Detection of motion artifacts in photoplethysmographic signals: Algorithms comparison

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Abstract— **The presence of motion artifacts in the photoplethysmographic (PPG) signals is one of the major obstacles in the extraction of reliable cardiovascular parameters in real time and continuous monitoring applications. In the current paper we present a comparison between two motion artifacts detection methodologies proposed by Couceiro et al. [1] and Correia T. [2]. The first method is based on the analysis of the variations in the time and period domain characteristics of the PPG signal. The second method analysis the differences between the changes in the Heart Rate measured from the PPG and the ECG signals. Both methodologies are validated in healthy and cardiovascular diseased volunteers, for 11 different motion artifact patterns. The results achieved by the presented methodologies show a better performance of the first algorithm (SE: 83% and SP: 87%) and the great importance of both time and period domain features in the discrimination of motion artifacts from clean PPG pulses.**

Keywords— **Photoplethysmography, electrocardiography, motion artifacts detection, feature selection, support vector machine**

I. Introduction

Photoplethysmography (PPG) is a non-invasive, low cost tool to continuously monitor blood volume changes in tissue as a function of time. From the analysis of infrared and near-infrared the oxygenation saturation levels can be easily determined using PPG signals, which has been accepted by the International Standards Organization (ISO) and the European Committee for Standardization as a standard non-invasive measure since 1987 [3]. Moreover, this technique has been widely applied in many clinical areas such as anesthesia, surgical recovery and critical care.

Motivated by unmet needs in low cost, non-intrusive and portable techniques in p-Health, the PPG technique has been intensively investigated in the last decades. Due to technological advances in the field of opto-electronics, clinical instrumentation and digital signal processing, this approach achieved a broader spectrum of potential applications, ranging from the field of clinical physiological monitoring to the vascular assessment, and autonomic function evaluation [4].

However, PPG signals can be easily influenced in the measurement process, which may lead to inaccurate interpretation of the PPG waveform. Well-known sources of error are ambient light at the photodetector, poor blood perfusion of the peripheral tissues and motion artifacts [5]. In uncontrolled environments such as the primary and home care settings, these potential error sources are more frequent and can become a serious obstacle to extract reliable PPG features in real time and continuous monitoring applications. Therefore, it is essential to provide a signal quality or trust metric that can be used in subsequent analysis steps.

Motion artifact detection and suppression is still a major challenge and has been subject of intensive research in the last decade. Various approaches have been investigated, where the corrupted signal is recovered or reconstructed by applying signal processing techniques such as adaptive filtering techniques [6-8], time-frequency analysis [9, 10] and source separation techniques [11]. However, PPG signals severely affected by noise and motion artifacts show dramatic changes in the waveform morphology, which compromise signal quality and therefore its suitability for further analysis. An alternative method is the robust detection of PPG signal sections corrupted by noise and motion artifacts and discard them in the subsequent processing steps. Techniques such as morphological analysis [5] and higher-order statistical analysis [12] have been proposed in this research field.

In this paper, two motion artifact detection algorithms are compared. In the first methodology the time and period domain characteristics of the PPG signal are extracted and the most relevant features are selected with normalized mutual information feature selection (NMIFS) algorithm [13] which are used as inputs to a Support Vector Machine (SVM) classification model. In the second methodology, the ECG and PPG signals are analysed in order to extract and compare the heart rate. The extracted differences are used to distinguish between good PPG sections and artifacts.

The reminder of the current paper is organized as follows. In section II, the experimental protocol is presented. The two methodologies are introduced in section III. The results and respective discussion are presented in section IV. Finally, the conclusions are summarized in section V.

II. Eperimental protocol

To evaluate the performance of the proposed algorithm, a data collection study was conducted aiming at the simultaneous collection of electrocardiographic (ECG) and photoplethysmograpic (PPG) signals from 16 volunteers: 8 healthy volunteers were enrolled at the Faculty of Sciences and Technology of the Coimbra University and 8 volunteers were enrolled at the cardiovascular department infirmary of the Hospital Center of Coimbra University. The collected data was visually inspected to verify if it fulfilled the objectives of the present work, leading to the exclusion of 1 patient, whose PPG signal to noise ratio was below an acceptable level. The biometric characteristics of the 15 patients involved in the present study are summarized in TABLE I. The PPG waveform was recorded from the tip of the index finger using the transmissive mode infrared finger probe, while the ECG was recorded using Einthoven-II lead configuration. The PPG and ECG signals were recorded using a HP-CMS monitor and were digitized at a sampling frequency of 125 Hz and 500 Hz, respectively.

