Finger and Forehead PPG Signal Comparison for Respiratory Rate Estimation Based on Pulse Amplitude Variability

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***Abstract*—Pulse photopletysmographic signal (PPG) is modulated by the respiratory rate, so there are some algorithms capable to extract respiratory information from the derived PPG signals, as the Pulse Amplitude Variability (PAV). Previous works have shown that the use of the PPG leads to different results depending on the PPG sensor location (finger and forehead). Therefore, a database recording finger and forehead PPG signals and respiration is done, breathing with fixed frequencies. Results show that while finger PAV signal works correctly, forehead PAV signal has a non respiratory component that do not allow to properly estimate the respiratory rate.**

I. Introduction

Pulse photopletysmographic signal (PPG) is a non-invasive technique widely used to obtain clinic monitoring information [1]. PPG has been applied in many different clinical settings, including the monitoring of blood oxygen saturation, heart rate and its variability, giving information about the autonomic nervous system, blood pressure, cardiac output and respiration [2], [3].

Focus on the respiratory information, the proposed methods to extract the respiratory rate from the PPG signal are usually based on the modulations induced by the respiration in the pulse rate, amplitude and width variabilities (PRV, PAV, and PWV, respectively). It is known that respiration modulates PPG signal through several effects [4]: PRV is modulated by respiration as heart rate variability (HRV) is, through a phenomenon well known as respiratory sinus arrhythmia (RSA); PAV is also modulated by respiration through variations in stroke volume and in blood vessels stiffness [4], and this phenomenon in addition to the pressure changes in the thorax during respiratory cycle modulates also the PWV [5].

The algorithm proposed in [5] was described to extract respiratory information based on this three respiratory derived signals. This method allows to extract the respiratory rate using only one signal or with a combination of them and was validated using finger PPG sensor. Nevertheless, finger is not the only possible location for PPG sensor. Forehead is a widely used place where PPG sensor can be located depending on the final application. There are some differences between finger and forehead PPG signals. Light-transmission configuration can be used in the finger but not in the forehead, where light-reflection is the only possible configuration. This affects to the PPG morphology, obtaining a smoother waveform when the signal is recorded in the forehead [6]. These characteristics in combination with the differences in arterial routes can generate differences in the estimated respiratory rate depending on the sensor location. In this work, a comparison between finger and forehead PPG signals for the estimation of the respiratory rate by means of PAV is presented.

II. Materials and Methods

A. Data collection

A database of 10 subjects was recorded to perform the analysis. For these 10 subjects (mean age of 31.0 ± 6.7 years), finger and forehead PPG signals were recorded simultaneously as well as a chest-band respiratory signal that will be used as the gold-standard. Both PPG signals and the respiratory chest-band one were recorded and sampled at 250 Hz with the Medicom System, ABP-10 module (Medicom MTD, Ltd, Russia).

The used protocol consisted of 7 different stages with a duration of 3 minutes each one: first, subjects are registered during spontaneous breathing; then a different respiratory rate is imposed in each of the remaining six stages, starting at 0.6 Hz and ending at 0.1 Hz in steps of 0.1 Hz. Only the last 2 minutes of each stage are used to extract the respiratory information of the PPG signal.

B. Respiratory signal estimation

From the PPG signal ($x_{\text{PPG}}(n)$), artefactual pulses were suppressed by using the artefact detector described in [7]. Then, the apex (n_{Ai}) and the basal (n_{Bi}) points of PPG pulses were automatically detected using an algorithm based on a low-pass differentiator filter [8]. Figure 1 represents a PPG

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signal (measured in arbitrary units, a.u.) where its more representative points are highlighted.

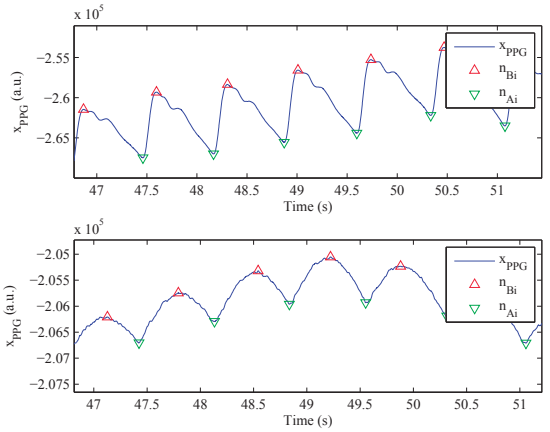

Fig. 1. PPG signals where its more representative points are highlighted: upper image, finger PPG; lower image, forehead PPG.

