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Telemetry-based vital sign monitoring for ambulatory hospital patients

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Abstract—**Early detection of deterioration in hospital patients followed by intervention and stabilization can prevent adverse events such as a cardiac arrest, unscheduled admission to ICU, or death. Patients at step-down units of hospitals tend to have their vital signs checked by nursing staff at 4-hourly intervals. If an abnormality develops in the period between nurse observations, it is likely to lead to an adverse event (which may have been preventable). Visensia is a real-time, continuous vital sign acquisition system, using data fusion in order to predict patient deterioration. Validation trials have shown that the system successfully provides early warning of adverse events, such as cardiac arrests. We tested the system on lower acuity, ambulatory patients in a hospital ward with the vital signs being collected using telemetry. In order to optimize processing, we have developed an algorithm for deriving the respiration rate of the patient from the ECG signal.**

I. INTRODUCTION

One of the most important actions which could be taken to improve patient safety in hospitals is to *"identify patients who are deteriorating and act early"* [1]. Up to 80% of ward patients have abnormal physiological parameters in the 24 h preceding intensive care (ICU) admission [2, 3]. Furthermore, retrospective surveys have shown that most patients suffering in-hospital cardiac arrests have had antecedent abnormal vital signs, often beginning between 6 and 8 h before the arrest [4-10]. Acutely ill patients (i.e. those in Level 2 and upper end of Level 1 in the NHS) have their vital signs (heart rate, breathing rate, oxygen levels, temperature and blood pressure) continuously monitored but patient monitors generate very high numbers of false alerts (e.g. 86% of all alerts were reported to be false in [11]) and as a result, nursing staff mostly ignore alarms from the monitors. As a result, abnormal vital signs developing in the periods between the 4-hourly checks, which may be precursors of adverse events, are often missed. Failure to recognize or act on these may contribute to emergency ICU admissions and increased hospital mortality [12]. The consequences are costly, in terms of patient outcomes, time and resources [13]. There is therefore an unmet clinical need for a robust and reliable system of generating alarms from continuous monitoring of at-risk patients in hospital.

A. The Visensia system

In order to address this clinical need, a real-time vital sign *data fusion* system was developed, Visensia (formerly BioSign™), based on a model of normality learnt from a dataset of vital signs acquired from hundreds of acutely-ill hospital patients [13,14]. The model of normality is an approximation to the unconditional probability density function (pdf) of the normal vital sign data in the training set. This model is stored in Visensia and used to evaluate the probability that the set of vital signs acquired second-by-second from the patient being monitored can be considered to be normal. The standard Visensia software is connected to the bedside patient monitors via a standard interface. The vital sign values are continuously displayed on the patient monitor and the probability of "normality" is expressed in terms of a single value, the Visensia Safety Index (VSI), which may also be displayed on the monitor or on the nurses' central station. Whenever the VSI is over a clinically validated threshold, an alert is generated, which could be used to trigger the intervention of a Medical Emergency Team or Rapid Response Team. An overview of the system can be found in [13] and [14].

The Visensia system was evaluated in three different validation trials with a total of 1660 patiens [15]. In a study at the University of Pittsburg Medical Centre, in a 24-bed Step-Down Unit (SDU), the system reduced the percentage of patients with prolonged physiological derangement from 18% to 5% (as a result of early intervention by the nursing staff). As a further consequence of this early intervention, there has been no unexpected cardiac arrest on the SDU in the last 18 months [16]. All of this has been achieved with a false alert rate of just one every 4.4 days.

B. Wireless monitoring

Data fusion has been shown to provide early warning of patient deterioration at the bedside. The next step is to apply the technique to less critically ill, ambulatory patients who may be monitored using telemetry. These patients are currently *unmonitored*. There are many challenges associated with operating in such a context: fewer vital signs are recorded and it is likely that there will be more missing data and increased artefact due to patient movement. In addition, a number of technical challenges need to be overcome: hospital Wi-Fi coverage needs to be comprehensive, and equipment battery life must be such that the nurses do not have to replace batteries too often. Other issues to be considered are: patient acceptability of the ECG and pulse oximetry sensors, and integration of the system within nursing practice (since blood pressure and temperature values need to be entered manually).

