Towards a Data Fusion Model for Predicting Deterioration in Dialysis Patients

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Abstract

The accumulation and relatively rapid removal of fluid in haemodialysis patients is often accompanied by intradialytic hypotension (IDH). Current patient monitoring during haemodialysis includes intermittent measurements of tympanic temperature, blood pressure and haematocrit. However, this information is mostly used retrospectively rather than as a means for preventing adverse events. We suggest the use of a probabilistic data fusion model based on dialysis vital sign data to predict IDH. We continuously monitored the vital signs of 40 haemodialysis patients during 8 sessions over a 6-month period in the Oxford Renal Unit. The study involved non-invasively monitoring the heart rate, blood oxygen saturation, systolic and diastolic blood pressures as well as the tympanic temperature throughout each dialysis session. The 4-dimensional vital sign data was initially visualised on 2D projections using the Neuroscale algorithm. The projections show a distinction between data from unstable and stable patients, with data from hypotensive events appearing outside the region of the 2D projection corresponding to "normal" physiology. A data fusion model based on an estimate of the probability density function of data from stable patients was then created. With this model, instabilities in patient physiology can be identified, and the adverse event can be predicted ahead of time in some cases.

1. Introduction

Dialysis-induced hypotension is one of the most common complications in haemodialysis treatment and occurs in 20-30% of all dialysis sessions [1], often in conjunction with symptoms such as cramps, nausea and vomiting [2]. Furthermore, intradialytic hypotension (IDH) is thought to increase mortality [3]. Current patient monitoring during dialysis treatment includes intermittent measurements of tympanic temperature, blood pressure and haematocrit, with medical intervention occurring once symptoms of IDH have been observed. However, preventative intervention would be more favourable for patient well-being, especially in the elderly and in patients with existing cardiovascular problems. Impairment of baroreceptor sensitivity [4] is one of many causes of IDH. In patients with an impaired baroreceptor reflex, the cardiovascular system does not show any negative feedback response to changes in blood volume resulting from ultrafiltration. In such patients, a reduction in blood pressure is not followed by compensatory tachycardia, which results in IDH. In the time domain, the standard deviation of RR intervals (SDNN) is a common measure of heart rate variability (HRV). Previous work has focussed on distinguishing between hypotension-prone and hypotension-resistant patients using HRV measures in the frequency domain [5]; however, there is no established method for predicting IDH.

Another approach is based on the fact that physiological parameters, such as the vital signs, change before an adverse event in a way that may be a precursor of patient deterioration. Different alarm systems have been developed for detecting patient deterioration and prompting staff intervention, with novelty detection being the most promising approach. Tarassenko et al. [6] recently developed a data fusion based patient monitoring system, that is able to identify abnormalities in a patient's vital signs based on a probabilistic model of normality in five dimensions (when five vital signs are being recorded), learned from a large sample of data previously collected from a representative group of patients. We propose a similar approach to provide early warning of IDH in dialysis patients by creating a probabilistic model of normality using vital sign data from "stable" haemodialysis patients, and then looking for deviations from that model.

2.1. Data collection

Vital-sign data, consisting of continuous, non-invasive recordings of the heart rate, blood oxygen saturation (SpO$_2$), electrocardiogram (ECG) and photoplethysmo-

	All Patients		Stable Patients		Training Data	
	μ	σ	μ	σ	μ	σ
HR (bpm)	77.50	17.34	78.25	14.77	76.42	14.42
HRV (bpm)	2.21	1.83	2.17	1.45	2.11	1.33
SpO$_2$ (%)	95.36	2.74	95.58	2.55	95.63	2.55
SDA BP (mmHg)	106.04	19.18	106.41	17.85	111.61	17.41
Temp (° C)	35.80	0.51	35.86	0.47	35.79	0.34

Table 1. Means and standard deviations of the dataset.