For both PPG signals, the PAV signal is estimated as the amplitude variation between the n_{Ai} and the n_{Bi}:

$$d^{\text{u}}_{\text{PAV}}(n) = \sum_i \left[x_{\text{PPG}}(n_{\text{Ai}}) - x_{\text{PPG}}(n_{\text{Bi}})\right] \delta(n - n_{\text{Ai}}). \quad (1)$$

Then, a median-absolute-deviation-based outlier rejection rule was applied, excluding the points with its distance to the signal median value is higher than the median distance of the rest of the points. The subsequent series were interpolated to 4 Hz by cubic splines. Then, a band-pass filter [0.075, 1] Hz was applied obtaining a signal which is denoted $d_{\text{PAV}}(n)$ in this paper. An example of PAV signal is shown in Figure 2, together with the respiratory signal.

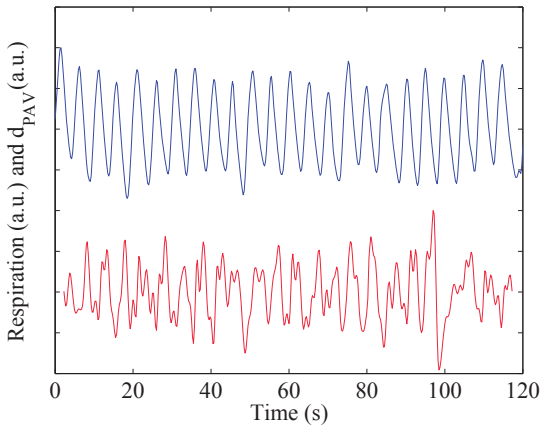

Fig. 2. Respiratory signal (blue) and PAV (red) of one subject in the 0.2 Hz stage.

C. Respiratory rate estimation

An algorithm based on [5] is applied over $d_{\text{PAV}}(n)$ to estimate respiratory rate (F_{R}) from "peaked-conditioned" averaged spectra.

For both cases (finger and forehead), a power spectrum density $S_{\text{k}}(f)$ is estimated every 5 seconds from the k^{th} 40 s length running window by the Welch periodogram, using sub-windows of 12 s and 50% of overlapping.

For each $S_{\text{k}}(f)$, the location of the largest peak $f^{\text{I}}_{\text{p}}(k)$ is detected. Then, a reference interval $\Omega_{\text{R}}(k)$ is established as:

$$\Omega_{\text{R}}(k) = \left[F_{\text{R}}(k-1) - \delta, F_{\text{R}}(k-1) + 2\delta\right], \quad (2)$$

where $F_{\text{R}}(k-1)$ is the respiratory frequency estimated from the previous $(k-1)$ window. All peaks larger than 85% of $f^{\text{I}}_{\text{p}}(k)$ inside $\Omega_{\text{R}}(k)$ are detected, and $f^{\text{II}}_{\text{p}}(k)$ is chosen as the nearest to $F_{\text{R}}(k-1)$. Note that $f^{\text{II}}_{\text{p}}(k)$ can be the same $f^{\text{I}}_{\text{p}}(k)$ if the largest peak is also the nearest to $F_{\text{R}}(k-1)$.

Subsequently, a measure of peakness is obtained from $S_{\text{k}}(f)$ as the percentage of power around the $f^{\text{II}}_{\text{p}}(k)$ with respect to the reference interval $\Omega_{\text{R}}(k)$. The peakness is defined as:

$$P_{\text{k}} = \frac{\int_{f^{\text{II}}_{\text{p}}(k)-0.6\delta}^{f^{\text{II}}_{\text{p}}(k)+0.6\delta} S_{\text{k}}(f)df}{\int_{F_{\text{R}}(k-1)-\delta}^{F_{\text{R}}(k-1)+2\delta} S_{\text{k}}(f)df} \times 100, \quad (3)$$

where δ has the experimental value of 0.1 as in [5]. Then, a peaked-conditioned average spectra, $\bar{S}_{\text{k}}(f)$, is obtained by averaging those $S_{\text{k}}(f)$ which are peaked enough:

$$\bar{S}_{\text{k}}(f) = \sum_{l=-L_s}^{L_s} \chi_{k-l} S_{k-l}(f), \quad (4)$$

where L_s was set to 2 in order to average a maximum of 5 spectra and χ_{k-l} is a criterion to consider whether the power spectrum $S_{k-l}(f)$ is peaked enough or not, allowing to take part in the average only to those $S_{\text{k}}(f)$ whose P_{k} is above 85%.

$$\chi_k = \begin{cases} 1, & P_{\text{k}} \geq 85 \\ 0, & otherwise \end{cases}, \quad (5)$$

Figure 3 displays two spectra as examples, one with $P_{\text{k}} < 85\%$ (not peaked enough to take part in the average), and another one with $P_{\text{k}} > 85\%$ (peaked enough to take part in the average).

