ECG, PPG and ABP Sensor Fusion for a PCA-based Respiratory Activity Estimation

S. Mann, R. Orglmeister

Chair of Electronics and Medical Signal Processing, TU-Berlin, Berlin, Germany, steffen.mann@tu-berlin.de

Chair of Electronics and Medical Signal Processing, TU-Berlin, Berlin, Germany

Structure: 1. Introduction / 2. Methods / 3. Results / 4. Conclusion

Abstract

Respiratory activity is an important parameter in clinical monitoring used in a wide range of areas like intensive care units (ICU), sports performance studies and sleep studies. Common methods measure the respiratory activity by means of facemasks (FM) or plethysmographic belts strapped around chest and/or abdomen. FMs are often too obtrusive when worn for a longer period of time while plethysmographic belts lack the necessary accuracy for acquiring the exact volume of air in-/ and exhaled and are prone to error from artefacts. It has been shown that respiratory induced modulations can be found in other vital signs like Electrocardiogram (ECG), Photoplethysmogram (PPG) and arterial blood pressure (ABP). It is possible to use these signals to derive respiration without the need for additional sensors. In this paper we propose to combine these cardiac signals and compensate for the pulse arrival time to derive the respiratory activity. Employing principal component analysis (PCA) to extract respiration from combined ECG, PPG and ABP can improve the results over single signal approaches.

1 Introduction

Cardiac signals are modulated in amplitude and frequency by the respiratory activity [1]. Therefore cardiac signals such as the electrocardiogram (ECG), photoplethysmogram (PPG) and arterial blood pressure (ABP) can be used to find the cardiac derived respiratory activity. As the modulations in these signals are very similar, this redundancy can be used by algorithms such as principal component analysis (PCA) to achieve a better estimation of the respiratory activity than can be achieved by single signal approaches. As cardiac and respiratory signals are often measured simultaneously, e.g. in intensive care units (ICU), sports performance evaluation and sleep studies, the cardiac derived respiratory signal can be used to decrease the number of sensors needed. Especially respiratory sensors like facemasks (FM) and plethysmographic belts are either very obtrusive (FM) or not very accurate for tasks demanding more than just the average breath rate. Therefore deriving this information from sensors already employed is very appealing.

2 Methods

Cardiac signals such as ECG and PPG are easy to measure noninvasively and therefore are often recorded, e.g. as a basic measure for cardiac activity, form of the pulse wave and oxygen saturation. Accurate and continuous measurement of blood pressure still is a very demanding task and relies on invasive methods or expensive equipment. It is however very common to measure it in intensive care units and sleep

studies. For this study we used data from the Physiobank [2] MIMIC Database [3]. The criteria for selecting suitable records from the MIMIC Database are described in the following section 2.1. The actual Signals are then discussed in section 2.2. Because the signals used were recorded at different parts of the body and the pulse wave passes through the body at a speed of $7\text{--}12 \frac{\text{m}}{\text{s}}$ [4] the signals had to be compensated for these signal dependent delays before further processing can take place (section 2.3). As respiratory activity consists of lower frequencies than the signals used to derive it, further preprocessing (section 2.5) can facilitate the PCA-based respiratory activity extraction described in section 2.4. Section 2.6 describes further processing for evaluation of the applied algorithms.

2.1 MIMIC Database

As physiologically relevant datasets for arterial blood pressure cannot be easily measured outside a clinical setup when using invasive methods, or require expensive clinical equipment, studies such as this one often have to rely on well documented databases such as the Physiobank Database, which offers a wide range of annotated clinical data. The Physiobank MIMIC Database was chosen because it offers a wide selection of recordings, most of them lasting between 10 and 50 hours. It focuses on intensive care unit patients "likely to be hemodynamically unstable during the planned recording period" [3] and is therefore suitable for testing algorithms on signals with changing signal quality and for testing the robustness of the algorithm. The recording of datasets for the MIMIC Database was not

supposed to interfere with other tasks in the ICU, therefore only the clinically relevant biosignals for each individual patient were recorded, resulting in a different set of signals in each recording. Therefore a selection of suitable patients had to be made taking into consideration the signals recorded for each dataset and the reasons for the patients stay in ICU. Only records containing at least one ECG channel, PPG, ABP and respiration were considered for evaluation giving a total of 38 possibly suitable patients. The considered patients ages ranged from 21 to 91 and consisted of mostly elderly people with a mean age of 70 and a standard deviation of 13 years[5]. Information given on the exact setup for each recording is scarce but important, e.g. whether a patient was artificially ventilated or had a cardiac pacemaker is not given. Even concrete information on the measurement technique, type of sensors or the place of the measurement (for ABP), seems to be missing. For example, some patients were suffering from respiratory failure or pulmonary edema and some of them might have been artificially ventilated during recording. These patients have been excluded as impaired respiratory functions or the impact of artificial ventilation on the cardiac signals are not part of this study, could however pose an interesting topic for further research. For final evaluation of the algorithms developed in this paper for each remaining patient two records of 10 minutes, one at the start of recording and one 20 hours later, were analysed for signal clipping and missing signals, e.g. zero-line in PPG probably due to shifted sensors. This left only a total of seven patients for evaluation (see table).

