Respiratory rate estimation from the oscillometric waveform obtained from a non-invasive cuff-based blood pressure device

M.A.F. Pimentel[1], M.D. Santos[1], C. Arteta[1], J.S. Domingos[1], M.A. Maraci[1], G.D. Clifford[1,2]

Abstract— **The presence of respiratory activity in the electrocardiogram (ECG), the pulse oximeter's photoplethysmographic and continuous arterial blood pressure signals is a well-documented phenomenon. In this paper, we demonstrate that such information is also present in the oscillometric signal acquired from automatic non-invasive blood pressure monitors, and may be used to estimate the vital sign respiratory rate (RR). We propose a novel method that combines the information from the two respiratory-induced variations (frequency and amplitude) via frequency analysis to both estimate RR and eliminate estimations considered to be unreliable because of poor signal quality. The method was evaluated using data acquired from 40 subjects containing ECG, respiration and blood pressure waveforms, the latter acquired using an in-house built blood pressure device that is able to connect to a mobile phone. Results demonstrated a good RR estimation accuracy of our method when compared to the reference values extracted from the reference respiration waveforms (mean absolute error of 2.69 breaths/min), which is comparable to existing methods in the literature that extract RR from other physiological signals. The proposed method has been implemented in Java on the Android device for use in an mHealth platform.**

I. INTRODUCTION

Extreme values of respiratory rate (RR) have been shown to be associated with an increased risk of adverse events in hospital patients [1], [2]. This has led to its inclusion in most numerical patient assessment systems, the use of which is widespread [3]. Hospital clinical staff are recommended and trained to measure RR from patients by counting the number of breaths in a 15 or 30-second window. Besides being prone to user-dependent subjective errors, this approach is time-consuming and adds to the heavy burden of data collection in busy clinical environments.

Automated techniques for measuring RR allow for almost continuous monitoring, which can improve temporal resolution, increase accuracy and save clinical time. Nevertheless, these techniques usually require the use of equipment which might interfere with natural breathing, such as spirometry, or might be uncomfortable for the patient, such as measurement via a band that encircles the chest and/or abdomen. The impedance plethysmography (IP) signals acquired with the latter are often unusable as a result of poor signal-to-noise ratio and presence of movement artifacts [4]. The electrocardiogram (ECG), photoplethysmogram, or continuous arterial blood pressure signals, have been considered as a source for extraction of respiratory information [5], [9], [10], [12]. Respiratory information may be modulated in these signals in two fundamental ways: amplitude modulation (AM), which is caused by changes in intrathoracic pressure during inspiration and expiration, and frequency modulation (FM), which corresponds to a variation in heart rate that occurs throughout the respiratory cycle (also known as *respiratory sinus arrhythmia*) [5].

The extraction of the respiration signal from the oscillometric waveform has been considered to suppress its effect in estimating the blood pressure [6]. In this paper, we show that we can extract the respiration signal from the oscillometric signal acquired from our (in-house developed) upper-arm non-invasive blood pressure device [7] and we propose a novel method to determine RR by combining the different variations of the oscillometric signal caused by respiration. Such an approach brings several advantages for in- or out-hospital assessment of RR: (1) it provides more useful clinical information from traditional non-invasive blood pressure monitors; (2) it is user-independent; (3) no extra equipment is required; (4) it reduces the duration of a patients clinical assessment; and (5) it reduces costs for care institutions.

II. METHODOLOGY

A. Data Collection

For the analysis described in this paper, we acquired data from a group of 40 healthy subjects (median age 26, range 21-44 years old; 14 females) who underwent 6 consecutive left-arm blood pressure measurements: 3 measurements at rest, followed by 3 measurements while squeezing a ball with the right hand. In both sessions, one of the measurements was taken using our non-invasive blood pressure device, from which we extracted the pressure signal (sampled at a rate of 150 Hz). Both measurements were preceded and followed by a blood pressure measurement using a commercially available blood pressure device (the clinically-validated Automatic Blood Pressure Monitor, M2 Basic model, from Omron, UK). Continuous single-lead ECG (256 Hz) and respiration IP (using two bands that encircle the chest and abdomen, 256 Hz) signals were also collected during each measurement (using the Visi-3 Digital Sleep System from Stowood Scientific Instruments Ltd., UK). The subjects were asked to sit upright and to perform normal breathing at their own natural pace during all measurements.

B. Data Preparation

A total of seventy-eight pressure signals containing reliable recordings of blood pressure measurements from the 40

[1]MAFP, MDS, CA, JD, MAM and GDC are with the Centre for Affordable Healthcare Technology, Kellogg College, Banbury Road, Oxford OX2 6PN, UK.