Finally, respiratory rate is estimated as the maximum of $\bar{S}_{\text{k}}(f)$:

$$F_{\text{R}}(k) = \arg\max_f \bar{S}_{\text{k}}(f). \quad (6)$$

D. Performance analysis

As mentioned previously, respiratory rate is estimated every 5 s. The median of all the estimations per stage in every subject is compared with the original rate obtained by the chest-band information. An experimental margin of error of ± 0.03 ($\pm 0.18 bpm$) is given to the estimation to consider that it matches with the gold-standard. If the match happens, a Correct Estimation (CE) is considered. If not, there is a Wrong

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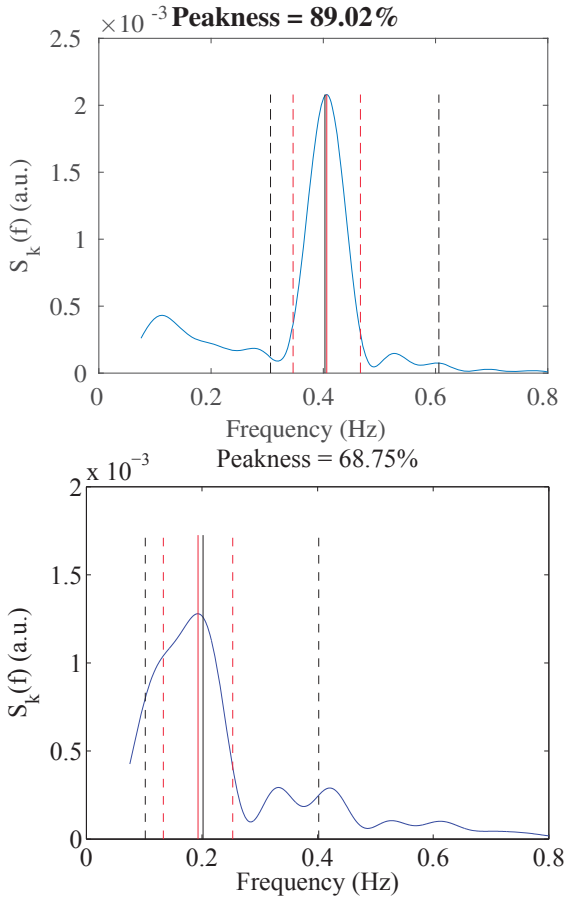

Fig. 3. Differences between spectra which satisfy the peakness condition and those which do not. Red lines illustrate the limits of the integrating interval of the numerator in P_{k} with the solid line marking the $f_{\mathrm{p}}^{\mathrm{II}}(k)$ value. Black dashed lines illustrate the reference interval $\Omega_{\mathrm{R}}(k)$, with the solid line representing the previous respiratory rate estimated $F_{\mathrm{R}}(k-1)$.

Estimation (WE). The percentage of correct estimations for each stage is used as a measure of both PAV performance.

$$\%CE = \frac{CE}{CE + WE} \times 100. \tag{7}$$

The algorithm used is based on spectral analysis for respiratory component detection. Therefore, knowing how relevant is the respiratory component in both PAV signals is an interesting point. The power around the frequency given by the respiratory chest-band (F_c, with a bandwidth of ± 0.05 Hz) with respect to the entire spectra of expected frequencies (from 0.05 to 0.65 Hz) is computed. The relative power in normalized units (P_R) is defined as:

$$P_R = \frac{\int_{f=F_c-0.05}^{f=F_c+0.05} \bar{S}_{\mathrm{k}}(f)}{\int_{f=0.05}^{f=0.65} \bar{S}_{\mathrm{k}}(f)}. \tag{8}$$

III. Results

Fig. 4 shows 6 time-frequency maps of the respiratory rate estimation. Each row represents one different stage: first row, 0.2 Hz stage; second row, 0.4 Hz; and third row, 0.6 Hz. Left column corresponds to the finger PAV signal and the right column corresponds to the forehead PAV signal.