Section II of this paper presents the results of a pilot study where the Visensia telemetry system was tested on ambulatory patients on Level 1 wards in the Oxford John Radcliffe hospital. The aim of this study was to identify and address the challenges that the wireless environment adds to the system; at this first stage, we did not assess the performance of the VSI in identifying patient deterioration. In addition to testing the system on ambulatory patients, we developed an algorithm which calculates the patient's breathing rate from their ECG signal.

The algorithm, presented in section III of the paper, will be incorporated into the telemetry system so that a robust estimate of the breathing rate can be obtained without any extra instrumentation connected to the patient.

Fig. 1. Patient PDA (right) and Central Station (left) of the Visensia telemetry system.

II. PILOT CLINICAL STUDY

A. Study design

We recruited 18 adult patients from the Gerontology, Surgical Emergency Unit (SEU), and Acute Stroke Unit (ASU). We included patients "stepping down" from the Intensive Care Unit (ICU) and who were sufficiently mobile that they could leave their bed space unaided. We excluded patients fitted with a pace-maker or suffering from Atrial Fibrillation (AF). All patients taking part were conscious and gave their informed consent before taking part in the study. They were then connected to a multi-parameter monitor, in the form of a hand-held PDA, which was attached to a bedside dock when the patients were in their bed and carried around with them when they left the bedside. In the original system, the PDA had a battery life of 3 hours but was charging while on the bedside dock; as a result, we monitored patients for up to 4 h. (Monitoring time has since been increased to 24 h). The following signals were collected:

1*)* Three leads of continuous ECG.

2) A single, continuous, electrical impedance pneumography signal recorded via a chest band, from which respiration rate can be calculated (used to validate the breathing rate algorithms).

3) Arterial oxygen saturation (SpO_2) measurements from pulse-oximetry (via a finger probe.)

These three parameters were measured continuously and transmitted to the PDA via Bluetooth and to the central station PC via the secure hospital Wi-Fi network. Figure 1 shows a picture of the patient PDA and central station PC where vital sign measurements and VSI are continuously displayed. To enable Bluetooth transmission, all sensors were connected with Bluetooth relay boxes which were either attached to the sensor as a box or worn as a band. The range of Bluetooth was 10 m and relay boxes were associated to the relevant PDA using a pin code and a unique mac address to avoid possible security problems. Figure 2 shows the Bluetooth relay band connected to the SpO_2 sensor. The ECG sensors are also shown being held by the subject.

In addition, regular measurements of blood pressure and temperature were entered by the nurse in the patient PDA. The patient PDA also displayed the VSI although in the current study no use was made of this information. In this initial study, only one multi-parameter monitor (PDA) was available for testing so only one patient could be monitored at any one time. The patients taking part in the study were encouraged to continue their normal daily routine in the ward while connected to the equipment so that situations in which the communication between the sensors and PDA or between the PDA and the central station PC might be compromised, could be identified.

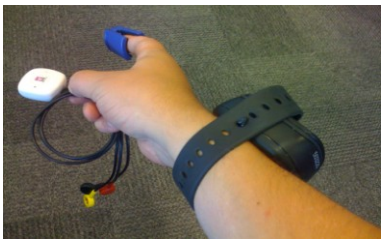

Fig. 2. Telemetry-based vital-sign sensors. The Bluetooth relay band is connected to the SpO_2 sensor and transmits the pulse-oximetry signal to the PDA

B. Signal Acquisition

Before starting the trial, the research nurse coordinating the study did two surveys of the hospital area while connected to the equipment. Wi-Fi signal strength and quality were subsequently reviewed and this identified some areas where the signal was either weak or non-existent (e.g., the hospital lifts, the parking area outside the hospital and the doctor's assessment room on one of the wards). The signal was found to be of good quality 93% of the time.

During this initial 18-patient study, the ECG signal was acquired 97% of the time while the SpO_2 signal was received 88% of the time. The reason is that the SpO_2 finger probe is more sensitive to movement as the patients use their hands in their daily routine. The validation respiration signal from the chest band was of adequate strength 96% of the time. However, instrumentation problems led to a useful impedance signal only being recorded from 4 patients (for a total of 11 hours). The data from those 4 patients were used for testing and validating the ECG-derived respiration algorithm, presented in the next section.