[2]GDC is with the Georgia Institute of Technology and Emory University, GA, USA.

Correspondence: marco.pimentel at eng.ox.ac.uk

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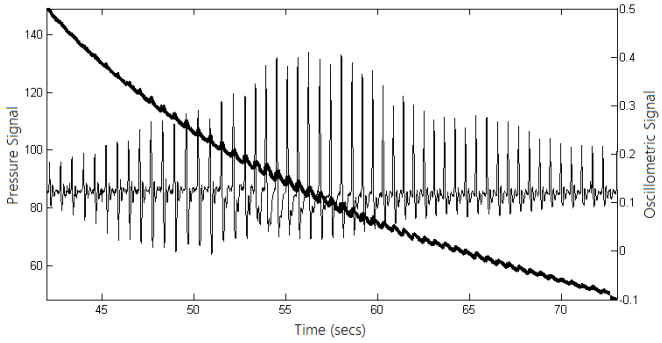

Fig. 1. Representation of the pressure signal and oscillometric waveform (thicker line) derived from the pressure signal acquired with our blood pressure monitor from one subject.

subjects were selected for the analysis (2 recordings were deemed to be of bad quality due to missing data). ECG, respiration and blood pressure recordings were manually synchronized by two independent research assistants, who labelled the beginning and end of all continuous recordings according to the duration of the correspondent pressure signal. The two respiration IP signals were used as the reference gold standard recordings for RR validation. The ECG signal was used as the reference gold standard recording for the heart rate validation, and as a second reference recording for the RR validation. The blood pressure measurements that preceded and followed each measurement performed with our device were used as the reference gold standard for the blood pressure validation.

All the data processing and statistical analysis was performed using the MATLAB software framework (Mathworks, Natick, MA, USA).

C. Respiratory rate extraction from the oscillometric waveform

Systolic and diastolic blood pressure values were estimated from the pressure and oscillometric waveforms (Figure 1) using the oscillometric method, which is the most widely used method in commercial blood pressure monitors [8]. The method has been described in previous work [7] and has shown to be an efficient and accurate way to estimate blood pressure. The heart rate was calculated from the frequency spectrum generated via the fast Fourier transform (FFT) of the oscillation waveform. The frequency component with the highest magnitude corresponds to the heart rate [7].

In our proposed method to extract RR, we explored the combination of different features (that have different frequency modulations) from the oscillometric waveform (Figure 2-(c)) as subsequently described. First, beat detection was performed using a signal segmentation algorithm that marks the peaks of each beat. For that, the mean value was removed from the signal, and the resultant signal was differentiated using a five-point digital differentiator. The signal energy of the differentiated signal was then determined and finally a threshold-based detection algorithm (using $T = 0.005$) was applied to detect the most significant local maxima of the signal.

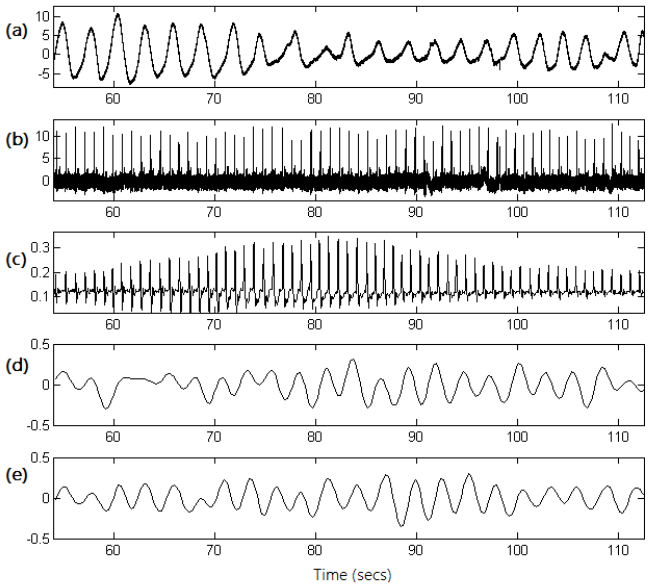

Fig. 2. Extraction of respiratory rate from the oscillometric signal. (a) Reference impedance plethysmography respiration signal (acquired from the abdomen); (b) ECG signal; (c) oscillometric waveform acquired with our blood pressure monitor; (d) frequency and (e) amplitude modulated waveforms derived from the oscillometric signal. The derived modulation signals, which are highly correlated with the reference respiration signal, are used to calculate the respiratory rate.

