Heart Rate assessment by means of a novel approach applied to signals of different nature

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Abstract. Electrocardiographic (ECG) signal presents many clinically relevant features (e.g. QT-interval, that is the duration of the ventricular depolarization). A novel processing technique has been demonstrated to be capable to measure some important characteristics according to the morphology of the waveform. Basing on that, the aim of this work is to propose an improved algorithm and to prove its efficacy in the assessment of the subject’s Heart Rate (HR) in comparison to standard algorithms (i.e. Pan & Tompkins). Results obtained in experimentally collected ECG signals for the identification of the main feature (R-peak) are comparable to those obtained with the traditional approach (sensitivity of 99.55% and 99.95%, respectively). Moreover, the use of this algorithm has been broaden to signals coming from different biomedical sensors (based on optical, acoustical and mechanical principles), all related to blood flow, for the computation of HR. In particular, it has been employed to PCG (Phonocardiography), PPG (Photoplethysmography) and VCG (Vibrocardiography), where standard algorithms could not be widely applied. HR results from a measurement campaign on 8 healthy subjects have shown, with respect to ECG, deviations (calculated as 2σ) of ±3.3 bpm, ±2.3 bpm and ±1.5 bpm for PCG, PPG and VCG, respectively. In conclusion, it is possible to state that the adopted algorithm is able to measure HR accurately from different biosignals. Future work will involve the extraction of additional morphological features in order to characterise the waveforms more deeply and to better describe the subject’s health status.

1. Introduction
Nowadays, the monitoring of physiological parameters is a fundamental issue not only in hospital environment, but also in different application fields, from physical activity assessment (1,2) to e-health applications (3,4), such as in systems designed for the elderly care (5–7), home care (8–11) and wearable devices (12–14). Important quantities to assess are the Heart Rate (HR), the Respiration Rate (RR), the arterial blood pressure values and the blood oxygen saturation.
In particular, Electrocardiography (ECG) is the gold standard technique to evaluate the performance of the cardiovascular system (15,16); its typical waveform shows many clinically relevant features (e.g. the PR interval represents the duration of the atria depolarization (17)). According to the review in (18), HR can be measured by means of “contact”, “fixed-in-environment” and “non-contact” sensors. In particular, among these devices the authors have considered the following ones:

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• Phonocardiograph (PCG), which is a contact sensor, furnishing an acoustic signal acquired by means of a cardiac microphone placed on the subject’s thorax, in proximity of the heart apex (19);
• Photoplethysmograph (PPG), a contact sensor too, providing an optical signal measuring the changes in light absorption by means of a photodiode placed in a standardized area illuminated by a LED; its signal is related to the blood flow and is similar to a typical arterial pressure waveform (20);
• Laser Doppler Vibrometer (LDV), providing a vibrocardiographic signal (VCG) consequent to the skin vibrations due to the blood flowing in the underlying vessel (21–23).

By considering the R-peak, ECG allows to easily assess HR, a fundamental parameter to monitor the subject’s health status (15), which can be affected by several conditions (e.g. anxiety, stress or illness (16,24)). As regards the other signals (i.e. PCG, PPG and VCG), the fundamental aspect is to extract a periodic feature correlated with the heartbeat:
• first sound (S1) in PCG signal, corresponding to the instant when atrioventricular valves close at the beginning of systole (25);
• the principal peak (P-peak) in PPG, representing the variation in blood volume caused by the pressure pulse of the cardiac cycle (20);
• the main peak (V-peak) in VCG, caused by the same physiological principle as P-peak.

In ‘figure 1’ there are reported the typical biological signals acquired by the above mentioned sensing technologies and the localisation of their main features allowing the computation of HR.

![Figure 1. Typical biological signals and their main peaks to compute HR: A) ECG with RR interval; B) PCG signal with S1S1 interval; C) PPG signal with PP interval; VCG signal with VV interval.](image)

There are standard algorithms to detect ECG main feature, that is QRS complex (i.e. ventricular depolarization (26)). Pan&Tompkins (P&T) algorithm (27) has been the main processing procedure for ECG waveform for many years. However, it cannot be used neither to identify features different from QRS complex, nor to successfully characterize signals different from ECG (i.e. photoplethysmographic signal). Recently other algorithms have been developed, such as the one proposed by Hu et al. (28), based on the morphology of the signal waveform.
The aim of this work is to modify this algorithm and to adapt it in order to fully characterize signals of different nature, all related to blood flow (18): ECG, PCG, PPG and VCG signals. The authors want to evaluate its performance in terms of HR computation in comparison with the one of P&T algorithm, computing sensibility and positive predictivity indices (29).

