly, since these signals can be unreliable, the FSLDS maintains a set of continuous hidden state variables, which represent our estimates of the true underlying physiological state of a patient, even in the presence of artifact.
- Finally, there is the discrete (switching) state variable, which maintains a higher-level representation and represents the general status (or regime) of a patient (e.g. whether the patient is stable or is undergoing an intervention). The discrete state is factored into a combination of factors, which correspond to variables that can be binary (e.g. damped ABP trace or not) or categorical (e.g. which of four blood sample stages the system is currently in).

The continuous and discrete states at a given time step depend on the corresponding values at the previous time step. The observations are each dependent on a corresponding continuous state variable but certain discrete states can remove that dependency e.g. if the ABP line is being flushed during a blood sample then the ABP observations are no longer dependent our estimate of patient physiology. During inference, we use the model to perform filtering, estimating the current regime and physiological state of the patient, given the previous hybrid state and the current observations. Further details are available in [6].

Five patients admitted to neurointensive care (NICU) following admission with TBI were studied. All analyses were performed upon routinely measured physiological parameters. Thus, the West of Scotland Research Ethics Committee waived the need for formal ethical approval. Waveform frequency data was streamed to a laptop from the Phillips Intellivue bedside monitors via the Medical Interface Bus (MIB) and using iexcellence software. Signals collected included electrocardiogram (ECG, 512 Hz), ABP (128 Hz) and ICP (128 Hz) as a minimum. Clinical staff documented any interventions to the patient, which were expected to cause artifact in the monitoring signals. The waveforms were then reviewed by a single clinician and events causing artifact annotated to the nearest second.

Waveform frequency data from the ECG, ABP and ICP signals were summarised down to 1 Hz resolution using a combination of beat-to-beat analysis with linear interpolation to resample to a regular signal. These data were then used to model three commonly occurring sources of artifact: arterial blood sampling, patient handling events such as endo-tracheal suction or turning, and damping of the ABP trace. These events were then used to develop the FSLDS model by comparing their features to 15 minutes of clinician-annotated stability near the beginning of the monitoring period. The resulting model was then trained and evaluated using leave-one-out cross validation. i.e. the whole dataset was evaluated in five passes, with each pass consisting of four patients used as the training data and the final patient as the test set. Model performance was evaluated using the area under the receiver operating characteristic curve metric (AUC).

RESULTS

<u>Quantification of the influence of artifact on hypotensive events</u>

In total, 3158 valid hypotensive events were found along with 1174 rejected hypotensive events in a dataset taken from 256 patients, giving a rejection rate of 27% (Table 1). Of the 256 patient records, only 187 have associated annotations in the database of nursing procedures. In this smaller group of patients, 722 artifact-corrupted hypotensive events were found of which only 217 (30%) could be confidently attributed to at least one annotation in the database. This leaves 505 rejected hypotension events (70%) that did not have a corresponding annotation. In total, 280 annotations were associated with those 217 events, the majority (46%) of which were turning procedures, followed by endotracheal suctioning (18%), transfer to CT (11%), patient hygiene (8%) and blood sampling (6%).

	All patients	Patients with nursing annotations
Patients (n)	256	187
Valid hypotensive events (n)	3158	2007
Rejected hypotensive events (n)	1174	722
Rejection rate (%)	27.1%	26.5%

TABLE 1 – Number of valid and rejected hypotensive events in the analysed sample from the BrainIT database.

Automatic detection of artifact

From five patients we collected a total of 133 hours of physiological data. The number and duration of annotated events with associated artifact in the physiological waveforms and used to construct the FSLDS model is illustrated in Table 2.

Event	Events per patient (n)	Duration of events (mm:ss)
Arterial blood sampling	5 [1 - 7]	01:29 [00:41 – 04:26]
Patient handling	8 [4 – 11]	01:47 [00:03 – 14:47]
Damping of ABP signal	1 [0 – 3]	00:30 [00:03 – 54:53]

TABLE 2 – Number and duration of common events associated with artifact in physiological signals. Results are given as median [range].

The model aims to identify an episode of blood sampling by breaking it down into four possible components of “ramp”, “zero”, “flush” and the allowance of “normal” within a blood sample. Figure 2 demonstrates how each of these components can become active during a single blood sample and the ROC curves for each component. The combined AUC for identifying a blood sample is 0.978. Similarly, the AUC for detection of ABP trace damping was 0.987.

FIGURE 2 – an example of a blood-sampling episode in the 1Hz data. The ability of the model to detect the discrete annotated components is shown. Of note is the illustration of the ability of the model to infer the underlying physiological state during an artifactual episode. ROC curves allow comparison of model performance for each component. *TPR* true positive rate, *FPR* false positive rate.

For the purposes of this pilot study, the FSLDS model was constructed to detect the events of endotracheal suction and patient turning as “patient handling”. Figure 3 highlights an example of a patient handling episode and how the model correctly detects this event but with much shorter duration than the clinician annotation. This was a common finding and resulted in an AUC of 0.765 for detection of a handling episode.

FIGURE 3 – an example of a patient-handling episode in the 1Hz data. The model detects this event but there is a marked discrepancy in the duration of the event when compared to clinical annotation. The ROC curves demonstrate reasonable model performance in four patients but with one clear outlier.