The intervals between successive peaks were calculated to derive the interbeat time series, which corresponds to the FM waveform (Figure 2-(d)). Fourier analysis requires evenly sampled data, and therefore, the time series was resampled onto an even 4 Hz grid using linear interpolation. The waveform was then filtered using a finite impulse response (FIR) band-pass filter with cut-off frequencies of 0.1 and 0.7 Hz (equivalent to respiratory rates of 6-42 breaths/min), and converted to the frequency domain using FFT. The resulting power spectrum of the signal was then analyzed for the frequency with maximum power within the expected respiratory frequency range (4-60 breaths/min).

The amplitude (maximum intensity) of the resulting series of peaks was also determined in order to derive the AM waveform (Figure 2-(e)). The baseline wander (which was determined using a $6^{th}-$order polynomial fit) was removed from the series and data were resampled at 4 Hz using linear interpolation. Equivalent to the FM method, the resulting signal was filtered using a FIR band-pass filter with cut-off frequencies of 0.1 and 0.7 Hz, and the FFT power spectrum of the signal was then analyzed for the maximum frequency content within the RR frequency range.

The AM and FM estimations were fused by either taking the estimation with higher intensity in the correspondent frequency spectrum, or calculating the mean of the AM and FM-based estimations if the difference between them was less than 3 breaths/min. Those measurements in which the difference between the AM and FM estimations was higher than 5 breaths/min were classified as low-quality estimations.

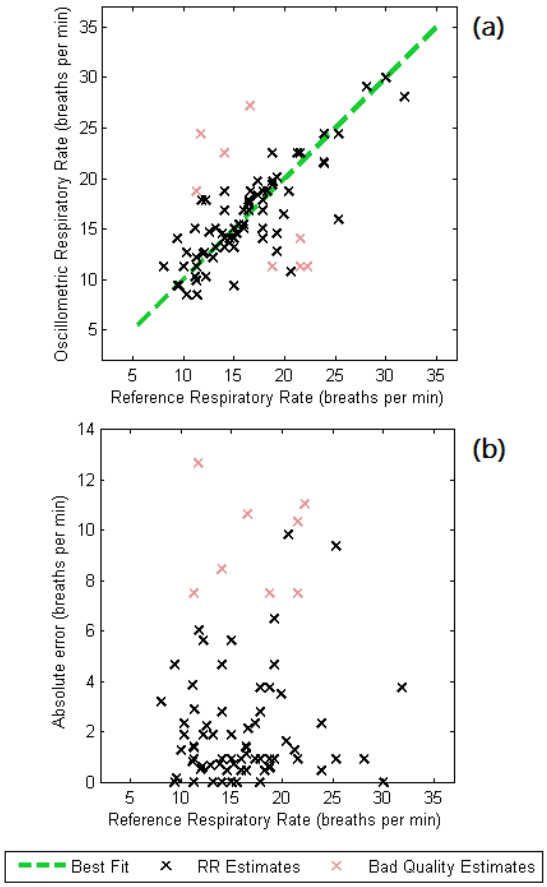

Fig. 3. (a) Scatter plot comparing the reference respiratory rate (RR) obtained from the respiration signals with the RR estimates obtained from the oscillometric signal acquired with the blood pressure monitor and "Best Fit" line ($R^2 = 0.9201$); (b) Absolute error for the range of reference RR values covered in the study. The proposed method, by combining the different modulations of respiration in the oscillometric signal, is able to eliminate some of the estimations with larger error.

D. Reference respiratory rate

In order to obtain a valid estimate of the reference RR during the blood pressure measurement, we calculated it from the two IP signals acquired using two frequency-based methods (Figure 2-(a)). Each respiration signal was downsampled to 4 Hz, after applying an anti-aliasing filter, and then filtered using a 0.1-0.7 Hz FIR band-pass filter. For the first frequency-based estimation method, we analyzed the FFT power spectrum of each waveform and identified the frequency with the largest power associated with it within the respiratory frequency range. For the second method, we fitted the filtered waveforms to a $7^{th}-$order autoregressive (AR) model and identified the respiratory pole as the pole with the highest magnitude within the respiratory frequency range. The frequency associated with that pole was selected as the one containing respiratory information [9]. Only those reference respiratory rates for which the agreement between both FFT and AR-based estimates from both IP signals was within 2 breaths/min were retained [9]. According to this analysis, all signals were deemed to be "valid", and the mean of the estimates was taken as the final gold standard reference respiratory rate value.