In order to conduct a wide variety of motion artifact patterns, the subjects were asked to execute two runs of eleven different types of hand and body movements, resulting in 22 records of 60 seconds for each subject. The movements are described as follows: 1) Disturbance of the PPG probe, causing variations in the contact point between fingertip and probe; 2) Gently bending of the index finger; 3) Repeated movement of the wrist, left and right; 4) Shaking the wrist; 5) Repeated movement of the epsilateral arm in the horizontal plane; 6) Repeated movement of the epsilateral arm in the vertical plane; 7) Lifting and lowering a book with both hands; 8) Repeated tapping of the table with the index finger; 9) Repeated raising and lowering of the arm; 10) Repeated sitting down and standing up; 11) Slow walking in a straight line. Each of the movements was performed in the 20 seconds centre epoch of the record and the records were annotated by a clinical expert.

III. Methods

A. Methodology 1 overview

The 1st methodology, proposed by [1], for the detection of motion artifacts consist in the following stages: a) Preprocessing; b) Segmentation; c) Feature extraction; d) Feature selection and e) Classification.

In the pre-processing stage, the high frequency components (above 18 Hz) of the PPG signal are removed, as well as the baseline wonder (bellow 0.23 Hz), which is subtracted from the filtered signal.

TABLE I . Patient characteristics

	Healthy Volunteers	***CVD volunteers***
Age	27,4±3,7	62±13,5
Weight	72,5±8	87,9±21,4
BMI	24,4±2,9	31,5±6,9
Male/Female	8/0	6/2

In the segmentation step, a histogram based threshold detection algorithm is applied to detect the PPG beats characteristics point (onset, peak and offset).

In the feature extraction step, several time domain and period domain characteristics are extracted. In the time domain analysis, the rate of change of main morphological characteristics (see Figure 1. - left) of the PPG pulses are assessed resulting in 7 features: 1) pulse amplitude; 2) pulse length; 3) pulse rate; 4) trough depth difference; 5) peak height difference; 6) pulse skewness; and 7) pulse kurtosis.

In the period domain analysis, the Discrete-time Short Time Fourier Transform in the period domain (PD-STFT) was applied using a rectangular-shaped sliding window and the rate of change of period spectra (see Figure 1. - right) principal components characteristics (1. height; 2. location; 3. width; and 4. area) and their relationships are evaluated, leading to the extraction of 19 features.

In summary, 26 features were extracted from the time and period domain analysis.

The selection of the extracted features was performed using the NMIFS [13] feature selection algorithm. Additionally, a ROC analysis was also performed to evaluate the capability of each feature to discriminate motion artifacts from clean PPG.

From the analysis of the computed scores, the 8 most relevant features were selected. From the time domain, the pulse amplitude (F_1), trough depth difference (F_4) and pulse skewness (F_6) were selected. From the period domain analysis the area of the 1st (F_{17}) and 3rd (F_{19}) peaks, and the relationship between the two most relevant peaks height (F_{20}), location (F_{21}) and area (F_{23}) have been selected.

A Support Vector Machine (SVM) has been adopted for the discrimination between motion artifacts and clean PPG. The classification process was performed using the algorithm C-SVC [14], with a radial basis function kernel.

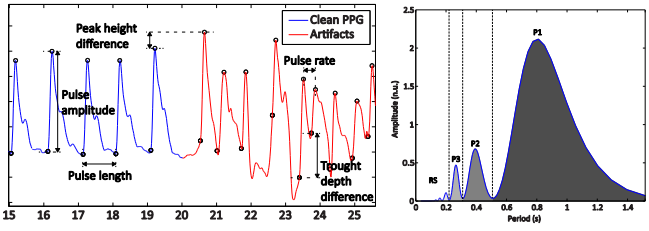

Figure 1. Time (left) and Period (right) domain characteristics of the PPG data

In order to find the parameters gamma (γ) and cost (C) that better suit the present classification problem, a grid-search method using 10-fold cross-validation was used.

This methodology was validated using a 10-fold cross-validation scheme and repeated 20 times.

B. Methodology 2 overview

The 2nd methodology, proposed by Correia T. [2], for the detection of motion artifacts is based on the comparison between the HR extracted from the ECG signal and the PPG signal. Since the ECG signal is less likely to be influenced by motion artifacts, the authors adopted this signal as a reference to extract the Heart Rate, and compare it to the Heart Rate extracted from the PPG features. Therefore, the time span between two consecutive pulse foots in the PPG signal is estimated with an algorithm slightly adapted from [15]. The correspondent time span between two consecutive R-peaks in the ECG signal are detected by a Pan-Tompkins algorithm [16]. Since these time spans correspond to the same heart beat, their values shall be similar. Otherwise one or both signals may be corrupted with noise and/or artifacts. The distinction between a clean PPG beat and an artifact is based on reaching a threshold. The optimal threshold of 3.6 bpm was extracted by a ROC analysis.