graph (PPG) waveforms, were collected during an observational pilot study at the Renal Unit of the Churchill hospital in Oxford. Haematocrit, blood pressure, tympanic and skin temperatures were recorded every 15 minutes, alongside machine treatment parameters such as the ultrafiltration rate, from Dialog$^+$ (B. Braun AG, Melsungen, Germany) machines. 39 patients were recruited after giving informed consent, with each patient being monitored over a total of 8 sessions (comprising two blocks of four consecutive sessions, separated by 3-5 months). The final dataset consists of vital-sign data collected from 38 haemodialysis patients in 272 sessions. Vital-sign values outside of predefined artefact-rejection limits were discarded. Ten patients were identified as stable patients by renal clinicians, and data from these patients was considered to reflect "normal" physiology during haemodialysis. Stable patients were defined to be those patients who had not presented with IDH during any previous haemodialysis treatments at the Renal Unit. The means and standard deviations of the vital sign data collected from patients labeled as "stable" and "unstable", alongside the means and standard deviations of the entire dataset are given in Table 1.

2.2. Data pre-processing

The vital signs in our dataset were recorded asynchronously, and thus we align the individual parameters such that we obtain sets of simultaneous, synchronous data by applying a zero-hold between measurements. Tympanic temperature measurements are taken only once every 15 minutes, and so random normally-distributed noise $N(\mu, \sigma^2)$, with $\mu = 0$ and $\sigma = 5/300$, is added to the held data. The data is then normalised using a zero-mean unit-variance transform $x_n = \frac{x - \mu_p}{\sigma_p}$, with the means and standard deviations of the data (μ_p, σ_p) set according to the values shown in Table 1. Such normalisation removes scaling differences in the data, such that each vital sign covers approximately the same range under "normal" conditions. The training set is defined to be the normalised vital-sign data from the first hour of each session, for the 10 stable patients, resulting in 5,467 training examples. In order to reduce the number of training data with minimal loss of useful information, one-minute medians of the vital sign data were found, and were then clustered into a subset of prototype patterns using the k-means clustering algorithm with k=500 clusters. The 100 cluster centres furthest

from the mean of the data in 4D space were discarded, and the remaining 400 cluster centres were retained as training data representing the 80% of the cluster centres that were "most normal".

2.3. Neuroscale algorithm

We visualised the 4D vital-sign data using the Neuroscale algorithm [8]. A radial basis function neural network is trained to project the 4D data into 2D for visualisation, such that the interpoint distances in the original 4D space are preserved in the 2D visualisation space. This distance-based error measure is the Sammon stress:

$$E = \frac{1}{\sum_{i=1}^{N} \sum_{j>i}^{N} d_{ij}^*} \sum_{i=1}^{N} \sum_{j>i}^{N} \frac{(d_{ij} - d_{ij}^*)^2}{d_{ij}^*} \qquad (1)$$

where d_{ij} denotes the Euclidian distance between two of N points x_i and x_j in an m-dimensional space R^m and d_{ij}^* represents the distance between the corresponding two points y_i and y_j in the lower, d-dimensional visualisation space R^d. The advantage of this method over other high-dimensional visualisation techniques is that it allows for the generalisation of the mapping to new data. The neural network was trained using the first hour of the 4D vital-sign data (heart rate, oxygen saturation, systolic-diastolic average (SDA) blood pressure and tympanic temperature) from sessions of patients identified as "stable". This initial hour of data is considered to be representative of the "most normal" haemodialysis patient physiology, given that the removal of several litres of fluid is disruptive to homeostasis. As the network is trained using only normal data, any examples reflecting "abnormal" physiology will be mapped outside of a region occupied by the normal data. When initializing the algorithm, the centres of the radial basis functions were chosen to be a random subset of the training data to assure correct localisation. The widths of the radial basis functions were all set to $\sigma = 1$ and the initial weights were drawn randomly from a normal distribution centred at zero with a standard deviation of $\sigma = 1/30$.