As it can be seen, finger PAV signal is useful to estimate the respiratory rate. Nevertheless, when PAV signal is recorded in the forehead, a component between 0.1 and 0.2 Hz is found in all the stages. This masks the possible presence of the expected respiratory information.

Table I shows the percentage of the correct estimations at each stage using the PAV signal extracted in the two different locations. The appearance of this component causes a huge decrease in the $\%CE$ in forehead PAV with respect to the finger one. Only in 0.1 and 0.2 Hz have similar values, and this happens because the non respiratory component is between this both values. Besides this, general results show a worse capacity to detect the correct rate in the higher frequencies with respect to the lower ones, independently of the sensor location.

TABLE I
PERCENTAGE OF THE CORRECT RESPIRATORY RATE ESTIMATION ($\%CE$) USING PAV IN BOTH LOCATIONS

Location	Natural	0.1	0.2	0.3	0.4	0.5	0.6
Finger	80	60	100	90	70	60	40
Forehead	70	60	80	20	10	10	0

Finally, Table II shows the inter-subjects mean and standard deviation (std) of the relative power in normalized units (n.u.) inside each band. A decrease of the relative power of the forehead is found in comparison with the finger at any stage.

TABLE II
MEAN ± STD OF THE RELATIVE POWER (N.U.) FOR EACH STAGE WHEN THE RESPIRATORY RATE IS EXTRACTED USING THE PAV SIGNAL IN BOTH PPG LOCATIONS

Location	0.1	0.2	0.3	0.4	0.5	0.6
Finger	25.95 ± 16.01	25.77 ± 18.91	40.27 ± 14.30	25.87 ± 21.84	38.80 ± 19.82	33.88 ± 12.98
Forehead	12.82 ± 13.15	19.65 ± 15.26	14.90 ± 9.09	12.59 ± 3.50	13.35 ± 2.77	17.01 ± 3.52

IV. Discussion

Several information can be extracted from the use of PAV signal to estimate the respiratory rate. Using this method it is

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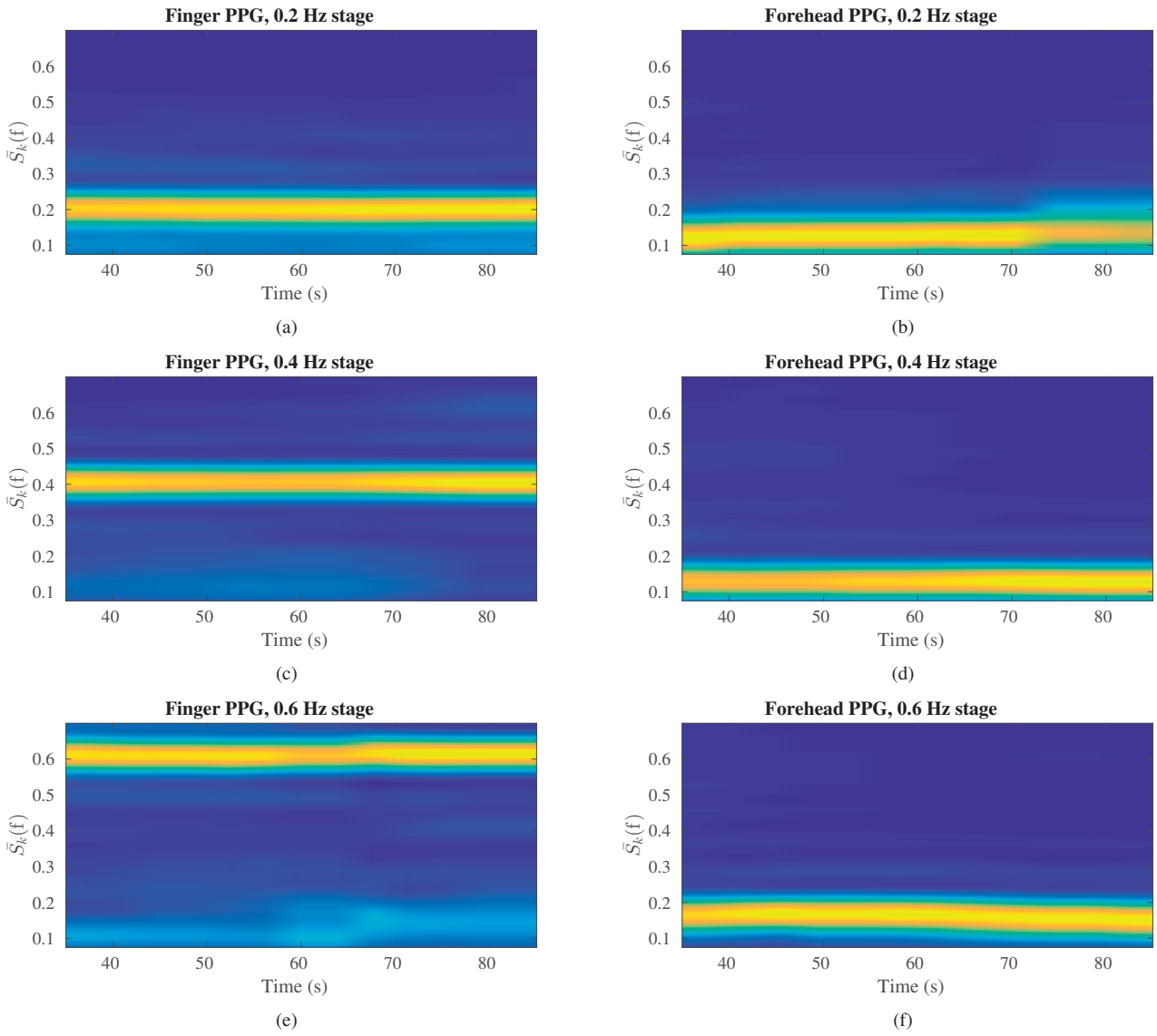