Figure 3 shows an example of the 3 vital sign parameters acquired via telemetry for an ambulatory patient monitored in the Gerontology ward for a period of 3 hours.

A number of elderly patients refused to take part in the study because they felt that the chest band measuring the impedance signal would cause discomfort. This highlighted the need to develop an algorithm which would calculate the breathing rate from the ECG signal.

III ECG-DERIVED RESPIRATION

Obtaining a reliable measure of a patient's breathing rate

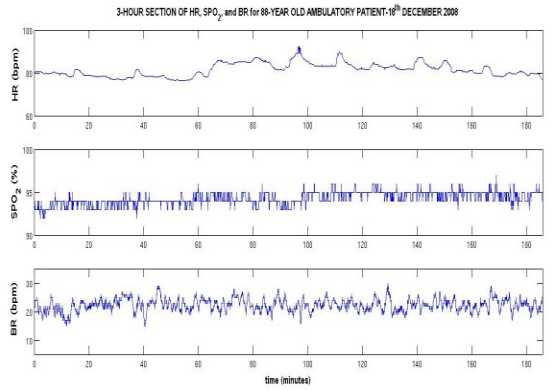

Fig. 3. The three vital sign parameters acquired from an ambulatory patient via the telemetry system. The top plot shows the Heart Rate (HR), the middle one the SpO_2 signal and the bottom one the derived respiratory signal, all averaged over 1 minute intervals.

from the ECG would be useful in this context for a number of reasons: firstly, we would not need to connect extra instrumentation to the patient; secondly, since the ECG waveform is displayed at a central station, the processing required to extract breathing rate could be centralized, allowing more flexibility to the choice of monitor attached to a particular patient.

The physiological mechanism which our algorithm is based on is Respiratory Sinus Arrhythmia (RSA), the cyclic variation in heart rate which is associated with respiration. RSA is reflected in the variation in the time between successive R-wave peaks, the R-R intervals. Plotting the value of the R-R interval against the time at which the interval ends produces a waveform which is synchronous with respiration. Since heart rate accelerates during inspiration, the times of the troughs of the R-R time-series correspond to the start of each respiration cycle. The signal obtained from the R-R time-series, assumed to be synchronous with respiration, is called the RSA-derived respiration signal, or RSA-DR.

RSA, as expressed in the R-R time series, has been used extensively in the past as the basis of algorithms for deriving respiration rate [17-18], with encouraging results. While past methods have been designed for, and validated on, data from subjects who lay supine during data acquisition, our algorithm is designed for, and tested on, ambulatory patients. It is a well-known fact that biomedical sensors are sensitive to subject movement; this needs to be addressed by our algorithm. In addition, while many past algorithms relied on manual inspections and retrospective processing, our system is designed for incorporation into a real-time telemetry monitoring system, all processing is, thus, fully automated.

A. The algorithm

1) Obtaining the RSA-DR

The first step requires the R-R time-series to be obtained from the series of beat-to-beat timing intervals. The R-wave peaks are identified using the Hamilton-Tompkins QRS detection algorithm [19]. The intervals between R-wave peaks give the R-R time-series.

Unexpected deviations due to sensor or motion artefacts were corrected firstly by ectopics removal using a 20% deviation criterion and then by *wavelet de-trending* in order to remove any irrelevant baseline drifts.

In the next step of our algorithm we cubic-spline interpolated the R-R time series and resampled at 4Hz. The frequency component related to respiration was then isolated by band-pass filtering the RR-time series in the 0.1-0.5 Hz band.

2) Reference respiratory signal

The reference signal used was an electrical impedance pneumography signal, indicative of the changes in thorax resistivity during breathing. The signal was wavelet-de-noised before being processed by a peak-detection algorithm for calculating the minute-by-minute breathing rate.

Figure 4 shows a plot of the RSA-DR derived from the ECG and the corresponding reference respiratory signal obtained from an ambulatory patient.

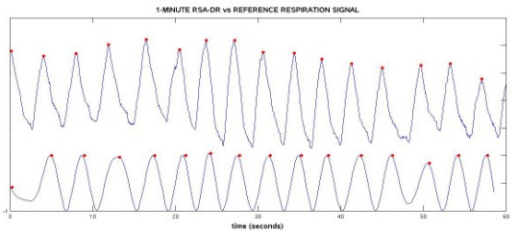

Fig. 4. Reference respiration signal (upper trace) and RSA-DR (lower trace). The signals have been scaled to permit visual comparison, hence no vertical axis scales are provided. There is an approximate correspondence between the peaks of the two traces.