In Materials and Methods paragraph the measurement setup and the processing technique are described; the results are reported in the following paragraph (Results) and discussed in the Discussion and Conclusion paragraph.

2. Materials and methods

2.1. Measurement setup

Eight healthy subjects (4 males, 4 females, aged 25±3 years, weight 61±13 kg and height 1.71±0.09 m) were investigated about their cardiac activity by means of the four sensing devices mentioned in the previous paragraph:

- ECG (ADInstruments MLA2540 5), II-lead;
- PCG (ADInstruments MLT201);
- PPG (Pulsed Amped Sensor);
- VCG (PDV 100, Polytec).

Such physiological signals were acquired by means of two proper 12-bit A/D acquisition boards: PowerLab 4/25 (ADInstruments) and NI 6008 (National Instruments). They were synchronized by means of the VCG signal, acquired to both the boards; in fact, with the first A/D board, necessary for the ECG acquisition, it is not possible to acquire all the sensors.

The sampling frequency was equal to 1 kHz and no digital filters were applied on the raw data; three 1-minute tests were made on each subject.

The measurement setup is reported in ‘figure 2’.

![Figure 2. Measurement setup: ECG electrodes were placed on the wrists and on the hip bone (reference signal); PCG microphone was fixed on the subject’s thorax near the heart apex; PPG sensor was applied on the left thumb; LDV was pointed in correspondence of the carotid artery (at a distance of 1 m)]
plaster near the heart apex on the subject’s thorax; PPG sensor was applied on the left thumb of the subject. Finally, the LDV was placed on a tripod, with the laser beam pointed perpendicularly on the subject’s skin surface in correspondence of the carotid artery (at a distance of 1 m), which was spread with an hydrating lotion (45% zinc oxide) in order to maximize its reflectivity.

2.2. Data processing

The first step in data processing was the mean removal and filtering of the signals. Butterworth 3rd order band-pass filters were used, with the following cut-off frequencies: 0.4-20 Hz for ECG, 10-30 Hz for PCG, 0.4-30 Hz for PPG and 5-15 Hz for VCG signals. Such cut-off frequencies were chosen by observing the waveform before and after the filtering process: the goal was to highlight the main feature on each signals, removing the noise without lose useful information.

To identify the main feature on each signal, an algorithm based on (28) was developed. The approach consists in the evaluation of the slope trend in a portion of the signal defined by a mobile window, whose length is set equal to the 90% of heart period computed in the first 5 s of the ECG signal (by identifying the R-peaks manually). A 70% overlap of adjacent windows was applied in order to avoid missed beats.

With regard to ECG signal, HR was computed both by means of the standard P&T algorithm and with the proposed method. In the other signals, only the second approach was applied, since P&T is not effective.

The evaluation of the algorithm performance was done by considering two indices: Sensitivity (Se) (1) and Positive Predictivity (+P) (2).

\[
Se = \frac{TP}{TP + FN}
\]

\[
+ P = \frac{TP}{TP + FP}
\]

where:
- TP are the True Positives, that is the number of correctly identified peaks
- FN are the False Negatives, that is the number of missed peaks
- FP are the False Positives, that is the number of wrongly identified peaks

The desirable situation is that Se and +P are both equal to 1, which means that all peaks are correctly identified and there are not false detections.

3. Results

HR results from this study on 8 healthy subjects are reported in this paragraph.

First, a comparison between Pan&Tompkins algorithm and the proposed approach is made in ECG signal. In ‘table 1’ there are FP, FN, TP, Se and +P mean values with the related standard deviation computed in the tested population.