Fig. 4. Time-frequency maps of the respiratory rate estimation using the finger (left) and the forehead (right) PPG signal in different stages: a) and b) in 0.2 Hz stage; c) and d) in 0.4 Hz stage; e) and f) in 0.6 Hz stage.

possible that, sometimes, respiratory rate can not be estimated in every time instant because the five promediated spectrum do not fulfill the peakness conditions. In this work this phenomena happens in 10 over the 70 total possible cases (10 subjects and 7 different stages) in the finger signal, with a median time of 33.03% where the estimation can not be done. In the forehead signal, this happens in 9 cases, with a median time of 36.36%.

The main result of this article is the fact that when PAV signal is used with the PPG sensor located in the forehead, a different behavior has been found. A component (maybe related to the sympathetic component) appears hiding completely the expected respiratory rate. This fact contrasts with the behavior observed when the respiratory rate is calculated with the same signal but recorded in the finger. In this case, the respiratory information can be observed as other works suggest [4], [5], allowing to obtain a proper estimation of the respiratory rate. The non respiratory component induced by the sympathetic modulation was observed in the finger PAV signal too, but it is only a slightly component that barely can be appreciated.

Attending to the performance results, it is confirmed that a higher mistake is made in the estimation of the respiratory rate when higher rates are recorded, in comparison with the lower ones, as another studies noticed, like in [5] where the error in the respiratory rate extraction using the PAV was lower when the frequency was behind 0.15 Hz.

Finally, the relative power in each band shows that respiratory information is more relevant when PPG signal is recorded in the finger instead of in the forehead. This explains the decrease of the accuracy when comparing the same stage for the two PPG signals.

As the main result of this study, the appearance of a non

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respiratory component in forehead PAV signal requires an exhaustive investigation to be done with more subjects and more in detail in order to find out why this component appears only in this signal. Besides, as the combined methods to extract respiratory information include PAV signal, a robust method to extract respiratory information from the PPG has to be implemented, no matter what location has the PPG sensor, to avoid possible wrong estimations.

V. Conclusion

In this work, finger and forehead PPG signals are used to estimate the respiratory rate by means of PAV and validated using a respiratory chest-band as the gold-standard. Results shows that using the finger PAV signal the respiratory rate can be extracted. However, a powerful component between 0.1 and 0.2 Hz appears when the forehead PAV signal is used, being impossible to estimate the respiratory component. This behavior cause a decrease in the power inside the band centered in the expected respiratory rate when a comparison is done between finger and forehead location, showing that respiratory information is less relevant in forehead spectral power distribution than in the finger one. These results suggest that forehead PAV is not useful as a signal to extract the respiratory rate. Therefore, an extensive study has to be made in order to clarify why this component appears and to establish a more robust method to extract respiratory information from PPG no matter where the sensor is located.

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