3) *Peak Detection*

In order to derive breathing rate from the ECG signal, a peak detection algorithm was applied to the RSA-DR time series, based on setting a threshold on the amplitude of the signal. Since the same peak detection algorithm is used on the de-noised reference respiration signal in order to validate the method, the threshold was initially set at the value minimizing the error between the number of troughs detected in the RSA-DR time series and the number of peaks in the reference respiration signal, over all of the telemetry vital sign data. The breathing rate was calculated for a number of overlapping 60 second windows, with the start of each window offset by 10 seconds from the start of the previous window. The number of breaths (peaks) was calculated for the RSA-DR and reference signals, which were then normalized to give a 'per-minute' breathing rate.

B. Results

Figure 5 shows the RSA-DR-estimated breathing rate over a 50-minute period on an ambulatory patient superimposed on the breathing rate calculated from the reference signal. The average breathing rate calculated over this period from the reference signal is 17.2 bpm whereas from the RSA-DR it is 18.5 bpm.

Figure 6 shows a scatter plot of the RSA-DR estimates (horizontal axis) against the reference signal values (vertical axis) for all four patients used for validating the ECG-

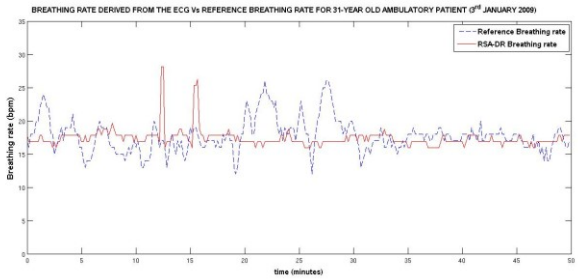

Fig. 5. RSA-DR estimated breathing rate (solid line) over a 50-minute period on an ambulatory patient superimposed on the breathing rate calculated from the reference signal (dashed line).

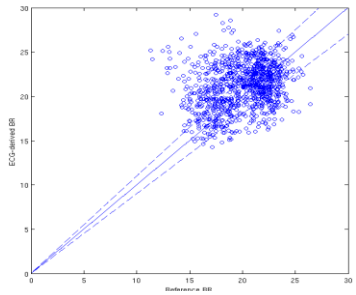

Fig. 6. Scatter plot of RSA-DR (vertical axis) against breathing rate calculated from the reference signal (horizontal axis) for all patients, with 10% error interval lines also shown.

derived respiration algorithm. 72% of minute-by-minute estimates are within a 10% error interval.

CONCLUSIONS AND FUTURE WORK

We tested a real-time, telemetry-based continuous electronic physiological monitoring system, Visensia, on lower-acuity ambulatory patients. The Wi-Fi signal was of sufficient strength 93% of the time. We acquired ECG, SpO_2 and respiration signals 97, 88 and 96% of the time, respectively. Initially, we could only monitor patients for a maximum of 4 hours at a time. We have now further developed the telemetry equipment to allow 24 h monitoring. The robustness and reliability of the system in a wireless environment will next be evaluated for simultaneous, multiple patient monitoring.

We also developed an algorithm for obtaining breathing rate from the ECG signal for ambulatory patients. We validated the algorithm on data from four patients and found that it correctly estimated the breathing rate within a 10% error band 72% of the time. The algorithm will be validated against a larger range of patients and integrated into the system so that no extra instrumentation is required in order to measure breathing rate. This will enable us to apply our data fusion algorithms to three continuously monitored parameters (heart rate, SpO_2 and breathing rate), regularly augmented by intermittent measurements of blood pressure and core temperature.

REFERENCES

[1] R. Thompson, *et al*., "Safer Care for the Acutely Ill patient: learning from serious incidents, fifth report from the Patient Safety Observatory", National Patient Safety Agency (NPSA), August 2007.

[2] D. R. Goldhill, L. Worthington, A. Mulcahy, *et al* , "The patient-at-risk team: identifying and managing seriously ill ward patients", *Anaesthesia*, no. 54, 1999, pp. 853-860.