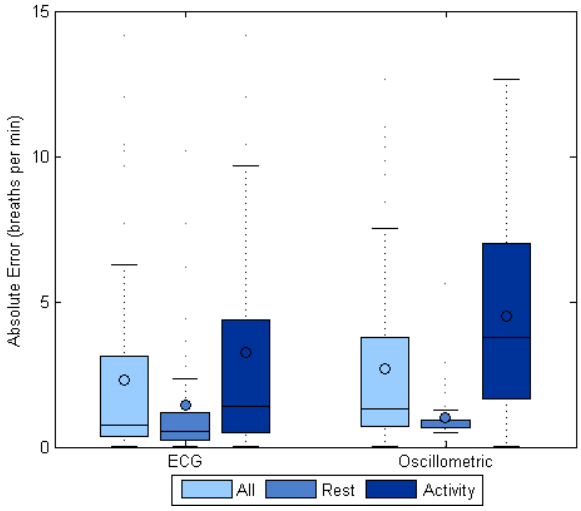

Fig. 4. Results from the sensitivity analysis comparing the performance of ECG-based with oscillometric-based methods to extract respiratory rate (RR) during different conditions. The boxplot shows the absolute error between the reference RR and the RR estimated during a rest protocol (Rest), after an active exercise protocol (Activity) and averaged accross both protocols (All). Lower quartile, median and upper quartile values are displayed as lower, middle, and upper horizontal lines of the boxes. Whiskers are used to represent the most extreme values within 1.5 times the interquartile range from the quartile. Outliers are displayed as dots. The circle markers correspond to the mean values for each group. No statistically significant difference ($p = 0.129$) between the RR derived by the ECG and the oscillometric method for each protocol was observed.

To assess further the performance of our proposed method, we compared its performance with that of extracting RR from the ECG recordings, for which several studies and methods have been proposed in the literature. We extracted respiratory information from the ECG recordings (see Figure 2-(b)) using the fusion method described in [9], which uses an AR model for both AM and FM waveforms extracted from the ECG signal.

E. Method Evaluation

The performance of the proposed algorithm was assessed using the mean absolute error (MAE) in the correspondent units, $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid \hat{y}_i - y_{ref,i} \mid$, where n is the number of recordings considered, and $\hat{y}_i$ and $y_{ref,i}$ are the estimated and reference values for recording i, respectively. We determined the estimation error not only considering all measurements together, but also considering the measurements performed in each session (i.e., during rest and during activity).

III. RESULTS AND DISCUSSION

Table I shows the overall MAE for the different vital signs extracted from our blood pressure device compared to the gold standard reference values. We observe that a good agreement between the estimated values for the blood pressure and heart rate was found, with a mean absolute error of less than 5 mmHg and 3 beats/min, respectively,

TABLE I

MEAN ABSOLUTE ERROR FOR EACH VITAL SIGN ESTIMATED USING THE BLOOD PRESSURE MONITOR. THE REFERENCE ESTIMATED POPULATION MEAN AND INTERQUARTILE RANGE VALUES ARE ALSO SHOWN.

	Mean (IQR)		
	Reference	Estimate	MAE
Systolic BP (mmHg)	123.4 (13.8)	124.5 (16.0)	3.57
Diastolic BP (mmHg)	73.3 (16.0)	73.0 (13.0)	2.45
Heart Rate (beats/min)	75.2 (15.8)	75.1 (18.2)	0.75
Resp. Rate (breaths/min)	16.3 (6.5)	16.1 (6.1)	2.69

which is within the accuracy levels required for the clinical validation of the device [13]. Crucially, we note that the MAE obtained for RR was 2.7 breaths/min, which is within the error found in previous studies of RR extraction from other physiological signals acquired non-invasively, such as ECG [9] and photoplethysmogram [10]). The RR MAE may be reduced if the "low-quality" measurements are not considered (see Figure 3). The combination of both AM and FM estimations was able to eliminate some of the largest estimation errors (8 measurements were eliminated), and consequently, improve the performance of the method (from 3.10 to 2.69 breaths/min). We note that the reference value is likely to contain estimation errors up to 2 breaths/min.

Figure 4 shows that the ECG-based method produced RR estimates with an overall lower error than those extracted from the oscillometric waveform. As noted by [6], this can be expected, since the oscillometric blood pressure recordings contain other low-frequency components that are very close to breathing. Because the ECG signal does not contain these perturbations so markedly, it provides a better reference signal for extracting respiratory rate. However, for the resting protocol, which is the clinically recommended approach, the oscillometric approach exhibits lower errors. Also, the differences between the estimation errors of the ECG recordings and those of the blood pressure recordings were not statiscally significant ($p = 0.129$, using a Wilcoxon-Mann-Whitney test). Furthermore, during the session in which the blood pressure measurement was performed at rest, which is the condition in which it should be performed, both methods perform similarly. This demonstrates that the oscillometric waveform contains reliable information of respiratory activity.

