Non-invasive Measurement of Respiratory Rate in Children Using the Photoplethysmogram

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Abstract—Respiratory rate is recognised as a valuable predictor of the severity of illness in children, but it is not currently feasible to measure this automatically in a triage environment. Autoregressive modelling on data from the pulse oximeter photoplethysmogram has the potential to introduce automated breathing measurement into the realm of paediatric triage.

Using autoregressive modelling, it is shown that respiratory rate can be extracted from the paediatric photoplethysmogram with a mean error of 3.4 breaths per minute.

I. INTRODUCTION

Between 40 and 50% of children attending primary care or emergency departments in the UK present with infectious illness or respiratory complaints [1], [2]. Accurate and efficient triage of these children is essential to identify those with potentially serious infections or serious complications of respiratory disorders.

An increased respiratory rate is an important clinical predictor of both the presence and severity of respiratory infections, as well as more serious complications such as sepsis [2], [3]. Respiratory rate is therefore a core “vital sign” measured in all clinical settings [4].

In most clinical settings, respiratory rate is currently measured manually, either with a stethoscope or by observation of the chest for a recommended period of 60 seconds [5], [6]. The accuracy of these measurements is limited both by the accuracy of the method, and the within-subject variation. Most studies have documented poor levels of accuracy and high inter-observer variability using manual counting of the respiratory rate [5], [7], [8], [9], [10].

Advances in technology allow measurements of many physiological variables to be made using non-invasive sensors, allowing clinicians to concentrate on obtaining a history of the problem and starting any emergency treatment that may be required. The pulse oximeter is of particular use in primary and emergency care, as it is relatively cheap, easy to use, non-invasive, and provides the clinician with information on blood oxygen saturation and heart rate. Extending the information available from the pulse oximeter to include respiratory rate would free up clinicians from time-consuming manual measurement of respiratory rate, as current automated methods are unsuitable or impractical for use in the paediatric triage situation. The pulse oximeter is also more ‘child-friendly’ than a stethoscope, as it does not require the removal of clothing or the proximity of a stranger, both of which can be distressing for a sick child.

It is known that the waveform output of a pulse oximeter (the photoplethysmogram, or PPG) contains information about the respiratory rate, and it has previously been shown by the authors [11] that this information can be extracted from adult recordings using autoregressive (AR) modelling. This paper seeks to show that respiratory rate can also be extracted from short recordings of the paediatric photoplethysmogram, similar to those that might be obtained in a triage situation.

II. EXPERIMENTAL DESIGN

Concurrent measurements of both the photoplethysmogram and reference respiratory rate are required to develop and validate paediatric respiratory rate algorithms. Therefore, the following study was devised to obtain this data from healthy children in a community setting.

The study was carried out in June 2007 at a primary school in Oxford, UK. Consent to being measured was obtained for thirty-six children (16 female, 20 male). The children were aged between 8 and 11 years, with a mean age of 9.9 years on the day of the study. Two separate Visi-3 systems (Stowood Scientific Instruments, Beckley, Oxon, UK) were used to measure the children before, during, and after two to three minutes of vigorous exercise (cycling on an exercise bicycle), with a typical recording length of 7 minutes. This allowed a wider variety of respiratory and heart rates to be captured than would be found from measuring the children at rest.

The Visi-3 system allows a wide range of physiological variables to be measured using a variety of sensors. For this study, nasal airflow and thoracic and abdominal effort sensors were used to measure respiratory activity, and the photoplethysmogram waveform, pulse rate, oxygen saturation and pulsatile index were recorded from the pulse oximeter. The pulsatile index is the ratio of the ac amplitude and dc level of the photoplethysmogram, and is useful for monitoring the adequacy of peripheral perfusion at the site of the oximeter probe. Sample rates were 256 Hz for the respiratory effort sensors and photoplethysmogram, 128 Hz for the nasal airflow, and 1 Hz for the pulse rate, oxygen saturation and pulsatile index.

All of the children had two respiratory effort bands fitted over their clothing, as demonstrated in Fig. 1. These are made of an elastic material with an integral wire, so that a change in the circumference of the band will result in a change in the inductance of the wire. The bands were placed around
The nasal cannula used in the study is a narrow gauge plastic tube with two prongs that fit into the nares, allowing airflow measurements to be made. As some people find this uncomfortable, the children in the study were allowed to choose not to have a cannula fitted, in which case only the effort bands would be used for breathing measurement. However, most of the children consented to having the cannula fitted and in place for the full length of the recording.

