Automatic premature ventricular contraction detection in photoplethysmographic signals

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***Abstract*—The purpose of this study was the development and investigation of the automatic Premature Ventricular Contraction (PVC) detection and classification method using Photoplethysmographic (PPG) signals. The main issue of using PPG for arrhythmia detection are the artefacts which may be falsely detected as an arrhythmic pulses. The method is based on 6 PPG features, obtained in 12 s analysis frame. The features are peak-to-peak intervals and PPG power derived features. The fundamental frequency of the PPG was used for feature extraction and normalization. The Artificial Neural Network with back-propagation was used for the PPG pulse classification. The PPG signals from Physionet MIMIC II and MIMIC databases were used for algorithm training and testing. PPG were annotated by referring to synchronously registered ECG signals. The method was evaluated by calculating sensitivity and specificity which for the two main PVC types are 96,05 / 95,37 % and 99,85 / 99,80 %, respectively. The study results suggest that PPG can be used for the reliable PVC detection.**

I. Introduction

Premature Ventricular Contractions (PVCs) are one of the most common heart rate irregularities. The PVCs are the early heart beats that originate in the ventricles and are initiated not by the sinoatrial node but by the secondary pacemakers - the ectopic focuses. PVCs may occur in healthy hearts with no significant impact on the overall health. Early studies suggested that in absence of structural heart diseases, the PVCs could be considered benign [1]. However, more recent studies deny benignity of the PVCs and link them to various health abnormalities and reveal their prognostic value [2]. In addition, study [3] shows that the PVCs are the predictors of the cardiac death even in men without known heart diseases. Increasing frequency of occurring PVCs was associated with the heart failure [9]. Study [4] concluded that frequent PVCs during physical exercise increase the risk of death from cardiovascular causes. Study [5] showed that frequent PVCs during the recovery is an even better risk predictor. PVCs are also found to trigger more serious heart arrhythmias such as atrial fibrillation (AF) [6], [7]. Due to electrolyte (e.g. calcium) imbalance, ventricular extrasystoles may occur during chronic kidney disease [8] which is closely related to cardiorenal syndrome.

The PVCs are relatively easily detected in the ECG signals by their distinctive shape. Their frequency and morphology is evaluated by using the Holter monitors. However, ECG electrodes attached to the patients chest may cause discomfort, limit the freedom of movement or increase the feeling of the unhealthiness, especially after wearing the device for as long as 24 h. Cheaper and more convenient alternative to screening with the Holter monitor might be the device based on the photoplethysmography (PPG).

The PPG is a non-invasive technique for the hemodynamic change monitoring in the tissue vascular system by illumination with the light of the certain wavelength. In contrast to the ECG, the PPG sensor is far more comfortable and convenient to use as it can be attached to the finger [10], integrated in to the ear phones [11] and the forehead band [12] or even used as the wrist sensor [13].

Previously, there were several attempts to detect premature beats in the PPG signals [10], [12], [14]. These methods exploit temporal and amplitude features extracted from the PPG signal morphology or complemented by the continuous wavelet transform.

In this study, the PVC detection and classification method based on the temporal and power (variance) derived features of the PPG is presented. The detected PPG pulses are classified with the Artificial Neural Network (ANN).

II. Method

A. Feature extraction

The scheme of the PVC detection and classification method is presented in figure 1. The method exploits temporal (peak-to-peak intervals) and signal power derived features (variance ratios) for the PVC detection and classification.

In order to reduce high frequency noises and base line wandering, the PPG signal is filtered with the low-pass (LPF) and the high-pass ($HPF^{\,1}$) finite impulse response (FIR) filters of 5 Hz and 0.4 Hz cut-off frequencies with the filter orders of 400 and 2000, respectively.

Next, feature extraction in 12 s analysis frame is performed. First, the fundamental frequency (FF) of the preprocessed PPG signal is estimated. The FF is used in the second high-pass ($HPF^{\,2}$) FIR filter with a variable cut-off frequency. The purpose of this filter is to extract fundamental frequency component of the PPG signal. The output of the $HPF^{\,2}$ is passed to the reference input of the Recursive Least Squares (RLS) adaptive filter. The adaptive filter removes the fundamental frequency component from the PPG signal, which in turn reveals the extrasistolic episodes by attenuating normal PPG pulses. The idea behind this is that extrasystolic pulses are of lower frequencies than normal beats, thus by removing fundamental frequency component, only the extasystolic and noisy components of the PPG signal are left.

In the next step, positive peaks in the preprocessed PPG signal are detected by threshold crossing technique and peak-to-peak intervals (PPI) are calculated. The PPI's are normalized according to the estimated FF. Further, the variance ratios (VRs) of the preprocessed PPG signal and PPG signal with the subtracted fundamental frequency component $PPG^{\,af}$ are calculated by formula (1):

$$VR_j = \frac{\sum_{i=1}^{PPI_j} \left(PPG_{\,i}^{\,af} - \overline{PPG^{\,af}} \right)^2}{\sum_{i=1}^{PPI_j} \left(PPG_{\,i} - \overline{PPG} \right)^2} \qquad (1)$$

where VR - variance ratio, $PPG^{\,af}$ - PPG filtered with an adaptive filter, PPG - PPG filtered with LPF and HPF^1, $\overline{PPG^{\,af}}$ - mean value of $PPG^{\,af}$, $\overline{PPG}$ - mean value of PPG, PPI - peak-to-peak interval length in samples, i - sample number, j - PPI interval number.