[3] D. R. Goldhill, S. A. White, A. Sumner, "Physiological values and procedures in the 24 hours before ICU admission from the ward", *Anaesthesia*, no 54, 1999, pp. 529-534.

[4] M. D. Buist, E. Jarmolowski, P. R. Burton, *et al.*, "Recognising clinical instability in hospital patients before cardiac-arrest or unplanned admission to intensive care. A pilot study in a tertiary-care hospital", *Medical Journal of Australia*, no 171, 1999, pp. 22-25.

[5] C. Franklin and J. Matthew, "Developing strategies to prevent in-hospital cardiac arrest: analyzing responses of physicians and nurses in the hours before the event", *Critical Care Medicine*, no.22, 1994, pp. 244-247.

[6] K. M. Hillman, P.J. Bristow , T. Chey, *et al. "*Antecedents to hospital deaths", *Internal Medicine Journal*, no. 31, 2001, pp. 343-348.

[7] F. L. Sax and M.E. Charlson, "Medical patients at high risk for catastrophic deterioration", *Critical Care Medicine*, mp 15, 1987, pp. 510-515.

[8] R. M. Schein, N. Haznay, M. Pena, B. H. Ruben, C. L. Sprung, "Clinical antecedents to in-hospital cardiopulmonary arrest", *Chest*, no 98, 1990, pp. 1388-1392.

[9] A. L. George, Jr, B. P. Folk 3rd, P. L. Crecelius, W. B. Campbell, "Pre-arrest morbidity and other correlates of survival after in-hospital cardiopulmonary barest", *American Journal of Medicine*, no 87, 1989, pp. 28-34.

[10] J. Kause, G. Smith, D. Prytherch, *et al*., "A comparison of antecedents to cardiac arrests, deaths and emergency intensive care admissions in Australia and New Zealand, and the United Kingdom- the ACADEMIA study." *Resuscitation*, no 62, 2004, pp. 275-282.

[11] C. L. Tsien and J. C. Fackler, "Poor prognosis for existing monitors in the instensive care unit", *Critical Care Medicine*, no 25, 1997, pp. 614-619.

[12] H. McGloin , S. K. Adam, M. Singer, "Unexpected deaths and referrals to intensive care of patients on general wards. Are some cases potentially avoidable?" *Journal of the Royal College of Physicians (London),* no. 33, 1999, pp. 255-259.

[13] L. Tarassenko , A. Hann , D. Young , "Integrated monitoring and analysis for early warning of patient deterioration", British Journal of Anaesthesia, no 97 (1), 2006, pp. 64-68.

[14] L. Tarassenko ,A. Hann ,A. Patterson, E. Braithwaite, K. Davidson, V. Barber & D. Young, "Multi-parameter monitoring for early warning of patient deterioration." *Proc. 3rd IEE Int. Seminar on Medical Applications of Signal Processing*, London, 2005, pp. 71-76.

[15] M. Hravnak, L. Edwards, A. Clontz, C. Valenta, M. A. DeVita and M. R. Pinsky. "Impact of an Electronic Integrated Monitoring System Upon the Incidence and Duration of Patient Instability on a Step Down Unit." *Proc. 4th International Symposium on Rapid Response Systems & Medical Emergency Teams*. Toronto, May 2008.

[16] RegenerativeMedicine.net. Accessed on 20th April 2009. Available: http://www.regenerativemedicine.net/NewsletterArchives.asp?qEmpID=715&qC

[17] D. Cysarz, R. Zerm, H. Bettermann, M. Frühwirth, M. Moser and M. Kröz. "Comparison of Respiratory Rates Derived from Heart Rate Variability, ECG Amplitude and Nasal/Oral Airflow". *Annals of Biomedical Engineering*, vol. 36, no. 12, 2008, pp. 2085-2094.

[18] J. F. Thayer, J. L. Sollers III, E. Ruiz-Padial and J. Vila, "Estimating Respiratory Frequency from Autoregressive Spectral Analysis of Heart Period", *IEEE Engineering in Medicine and Biology Magazine,* vol. 21, 2002, pp. 41-45.

[19] P. S. Hamilton and W. J. Tompkins. "Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database", *IEEE Trans. Biomedical Engineering*, vol. 33, no. 12, 1986, pp. 1157-1165.