A transmission type pulse oximeter (Masimo Corporation, California, USA) was used to measure the photoplethysmogram, pulse rate, oxygen saturation, and pulsatile index. This was placed on the child’s middle or index finger. Both paediatric (LNOP DCIP) and adult sensors (LNOP DCI) were available, with most children being fitted with a paediatric sensor.

The data recorded by the Visi-3 system can be extracted as a text file, and this facility was used to import the data into Matlab (The Mathworks, Massachusetts, USA), for further processing.

A. Reference respiratory rates

Accurate non-invasive measurement of respiratory rate is very difficult with existing technologies, and none of the three measures used in this study can be relied upon to provide accurate measurements of respiratory rate at all times. In the case of nasal airflow measurements, the subject would ideally be required to breathe predominantly through their nose during both inspiration and expiration, to ensure that all breaths result in nasal airflow. For respiratory effort measurements, best results are obtained with high tidal volumes, resulting in large changes in thoracic and abdominal circumference, and use of both chest and abdominal muscles in the breathing process. Activities such as talking will also cause difficulty in obtaining accurate respiratory rates using either method.

In the case of this study, it was impractical to require the children to breathe in a particular manner while also engaging in physical activity. There is also the issue of small signals on all three waveforms due to the children’s lower tidal volume compared with adult subjects. Therefore, care has to be taken when analysing this data to obtain reference respiratory rates.

A semi-automated method was used to identify breath times in the three respiratory waveforms (nasal airflow, thoracic effort and abdominal effort). This allowed human intervention to correct for noisy waveforms and varying tidal volume. These breath times can then be used to calculate an ensemble respiratory rate over a given time interval.

Due to the factors described above, the reference respiratory rates do not always agree, and it is not possible to tell which one most accurately reflects the true respiratory rate at any given time. The following strategy is therefore adopted: the recording is split up into a number of overlapping 30-second windows, with the start of each window offset by 5 seconds from the start of the previous window. A respiratory rate for each window is calculated from the breath times for each reference method, and the median of these rates is taken as the reference rate at the centre point of the window.

B. Data used for this investigation

For this investigation, we are interested in short-term monitoring of a relatively stable respiratory rate, as this is what we would expect to find in a paediatric triage situation. The reference respiratory rates of the children were examined visually, and fourteen sections containing relatively constant respiratory rates and reasonable agreement between the reference measurements were identified. The sections are between 100 and 200 seconds in length, which corresponds to a realistic length of time for triage measurement, and are sourced from the traces of 11 different children (5 male, 6 female). In the three cases where two sections were used from the same trace, the sections are non-overlapping, so that there is no duplication of data. Of the 14 sections, 6 were measured in the rest period before exercise, 6 during the recovery rest period after exercise, and 2 during the exercise period.

For each section, a series of reference respiratory rates were calculated using the windowing method described above. Although the sections were chosen to demonstrate stable respiratory rates, there is inevitably some variation in the respiratory rate over the section (up to 8.5 breaths per minute), due to the varying levels of physical activity being carried out during the measurement period. For comparison with the results from the PPG analysis, the median value over the period is taken as the reference respiratory rate. These median respiratory rates span a range from 11 to 39 breaths...
per minute, providing coverage of both resting and elevated rates for this age range.

III. MEASURING RESPIRATORY RATE FROM THE PHOTOPLETHYSMOGRAM

A number of methods have been described for obtaining the respiratory rate, or breathing-synchronous waveforms, from the photoplethysmogram. These include digital filtering techniques [12], [13], Fourier transforms [14], and complex wavelet decomposition [15]. However, of these, only wavelet transforms have been applied to paediatric data [16].

In a previous paper [11], we compared a number of methods, including wavelet transforms, on data from adult subjects, and also introduced a novel method based on autoregressive (AR) modelling. Both AR modelling and digital filtering were found to be more accurate in predicting breathing rate than wavelet transforms, and had significantly lower computational requirements, making it possible to track breathing in real time.

A. Autoregressive modelling

Autoregressive (AR) modelling is a frequency-based signal analysis technique, which has previously been applied to a number of physiological signals, including the EEG [17] and the intrapartum cardiocogram [18].