2.4. The patient status index

To construct the model of normality, we make the assumption that the vital-sign data is drawn from an underlying probability density function (pdf), and that the data is independent and identically distributed. We used the Parzen windows method [9] to estimate the pdf of our 400 prototype patterns. This pdf may then be used to obtain an estimate of the probability density $p(\mathbf{x})$ of a new data pattern $\mathbf{x}$ with respect to the data in the training set. The novelty score Q of new data is defined to be $Q(\mathbf{x}) = -\ln p(\mathbf{x})$, such that "abnormal" data, which has a low value of $p(\mathbf{x})$
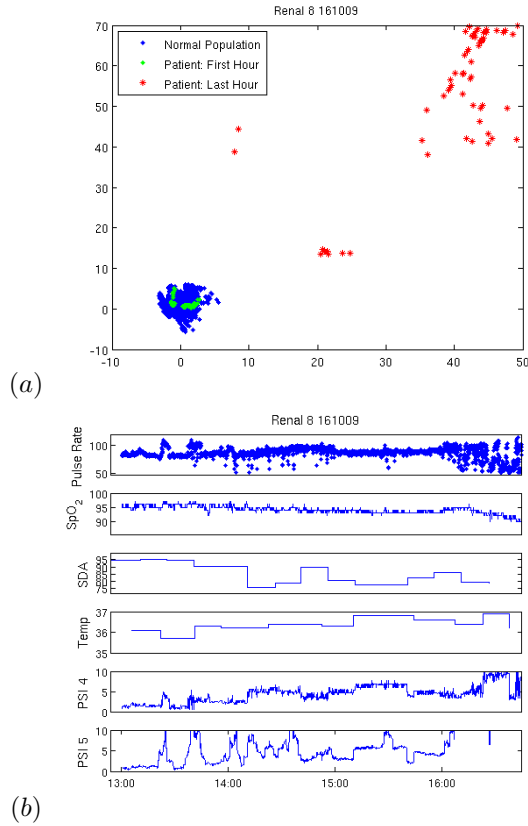
(a)

(b)

Figure 1. (a) Neuroscale visualisation of 4D vital signs. (b) Vital-sign and PSI data for patient Renal 8.

takes a high novelty score $Q(\mathbf{x})$. It can therefore be used as a patient status index (PSI), with low values indicating "normality".

Two models of normality were constructed to calculate the PSI. Firstly, a four-dimensional model consisting of the vital signs (heart rate, oxygen saturation, SDA blood pressure and tympanic temperature) was created to calculate "PSI4". A second, five-dimensional model was created, including HRV SDNN [10], in addition to the vital signs, giving "PSI5". We calculated the standard deviation of normal-to-normal RR intervals (SDNN) by centering a 5-minute window on each heart rate measurement and calculating the standard deviation of the heart rate measurements in each window. Furthermore, we use SDNN to detect rapid fluctuations in the heart rate (rather than gradual trends which are already modelled my the HR vital-sign). We therefore removed the trend from the heart rate prior to calculating the SDNN.

3. Results

We now investigate sample patient data on Neuroscale maps against a background of "normal" patient data, which

constituted the training data, to visually compare the physiological state of the test patient with a pre-defined normal population. The first hour of data is plotted in green, and the last hour in red. We present case studies of two patients with episodes of IDH. The data from the first hour of
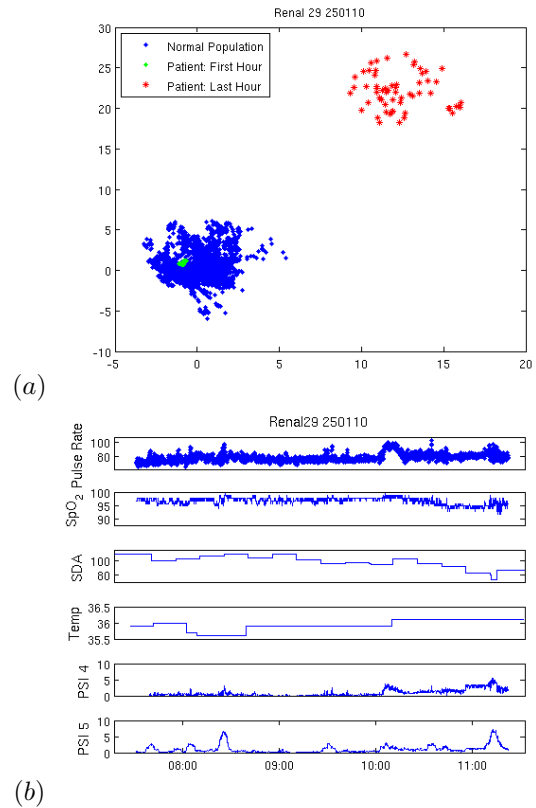

