MEDICAL SIGNAL PROCESSING USING THE SOFTWARE MONITOR

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1 Introduction

The Software Monitor is a portable PC which is capable of processing and analysing in real time the vital physiological signals recorded non-invasively from healthy subjects or unwell hospital patients. Its main advantage is that it offers, in one intelligent monitor, the fusion of multiple sources of information. This makes it possible to track physiological instability (since unexpected combinations of changes are often an indication of deterioration) and to generate reliable alarms (since robustness is increased as a result of using multiple sources of information). In the current version of the Software Monitor, the following vital signs are being recorded: three channels of ECG (electrocardiogram), blood pressure using an inflatable cuff, oxygen saturation using pulse oximetry, respiration using impedance pneumography and skin temperature using a thermistor inside the blood pressure cuff. All of these signals are sampled at different rates (from the ECG which is sampled at 256 Hz to the blood pressure which is only measured two or three times per hour) but the data samples from each channel are given a timestamp which is synchronised with a master clock (Townsend and Tarassenko, 2000). The number of physiological signals could be increased if desired as this simply requires the appropriate sensor, associated electronics and a corresponding software module.

The first application of the Software Monitor is in "high-dependency care" which is aimed at patients who are generally considered too ill to be satisfactorily cared for on the ordinary wards but who fail to meet admission criteria for Intensive Care. The provision of high-dependency care can improve clinical outcome and reduce the need for Intensive Care by detecting deterioration and intervening early in the clinical course of the disease process. However, a significant bar to the provision of high-dependency care is the availability and cost of appropriately trained nursing and medical staff. The development of intelligent integrated monitoring offers a relatively inexpensive but effective method of improving patient surveillance and care.

2 Database

In order to develop the data visualisation and fusion algorithms for the Software Monitor, we have built up a database of carefully annotated signals collected for a minimum of 24 hours (and sometimes several days) from each of a group of 120 patients at the John Radcliffe Hospital. Ethics approval was granted before this data collection exercise started and informed consent is obtained in every case. We are now developing algorithms for retrospective analysis of these signals, concentrating primarily on four groups of patients:

- patients monitored for at least 24 hours after a myocardial infarct ("heart attack") and again for a few hours five days later;

- patients with severe heart failure;
- patients with acute respiratory problems (for example, acute asthma or pneumonia);
- elderly patients with hip fracture, whom we monitor both pre- and post-operatively; this is a patient group for which the mortality rate one year after the operation is of the order of 20%.

3 Feature extraction

The data-driven models of patient state are based around both primary parameters (for example, the value of oxygen saturation or mean blood pressure) and secondary parameters which are derived from the former. Data fusion techniques are used at every level of signal processing in the Software Monitor project, as the main requirement is for *robust* signal processing. For example, the impedance pneumography signal is extremely noisy and often fails to give any indication of the patient's respiration. Thus breathing information is also extracted from the ECG signal, both by tracking the respiration-induced changes in baseline (Felblinger and Bosch, 1997) and using time-delay embeddings of the ECG waveform followed by singular value decomposition of the delay vectors (Lowe, 1998). Similarly, the measurement of heart rate from the ECG waveform should be simple enough but the waveform is often corrupted by movement artefact. A much more robust value of heart rate can be obtained by fusing that obtained from the ECG waveform with the estimate derived from the pulse oximetry waveform (which is also cardiac-synchronous, although there is some dependence on the breathing cycle). Provided that the finger on which the pulse oximetry probe is positioned does not move at the same time as the ECG electrodes on the chest, the fused heart rate provides an estimate which is far less affected by patient movement. In a similar way, an improved estimate of respiration rate can be derived by fusing the information obtained from impedance pneumography with that derived from the ECG waveform.

A further secondary parameter of interest for cardiac patients especially is heart rate variability (HRV). HRV is a measure of autonomic nervous system activity and low HRV following a heart attack is associated with increased mortality in the long-term (Kleiger *et al*, 1987). Many patients on Coronary Care Units have unstable coronary syndromes (myocardial ischaemia), often associated with a high frequency of Ventricular Ectopic (VE) beats and/or Supra-Ventricular Ectopic (SVE) beats. Normal beats arise from the sino-atrial node, whereas ectopic beats originate from other regions of the heart. It is important to detect VEs and SVEs reliably, as their timing does not reflect the neuronal changes that HRV parameters seek to reflect, and their inclusion therefore corrupts measurement of "true" HRV. The reliable detection of ectopic beats requires the fusion of three methods, each of which provides information about the occurrence of these abnormal beats: Principal Component Analysis (PCA) to learn the morphology of normal beats, including inter-beat variability, for that patient (Clifford *et al*, 2000; Tarassenko *et al*, 2001), Kalman filtering to detect unexpected changes in the interval between consecutive beats and Independent Component Analysis (ICA) to differentiate between movement artefact and ectopic beats.

4 Data visualisation

Sammon's mapping (Sammon, 1969) is a well-known multi-dimensional scaling technique which can be used for visualising high-dimensional data. For P patterns, a configuration of image points $\mathbf{y}^1, \ldots, \mathbf{y}^P$, is sought in the 2-D visualisation space, such that the $P(P-1)/2$ distances d_{ij} between image points are as close as possible to the corresponding original distances δ_{ij},

where δ_{ij} is the Euclidean distance between $\mathbf{x}^i$ and $\mathbf{x}^j$ in the original high-dimensional input space. The recently developed extension to Sammon's mapping, Neuroscale (Tipping and Lowe, 1997), overcomes its main limitation as it allows previously unseen data to be displayed using the map constructed from the training dataset.

We use Neuroscale for data exploration in two different ways: in the first instance we construct a visualisation space using all the data available for that patient; we then make use of the interpolating properties of the Neuroscale algorithm to visualise the changes in patient state by following the trajectories generated in the 2-D map from the start of monitoring to the end. In the second instance, we use the multi-dimensional data available from *all* patients in that group to construct the map so that we can then compare one patient with another. With the patient-specific application of the algorithm, the usual zero-mean, unit-variance normalisation transform is applied to the input features prior to visualisation. When the intention is to visualise a given patient's data with respect to the rest of that group, we can use the same normalising strategy across the group but we are also experimenting with normalisation based on prior knowledge. This involves clinical experts making judgements about the importance of the features in the various patient groups: for example, is a 0.5°C change in skin temperature equivalent (in terms of the patient's condition) to a 50 mm Hg change in blood pressure?

With both types of application of the Neuroscale algorithm, the visualisation space is first defined using the K-means algorithm to pre-cluster in order to reduce the number of patterns since, after synchronisation, a feature is generated every second and for P feature vectors, there are $P^2/2$ distances to be adjusted.

5 Conclusion

By following trajectories in the visualisation space, we have been able to track changes in patient state, following recovery from a heart attack for example. We have also been able to compare patients within a group and define "normality" *for that group* (and not with respect to normal subjects). We are now extending the work by applying the novelty detection techniques recently developed in our research group (Tarassenko *et al*, 2000; Utete *et al*, 2000) to highlight significant changes in this multi-parameter space.

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