IV. Results and discussion

330 recorded signals were analyzed and each section was classified using the presented methodologies in a beat-to-beat basis and compared to the manually annotated classification. The performances of both algorithms were evaluated for the overall dataset (Global), and the two corresponding subsets, the "healthy volunteers" (Healthy) and "CVD volunteers" (CVD) subsets. Additionally, the performances were also evaluated for each individual artifacts generator movement. A 10-fold cross validation scheme has been adopted, with the following performance metrics: sensitivity (SE) and specificity (SP), and accuracy (ACC).

As can be observed in TABLE II the 1st methodology achieved a good performance in the classification of both corrupted and clean PPG sections, in all the three contexts (Global, Healthy and CVD), with an accuracy of approximately (85.3%). Despite a high sensitivity (83.1%) and specificity (86.9%) in the global dataset, it is possible to observe a minor decrease of sensitivity (75.1%) and correspondent specificity increase (92.9%) for the Healthy dataset, followed by minor increase of sensitivity (92.1%) and correspondent specificity (80.4%) decrease for the CVD dataset.

Contrarily, the 2nd methodology presented worst results in all the three contexts and performance metrics, with a global accuracy of 70.4% and a performance decrease of about 15%.

From TABLE II one can also observe that the majority of the movement artifacts are identified by the 1st methodology with accuracy over 85%. However there is decrease in the detection performance for 3rd and 8th movement artifacts, which is possibly associated with low corruption of the PPG data when performing the left/right wrist movement and an increase in the periodicity in the table tapping movement. On the other hand, the 1st algorithm achieves the best results (ap. 87% accuracy) in the 4th, 6th and 9th movements.

It can be also observed a decrease in the accuracy of the 2nd methodology of about 15%. The majority of the movement artifacts (6 movements) are detected with an accuracy above 71%, while the remaining are detected with an accu-

TABLE II . Performance results of both methodologies for each each context

Context	***Performance metric (avg ± std)***					
	Methodology 1			***Methodology 2***		
	SE	***SP***	***ACC***	***SE***	***SP***	***ACC***
Global	0.831±0.008	0.869±0.006	0.8527±0.005	0.737±0	0.681±0	0.704±0
Healthy	0.751±0.013	0.929±0.007	0.8529±0.007	0.796±0	0.622±0	0.692±0
CVD	0.921±0.008	0.804±0.010	0.8525±0.007	0.690±0	0.731±0	0.714±0
Movement 1	0.809±0.029	0.899±0.019	0.865±0.016	0.740±0	0.713±0	0.723±0
Movement 2	0.901±0.021	0.846±0.024	0.871±0.016	0.745±0	0.730±0	0.736±0
Movement 3	0.690±0.033	0.909±0.018	0.820±0.016	0.607±0	0.696±0	0.662±0
Movement 4	0.825±0.029	0.908±0.018	0.876±0.017	0.778±0	0.618±0	0.680±0
Movement 5	0.813±0.025	0.890±0.017	0.860±0.013	0.696±0	0.641±0	0.661±0
Movement 6	0.870±0.023	0.880±0.019	0.876±0.016	0.754±0	0.630±0	0.676±0
Movement 7	0.874±0.023	0.832±0.023	0.851±0.017	0.800±0	0.706±0	0.747±0
Movement 8	0.713±0.033	0.817±0.024	0.772±0.020	0.781±0	0.660±0	0.713±0
Movement 9	0.882±0.023	0.871±0.020	0.876±0.014	0.731±0	0.729±0	0.730±0
Movement 10	0.896±0.019	0.829±0.021	0.859±0.014	0.724±0	0.662±0	0.690±0
Movement 11	0.843±0.026	0.867±0.021	0.857±0.015	0.730±0	0.718±0	0.723±0

racy above 66%. The 2nd methodology achieves the best results in the 2nd, 7th and 9th movement artifacts.

V. Conclusion

In the current paper a comparison between two methodologies for the detection of motion artifacts in photoplethysmographic signals has been presented. The first method is based on the analysis of the variations in the time and period domain characteristics of the PPG signal while the second method uses a threshold based approach to analyze the differences between the changes in the Heart Rate measured from the PPG and the ECG signals, representative of corrupted PPG sections. The presented methodologies were tested in 15 subjects (healthy and CVD) and 11 different motion sources. To validate the presented algorithms a 10-fold cross-validation scheme was adopted for the 1st algorithm. Our results suggest that both morphological and period domain features used for the 1st methodology yield an important enhancement in performance with a higher sensitivity, specificity and accuracy in both subject and movements contexts, when compared with the 2nd algorithm. Additionally, the dependence of the 2nd algorithm on the ECG analysis can be considered as an important drawback in contexts where this sensor is not available. However, in terms of computational complexity the 2nd algorithm presents an important advantage for p-health environments where the computational efficiency is essential.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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