classification	Resp. failure	Pulm. edema	Other	none	Total
considered	10	9	17	2	38
chosen	0	0	7	0	7

2.2 Signals

The ECG gives account of the electrical activity of the heart. By measuring the effect of polarisation and depolarisation of heart-cells it gives information about the contraction of the heart muscles. The ECG can easily be measured, e.g. by surface electrodes placed on the chest. The Photoplethysmogram is usually recorded using a finger-clip which measures the variation in the amount of light absorbed or reflected by the finger and the blood passing through it. The finger itself absorbs a constant amount of light whereas the blood pulsing through the finger accounts for a varying component that corresponds to the amount of blood currently passing through the finger and is therefore related to the pulse wave passing through the finger. Measuring the blood pressure continuously is more difficult and requires invasive measurement and/or expensive equipment. All signals are sampled at 125 Hz. Figure 1 shows the typical shape of the respiratory induced signal modulations, depicted here for the ECG. As indicated by the red line, connecting the R-peaks, and cyan line, which connects the peaks of the T-wave, the ECG shows modulations in amplitude as well as in the time between consecutive contractions of the heart muscle. These modulations are induced by the respiratory activity. Similar modulations can be found in

the PPG and ABP.

Fig. 1: Effect of Respiration on the ECG signal. The red line connects the R-peaks and the cyan line the peaks of the T-wave

2.3 Pulse Arrival Time compensation

As the signals used in this study are recorded at different locations, the time needed by the pulse wave to reach each individual sensor has to be considered. As the electric field is spread through the body instantaneously, respiratory induced changes to the ECG reach the sensor almost immediately. The pulse wave responsible for passing the impact of respiration on the blood pressure and PPG however propagates at a much lower speed of only $7\text{--}12 \frac{\text{m}}{\text{s}}$. Therefore the respiratory impact reaches the blood pressure sensor after it has already been detected by the ECG, and the finger-clip even later. Typical durations for the pulse to reach the PPG-fingerclip for healthy people lie between $0.2 - 0.5 \text{ s}$ [4], depending on age and health of the subject. This time delay has to be compensated before further signal processing can take place. There are several definitions of the pulse arrival time (PAT), in this study we used the time between R-Peaks in the ECG and the maximum increase in blood pressure and PPG signals. As the R-Peak corresponds to the greatest contraction of the heart it therefore should cause the greatest increase in blood pressure. To determine the maximum increase in PPG and ABP a moving average filter was used to smoothen the differentiated signals before applying a simple peak-detection algorithm. For R-Peaks we used the annotation data whenever they existed.

2.4 Principle Component Analysis

Principal Component Analysis is a linear transformation

$$\mathbf{y} = \mathbf{A}\mathbf{x} \quad (1)$$

that transforms a set of inputdata $\mathbf{x}$ to reduce redundancy induced by correlation. This technique is often used for dimension reduction, feature extraction, data-decorrelation

and whitening [6]. It can be described as the problem of finding an orthogonal transformation matrix $\mathbf{A}$ that decorrelates the elements of a centered vector $\mathbf{x}$. The Transformation also maximises the variance of the principal components, which are the elements of $\mathbf{y}$, and makes the covariance matrix of the transformed dataset $\mathbf{y}$ diagonal. The solution of maximizing the variance is given by the eigenvectors of the covariance matrix $\mathbf{C}_x$ of $\mathbf{x}$ [7]. To compute the principal components we chose to use singular value decomposition as described in [8]. The calculated principal components do not account for scaling or sign of the signal.

2.5 Signal preprocessing

Respiratory activity is often measured as breaths per minute (BPM). Common values for the breath rate are in the order of 10-20 BPM. Cardiac rate however has a much higher frequency of 50-80 beats per minute. Therefore Butterworth lowpass filtering with a cutoff frequency of 0.33 Hz eliminates most of the undesired frequencies of the cardiac activity. A Butterworth highpass filter with a cutoff frequency of 0.04 Hz eliminates low frequency artefacts. As the PCA requires zero mean data in addition to the low frequency highpass filter the remaining signal-mean is also subtracted from the three channels.

2.6 Postprocessing for evaluation

For the purpose of evaluation both the measured and the derived respiratory signals were compared with regard to their average and momentary breathing-rate, the duration as well as the maximum amplitude of inhalation. After subtracting the moving average from both signals a peak detection algorithm was used to identify individual breaths and a zero crossing detection was used to calculate the duration of each individual breath. For evaluation of the mean breathing rate the Fourier analysis of one minute of recorded and derived respiration was compared. The momentary breathing rate was established by the inverse of the period between two consecutive inhalations.