(a)

(b)

Figure 2. (a) Neuroscale visualisation of 4D vital signs. (b) Vital-sign and PSI data for patient Renal 29.

dialysis of patient Renal 8 (shown in Fig. 1a) is projected in the region of normality shown by the blue cluster and is not indicative of abnormal vital signs. The last hour of data, highlighted in red, is clearly projected outside of the region of normality. We assume that, given our definition of normality, this indicates abnormalities in the patient's vital signs. Looking at the vital sign data for this session (shown in Fig. 1b), it may be seen that the last hour of vital sign data shows abnormalities: throughout the session, the patient's blood oxygen saturation is maintained at around 95% (the mean SpO_2 value of the training data) but in the last hour there is a steady desaturation towards 90%, which is two standard deviations below the mean. The heart rate, relatively steady at 80 bpm, generally decreases in the final hour and fluctuates between 80 and 50 bpm, the latter value being up to two standard deviations from the mean. The temperature rises from $36°C$ in the first hour to $37°C$ $(+3\sigma)$ in the final hour. The SDA blood pressure, initially

at 90 mmHg (-1σ), falls below 80 mmHg (-2σ) towards the end of the session, which is indicative of IDH.

Fig. 1b also shows the patient status indices based on the four- and five-dimensional models. The hypotensive episode just after 14:00 is reflected in a change in both PSI4 and PSI5. Prior to this episode, the drop in SDA blood pressure is preceded by two episodes of increased heart rate, at 13:20 and 13:40. The PSI4 rises as the HRV increases. However, this is due to the fact that the heart rate rises above 100 bpm which is one standard deviation away from the mean value of the training data, rather than due to the sudden change in heart rate (recalling that the 4D model does not include HRV). By comparison, the PSI5 provided by using the 5D model, shows rapid fluctuations towards the end of the session, taking values of up to 40 (log scale). Two peaks in the PSI5, corresponding to the two rapid changes in heart rate, precede the event at 14:00.

Fig. 2a shows another example of a patient experiencing IDH. Again, the first hour of projected data lies within the region of normality, while the event data lies outside of it. A sudden decrease in SDA blood pressure just after 11:00 is preceded by an increase in HRV. The patient's heart rate varies between 65 (-1σ) and 100 bpm ($+1\sigma$) in the hours preceding the event, with a particularly prominent rise and fall in heart rate just after 10:00. PSI4 does not model the rapid fluctuations in heart rate, as all vital signs remain within their respective normal ranges. By including HRV as a fifth dimension in the model of normality, multiple peaks are observed in PSI5 prior to the event, at 08:30, 10:00, and at the event after 11:00.

4. Discussion

The results of the 2D visualisation of patient data show that it is possible to distinguish between normal and abnormal patient physiology during haemodialysis based on patient vital signs, given an adequate definition of "normal" physiology. Abnormal vital-sign data is mapped outside of the pre-defined region of normality. This motivates the use of vital signs to provide early warning of patient deterioration in dialysis patients. Applying the 4D model of normality to patient data with episodes of IDH, we see that the model is capable of detecting IDH, but its predictive value is limited to cases for which the parameters leave their respective "normal" ranges prior to the event.

In the data collected for this study, IDH is preceded by rapid, significant variations in heart rate in some cases. We postulate that IDH occurs in these patients as a result of the inability of the cardiovascular system to maintain perfusion pressure in the presence of fluid removal. Furthermore, given previous evidence of HRV being a relevant parameter for IDH prediction in hypotension-prone patients, we chose to add a measure of HRV (SDNN) to our model of normality. The inclusion of a measure of HRV in the PSI shows significant improvement in its predictive value. A high variability in heart rate is one example where the absence or inadequacy of physiological compensation mechanisms leads to IDH. In future work, other measures capable of characterizing the different physiological phenomena leading to instability (such as breathing rate or the pulse transit time) will be investigated and assessed for their added value with respect to the predictive capability of the PSI5 index.

Acknowledgements

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