AR modelling can be formulated as a linear prediction problem, where the current value $x(n)$ can be modelled as a linearly weighted sum of the preceding $p$ values. The parameter $p$ is the model order, which is usually much smaller than the length of the sequence $N$.

$$x(n) = - \sum_{k=1}^{p} a_k x(n-k) + e(n)$$  (1)

The value of the output $x(n)$ is therefore a linear regression on itself, with an error $e(n)$, which is assumed to be normally distributed with zero mean and a variance of $\sigma^2$. The problem can also be visualised in terms of a system with input $e(n)$, and output $x(n)$, in which case the transfer function $H$ can be formulated as shown below:

$$H(z) = \frac{1}{\sum_{k=0}^{p} a_k z^{-k}}$$  (2)

$$= \frac{z^p}{(z - z_1)(z - z_2) \ldots (z - z_p)}$$

As shown in (2), the denominator of $H(z)$ can be factorised into $p$ terms. Each of these terms defines a root $z_i$ of the denominator of $H(z)$, corresponding to a pole of $H(z)$. Since $H(z)$ has no zeros away from the origin, the AR model is an all-pole model. The poles occur in complex-conjugate pairs, and define spectral peaks in the power spectrum of the signal, with higher magnitude poles corresponding to higher magnitude peaks. The resonant frequency of each spectral peak is given by the phase angle of the corresponding pole.

The phase angle $\theta$ corresponding to a given frequency $f$, is defined by (3), which shows that it is also dependent on the sampling interval $\Delta t$.

$$\theta = 2 \pi f \Delta t$$  (3)

B. Applying AR modelling to the paediatric photoplethysmogram

The AR method is applied to 30-second sections of the photoplethysmogram, corresponding to the windows used for calculation of the reference respiratory rates. To increase the stability of the AR model, and reduce the influence of dc poles, the signal is first detrended. A digital low-pass filter is then applied to the signal to attenuate frequencies corresponding to the heart rate. The filter is designed using a Kaiser windowing function, with a transition band from 0.6–1 Hz (36–60 breaths per minute), 5% ripple in the pass-band, and 30 dB attenuation in the stop-band.

The filtered signal is downsampled to increase the range of angles that correspond to respiratory frequencies, and so improve the accuracy of the AR model. An AR model is constructed using the Burg algorithm [19], and the breathing pole is identified based on pole magnitude and the likely frequency range of paediatric respiratory rates. The sampling frequency after downsampling and the AR model order both affect the eventual accuracy of the method, and the optimum combination is dependent on both the signal to be analysed, and the length of the window. A combination of 1.5 Hz downsampled frequency and 11th order AR model were found to perform best for the signals described in this paper.

As with the reference respiratory rates, the photoplethysmogram-derived respiratory rate is calculated as the median value over the section.

IV. RESULTS

For each of the fourteen sections investigated, we calculated two respiratory rates: one based on a consensus from the reference measures, and one from AR modelling of the photoplethysmogram. Fig. 3 shows that the correspondence
between these two rates for all 14 sections of photoplethysmogram analysed for this paper, and it can be seen that there is good agreement between the two.

The average error is just 3.4 breaths per minute, which lies well within the measured variation in the reference respiratory rates within the sections (3.5–8.5 breaths per minute). Since previous studies have observed within-subject variations of up to 21 breaths per minute [5], this level of error is unlikely to be clinically important. The respiratory rate measured using the AR method does not seem to show any particular bias, and the accuracy does not seem to be dependent on the true respiratory rate.

V. CONCLUSIONS AND FUTURE WORK

These results indicate that AR modelling could be used to measure the respiratory rate of children from a short section of photoplethysmogram. This would allow automated, non-invasive and highly accurate measurement of respiratory rate in addition to heart rate and oxygen saturations using a modified pulse oximeter. This would greatly improve the routine measurement of these vital signs in busy clinical settings and permit better informed decisions about triage and diagnosis.

Further validation of the method is required, preferably using data collected in a clinical setting, and from a wider age range. It might be possible to improve the accuracy of the AR method by using a more complex pole choice algorithm, incorporating additional information such as the current pulse rate, the child’s age, or estimates of the respiratory rate from earlier windows to assist in location of the breathing pole. This may also make it possible to track paediatric respiratory rates over longer monitoring periods, which would be of use in a hospital ward or palliative care setting. Respiratory rates may be clinically valuable in these settings, but children are unlikely to tolerate current methods of non-invasive breathing measurement.

VI. ACKNOWLEDGEMENTS

The authors would like to thank Sarah Nash and the staff and pupils of St Michael’s CE Primary School for their assistance in collecting the data for this research.

S. Fleming is funded by the EPSRC through the Oxford Life Sciences Interface DTC. Funding for this study was provided to the Department of Primary Health Care as part of the NIHR School of Primary Care Research. Ethics approval was obtained from Oxford Research Ethics Committee.

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