3 Results

The first step of signal processing consisted of the compensation of time delays between ECG, PPG and ABP resulting from different locations of the sensors. Figure 2 shows the original signals (top) and the results of compensation of pulse arrival time (bottom) with the maximum increase in ABP and PPG aligned to the R-peaks of the ECG. In figure 3 the three Principal Components (in blue) of the three lowpass filtered cardiac signals are given. Even though they all show some resemblance to the respiratory signal (depicted in green), the first principal component is the best approximation of respiratory activity and will be used as the estimation of respiration. As the ABP and PPG were only synchronised with respect to the ECG by the pulse arrival

time compensation there is still a small time delay between recorded and estimated respiratory signal. Figure 4 shows both signals after normalization, compensation for the remaining time delay by correlating both signals and removing a the moving average, that was calculated over a period of 5 s, from both signals.

Fig. 2: Compensation of the pulse arrival time. Original recorded signals (top) and PAT compensated (bottom)

Fig. 3: Principle Components of the lowpass filtered PAT compensated cardiac signals (ECG, ABP and PPG)

While the recorded respiratory signal has only clear peaks at inspiration (positive peaks) the derived respiratory activity has smooth peaks for inspiration and exhalation. Inspiration is however closely matched by the derived respiratory signal with respect to respiratory rate and length of inspiration. Further information on how the respiration was recorded might explain the behaviour of the recorded signal for expiration. There are several ways of looking at the breathing rate. In many papers only spectral analysis of the recorded and the derived respiratory signals is used as indicator of

how accurate the algorithms work, this seems to be a weak feature for evaluation as there might still be larger discrepancies in the timing of individual breaths. Figure 5 shows the discrete fourier transformation for both signals, the peak at 12.1 of both signals coincides with the average breathing frequency of ≈ 12 BPM. A more reliable approach seems to be the evaluation of the momentary breathing rate for both signals by using the inverse of the period between two consecutive breaths as shown in the bottom part of figure 4. Even the momentary respiratory rate measured between two consecutive maxima of inhalation for the recorded and derived respiratory signal match each other with an accuracy of more than 90 %. The detected duration of the individual inhalations show the same accuracy. There are however discrepancies in the peak amplitude. However for basic analysis breath rate and duration of inspiration can be acquired accurately, even if one of the signals is corrupted by noise or artefacts.

Fig. 4: Normalised and time delayed first principal component and the recorded respiratory signal(top) and the momentary breath to breath breathing rate (bottom)

Fig. 5: Spectrum of the derived and recorded respiratory signal. Both show the same mean frequency of 12.1 BPM

4 Conclusion

Principal component analysis is able to derive respiratory activity from multi modal cardiac signals, even when some of the signals are corrupted by noise or artefacts. This makes it possible to reduce the number of sensors needed in clinical setups. Estimation of the average breathing rate by discrete fourieranalysis provides very accurate results over periods of constant breathing and even the momentary breathing rate between two consecutive inspiration and the duration of inspiration can be reliably extracted. However further work needs to be done to evaluate the relationship between derived and recorded respiration amplitudes. As most datasets consisted of continuous regular breathing at constant rate for patients lying in ICU more data is required. It would be of interest to gather and analyse further data with different postures and an given respiratory exercises like fast and slow, deep and shallow breathing, coughing etc. Other combinations of vital signs could also be explored. The exact waveform for expiration could also be considered in future work, when more details on the sensors used is known.

References:

- [1] Ding S., Zhu X. Chen W. Wei D.: *Derivation of Respiratory Signal from Single-Channel ECGs Based on Source Statistics*, International Journal of Bioelectromagnetism, 2004
- [2] Goldberger AL., Amaral LAN., Glass L., Hausdorff JM., Ivanov PCh., Mark RG., Mietus JE., Moody GB., Peng C-K., Stanley HE. *PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals*, Circulation 101(23):e215-e220 [Circulation Electronic Pages; <http://circ.ahajournals.org/cgi/content/full/101/23/e215>]; 2000 (June 13).
- [3] Moody GB., Mark RG. *A Database to Support Development and Evaluation of Intelligent Intensive Care Monitoring*, Computers in Cardiology 23:657660 (1996)
- [4] Koivistoinen, T., Kbi, T. Jula, A. et Al., *Pulse wave velocity reference values in healthy adults aged 2675 years*, Blackwell Publishing Ltd, Clinical Physiology and Functional Imaging, 2007 p.191-196
- [5] *MIMIC DATABASE INDEX*, <http://www.physionet.org/physiobank/database/mimicdb/mimic-index.shtml>, date: 24.062012
- [6] Jolliffe I.T., *Principal Component Analysis*, New York: Springer, 2002
- [7] Hyvärinen, A., Karhunen, J., Oja, E. *Independent Component Analysis*, John Wiley & Sons, 2001
- [8] Jackson, J.E.: *A User's Guide to Principal Components*, New Jersey: John Wiley & Sons, 2003