The proposed approach was applied to all the acquired signals to compute HR. The results and the related percentage deviation of PCG, PPG and VCG with respect to ECG (i.e. gold standard) are reported in ‘table 2’ in terms of Heart Periods (HP), to better highlight the deviations with respect to ECG. Mean value and standard deviation computed in the three tests on each subjects are reported.
Table 1. Comparison between the performances of P&T algorithm and the proposed approach – ECG signal

| Method            | FP [m (σ %)] | FN [m (σ %)] | TP [m (σ %)] | Se [m (σ %)] | +P [m (σ %)] |
|-------------------|--------------|--------------|--------------|--------------|--------------|
| P&T               | 0.34 (0.20)  | 0.06 (0.08)  | 99.94 (10.49)| 99.95 (0.06) | 99.64 (0.21) |
| Proposed approach | 0.28 (0.31)  | 0.39 (0.30)  | 99.61 (10.63)| 99.95 (0.36) | 99.68 (0.38) |

Table 2. HP [ms] computation by means of the novel approach in the acquired signals and percentage deviations (%d) of PCG, PPG and VCG with respect to ECG

| Subject | ECG | PCG (%d) | PPG (%d) | VCG (%d) |
|---------|-----|----------|----------|----------|
| 1       | 674 | 675 (0.1)| 676 (0.1)| 674 (-0.2) |
| 2       | 725 | 722 (-0.4)| 723 (0.1)| 724 (0.0) |
| 3       | 596 | 600 (0.7)| 598 (0.4)| 596 (0.4) |
| 4       | 968 | 967 (-0.1)| 966 (-0.1)| 968 (0.3) |
| 5       | 1028 | 1028 (0.1)| 1028 (0.0)| 1028 (0.0) |
| 6       | 766 | 769 (0.3)| 767 (-0.2)| 765 (-0.2) |
| 7       | 1112 | 1106 (-0.5)| 1115 (0.8)| 1112 (-0.2) |
| 8       | 774 | 776 (0.2)| 777 (0.2)| 774 (-0.5) |

Considering HR [bpm] (i.e. the inverse of HP [s], multiplied by 60, it is possible to state that the deviations (calculated as 2σ) are equal to ±3.3 bpm, ±2.3 bpm and ±1.5 bpm for PCG, PPG and VCG, respectively.

Moreover, the proposed algorithm allows to fully characterize a signal; an example of the identification of all the characteristic peaks of ECG waveform is reported in ‘figure 3’.
Figure 3. Example of the morphological characterisation of an ECG waveform by means of the proposed algorithm: R-peak, that is the main peak; P-wave, corresponding to the atria depolarization; Q-wave and S-wave, forming (together with R-peak) the QRS complex of the ventricles depolarisation; T-wave, representing the ventricles ripolarisation.

4. Discussion and conclusions

The performance of the proposed approach in computing HR (or, equivalently, HP) from ECG signal is comparable to the one of the standard P&T algorithm. In fact, the adopted method reports a sensitivity of 99.95% and a positive predictivity of 99.68%, comparable to 99.65% and 99.64% reported by P&T, respectively.

An advantage of the proposed approach is the effectiveness in the morphological characterization of non-ECG signals, such as PCG, PPG and VCG (but, in the future, its application could be also widened to different ones). In fact, in HR computation deviations of ±3.3 bpm, ±2.3 bpm and ±1.5 bpm are reported for PCG, PPG and VCG, respectively, with respect to ECG (i.e. gold standard technique for HR measure).

In conclusion, it is possible to state that the proposed approach is effective in the measurement of HR from signals of different nature (i.e. ECG, that is an electric signal; PCG, that is an acoustic signal; PPG, that is an optical signal; VCG, that is a mechanical signal).

In addition, it allows to identify not only the main feature of a signal, but also other morphological characteristics (‘figure3’).

In the future, it would be interesting to extend the use of this algorithm, for example to identify different features in the acquired signals, looking for correlations in clinically relevant time intervals (e.g. to find an interval in VCG signal correlated to QT of ECG, to have an estimation of the duration of the ventricular depolarization obtained with a non-contact technique). In this way, the subject’s health status could be described more in detail, providing an advantage above all if particular subjects have to be tested (e.g. non-contact measurements are particularly important in burnt patients or preterm infants, whose skin is particularly fragile and electrodes are difficulty placed (22)).

5. References

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