IV. CONCLUSIONS

In this paper, we proposed and evaluated a novel algorithm for extraction of respiratory rate from the oscillometric signal captured by a non-invasive cuff-based blood pressure device. A prototype protocol was developed for assessing the performance of the method and for simultaneous recordings of blood pressure and respiratory signals. Results exhibited a good agreement between RR estimates from the blood pressure monitor and the reference respiration signals. This work has demonstrated that it is possible to extract breathing information from oscillometric recordings, which significantly enhances the capabilities of automatic non-invasive blood pressure devices by providing the possibility of incorporating important physiological parameters such as respiratory rate or respiratory sinus arrhythmia without significant added cost or complexity. Such a device will be able to provide the users with a better state of their health, as the respiratory rate is an important vital sign that is known to be correlated to other physiological conditions such as stress and obesity, and reduce the cost and time to assess the physiological status.

Future work includes the extraction of more physiological and clinically relevant features from the oscillometric signal, such as the arterial stiffness [11], which can be used to further enhance non-invasive blood pressure devices.

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REFERENCES

[1] M. Cretikos, J. Chen, K. Hillman, R. Bellomo, S. Finfer, A. Flabouris et al,The objective medical emergency team activation criteria: A case-control study, Resuscitation, vol. 73, no. 1, pp. 6-72, 2007.

[2] J. Kause, G. Smith, D. Prytherch, M. Parr, A. Flabouris, K. Hillman 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, vol. 62, no. 3, pp. 27-282, 2004.

[3] H. Gao, A. McDonnell, D. Harrison, T. Moore, S. Adam, K. Daly, L. Esmonde, D. Goldhill, G. Parry, A. Rashidian et al., Systematic review and evaluation of physiological track and trigger warning systems for identifying at-risk patients on the ward, Intensive Care Medicine, vol. 33, no. 4, pp. 66-679, 2007.

[4] V. Larsen, P. Christensen, H. Oxhj, and T. Brask, Impedance pneumography for long-term monitoring of respiration during sleep in adult males, Clinical Physiology, vol. 4, no. 4, pp. 333342, 1984.

[5] G.D. Clifford, F. Azuaje, P. McSharry, Advanced methods and tools for ECG data analysis. Artech House, 2006.

[6] M. Bolic, V.Z. Groza, H.R. Dajani, I. Batkin, S. Rajan, Extraction of Breathing Signal and Suppression of Its Effects in Oscillometric Blood Pressure Measurement, IEEE Transactions on Instrumentation and Measurement, vol. 60, no. 5, pp. 1741-1750, 2011.

[7] C. Arteta, J. Domingos, M.A.F. Pimentel, M.D. Santos, C. Chiffot, D. Springer, A. Raghu, G.D. Clifford, Low-Cost Blood Pressure Monitor Device for Developing Countries, Wireless Mobile Communication and Healthcare, vol. 83, pp. 335-342, 2012.

[8] A. Ball-Llovera, R. Del Re, R. Ruso, J. Ramos, O. Batista, I. Niubo, An experience in implementing the oscillometric algorithm for the noninvasive determination of human blood pressure, Proceedings of the 25th Annual International Conference of the IEEE, vol. 4, pp. 3173-3175, 2003.

[9] C. Orphanidou, S. Fleming, S.A. Shah, L. Tarassenko, Data fusion for estimating respiratory rate from a single-lead ECG, Biomedical Signal Processing and Control, vol. 8, pp. 98-105, 2013.

[10] W. Karlen, S. Raman, J.M. Ansermino, G.A. Dumont, Multiparameter Respiratory Rate Estimation from the Photoplethysmogram, IEEE Transactions on Biomedical Engineering, vol. 60, no. 7, pp. 1946-1953, 2013.

[11] S. Liu, J. Wang, Z. Wen, Extraction of an Arterial Stiffness Index from Oscillometry, Journal of Medical and Biological Engineering, vol. 27, no. 3, pp. 116-123, 2007.

[12] S. Nemati, M. Atul, G.D. Clifford, "Data fusion for improved respiration rate estimation." EURASIP Journal on Advances in Signal Processing, vol. 2010, pp. 1-10, 2010.

[13] E. O'Brien, B. Waeber, G. Parati, J. Staessen, M.G. Myers, "Blood pressure measuring devices: recommendations of the European Society of Hypertension." BMJ: British Medical Journal, vol. 322, no. 7285, pp. 531-536, 2001.