DISCUSSION

From our analysis of the BrainIT database it is clear that a significant percentage of hypotension events contain artifact or missing data. However, the quality and timing of annotations associated with these events is relatively poor. Nevertheless, these analyses show that approximately 30% of hypotensive events are not quantified and thus missing as potential treatment targets. To increase the amount of available data to input to predictive models for hypotension events or intracranial hypertension it would be ideal if we could automatically detect artifact in the physiological signals. Focusing upon blood sampling, endo-tracheal suctioning and patient handling events as artifact sources is reasonable as, in this study, they constitute nearly 90% of annotated events associated with hypotension.

The pilot project provides proof of concept for the automatic detection of artifact from high frequency NICU data using FSLDS. As assessed by AUC, the ability to detect arterial blood sampling and a damped ABP trace is already promising even using this small dataset. The model did not perform as well when detecting patient handling events. This is likely to be explained, at least partially, by the more physiologically complex nature of these events. Also, the clinician annotations took into account information from all available physiological signals (including pulse oximetry, exhaled carbon dioxide monitoring and respiratory impedance), while the model was restricted to ECG, ABP and ICP. New models are now being tested that incorporate all available physiological signals.

A Chief Scientist Office (Scotland) funded project is now underway with the aims of achieving a networked solution to waveform frequency data capture, training the FSLDS model on a larger dataset, and running the FSLDS model in real time to automatically detect artifact in NICU data.

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CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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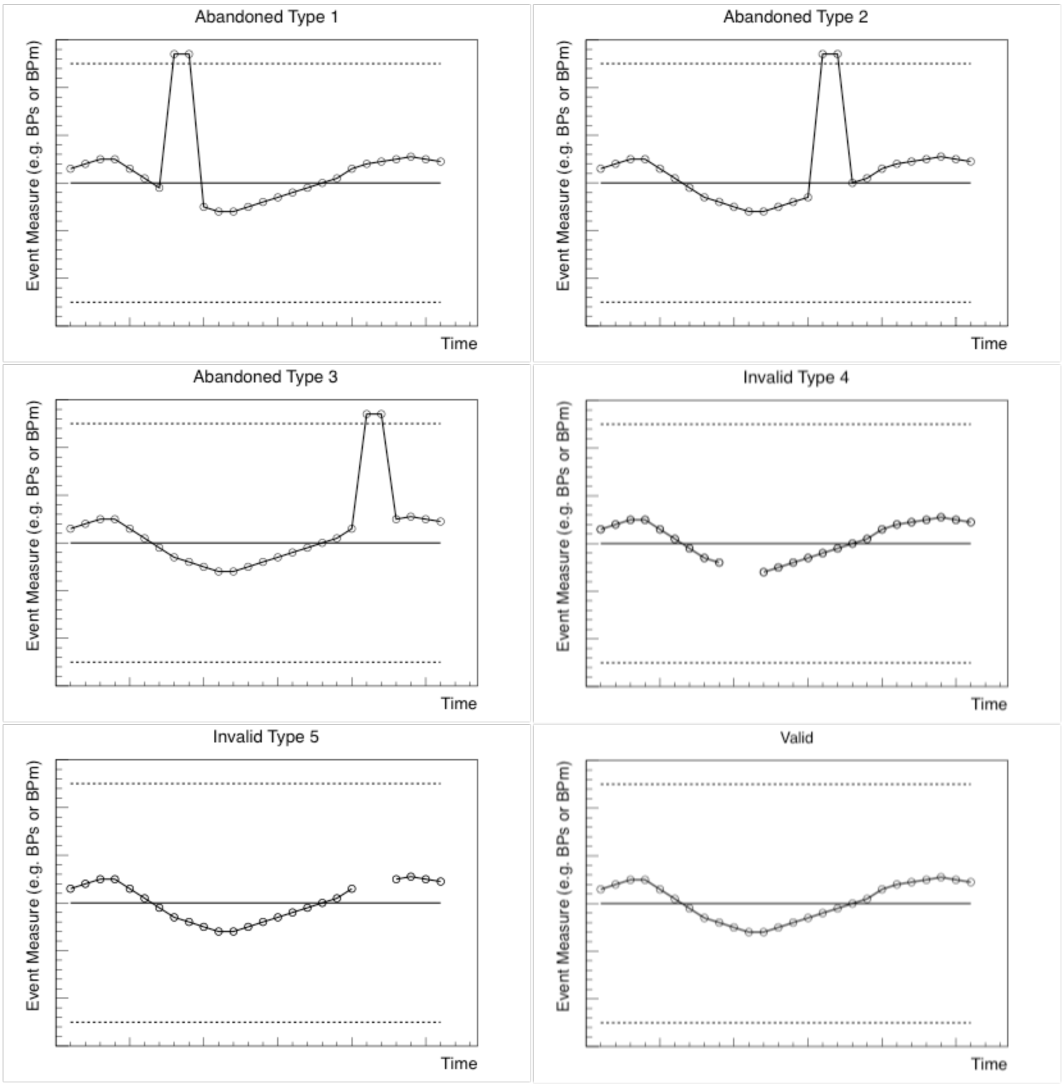
FIGURES

Figure 1



Figures 2 (left) and 3 (right)