The VRs are calculated in the PPI interval window of the current PPG pulse. The variance ratio normalizes PVC episodes and minimizes amplitude of the normal beats: the power of $PPG^{\,af}$ at PVC episodes is high and the power of the $PPG^{\,af}$ at normal beats due to removed fundamental component is small.

The fundamental frequency (FF) of the PPG signal is estimated by applying series of operations. First, in order to smooth the PPG, it is filtered with the moving average filter. Next, the PPG clipping is performed for the purpose of high amplitude impulse noise influence reduction. Further, the 1^{st} derivative of the clipped PPG signal is calculated. The 1st derivative reveals higher frequency components of the PPG signal where the fundamental component is of the highest energy. Finally, the FF is estimated by the highest amplitude in the power spectral density (PSD) function. Outliers are inevitable, thus in order to remove them, the frequency array is filtered with the 5th order median filter.

B. Classification

The ANN with one hidden layer was used for the PPG pulse classification into 3 major classes:

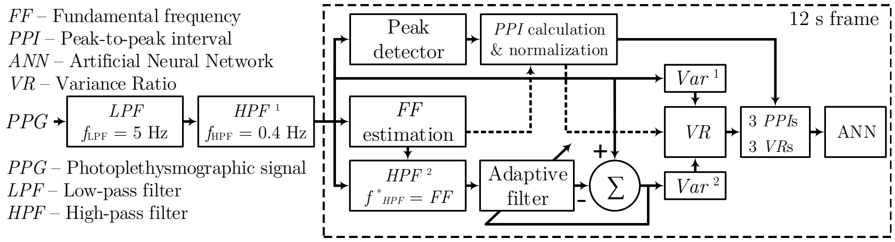

Figure 1: Scheme of the proposed method

PVC^1, PVC^2 (refer to figure 3) and $NORM$. The classifier scheme is presented in the figure 2. In all, 6 PPG feature were used: 3 successive PPIs and 3 successive variance ratios.

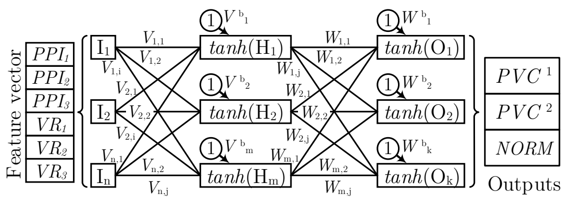

Figure 2: The PPG pulse classification scheme

III. Data

A total of 18 PPG signals from the PhysioNet [15] MIMIC II v3 part 0 database were used for training and 25 PPG signals from MIMIC database were used for algorithm testing. The PPG signals were manually annotated by using synchronously registered ECG signals as the reference. Both the PPG and the ECG signals were resampled to 500 Hz. The PPG signals used in this study contain various types of extrasystolic beats, artefacts or absolutely normal beats. Two major types of the PVC pulses may be observed in the PPG (Fig. 3):

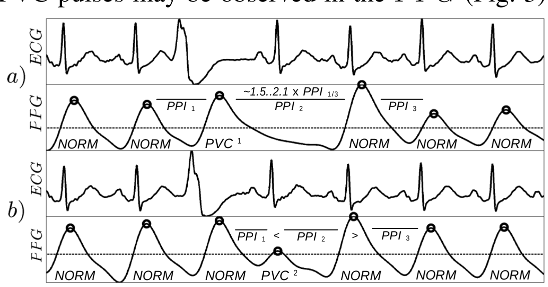

Figure 3: Types of PVCs in the PPG signals: a) with premature pulse PVC^2 b) without premature pulse PVC^1

Criterias for discarding signals were the absence of the ECG or PPG signals, severely corrupted signals and various pathologies which would not let correct annotation of the PPG signals. The signals used for testing are shown in the table I:

Table I: Data

Signal	PVC^1#	PVC^2#	Signal	PVC^1#	PVC^2#
039m	0	0	404m	0	196
041m	0	0	408m	9	2
055m	1	0	439m	12	0
211m	0	0	442m	1249	364
212m	154	0	444m	7	9
218m	0	0	449m	5	1
221m	11	0	466m	3	4
224m	0	0	471m	1	0
225m	0	9	474m	0	0
230m	0	4	482m	48	30
237m	29	5	484m	74	9
252m	0	0	485m	751	15
253m	0	0			
Total:	195	18	Total:	2159	630

IV. Results

The results expressed in specificity (Spe), sensitivity (Sen), the overall accuracy (Acc) and the Matthews correlation coefficient (MCC) are presented in table II:

Table II: The results

Class ⇒	$NORM$	PVC^1	PVC^2
Sen	99,66 %	96,05 %	95,37 %
Spe	96,57 %	99,85 %	99,80 %
Acc	99,62 %	99,81 %	99,79 %
MCC	86,75 %	90,88 %	73,76 %

Table III: Confusion matrix

Class ⇒	$NORM$	PVC^1	PVC^2
$NORM$	234982	74	29
PVC^1	362	2261	1
PVC^2	444	19	618

V. Discussion and Conclusions

The presented PVC detection method is capable of detecting not only single premature ventricular contractions but also bigeminy (where every second beat is extrasystolic). The PPG pulse detection and classification effectiveness mainly depends on the precision of the fundamental frequency estimation which in turn depends on the quality of the PPG signals. The presented algorithm is capable of separating artefacts from normal and premature beats thus decreasing false alarms. These qualities are vital for the application in the wearable systems. The ANN was chosen due to its universality and ability to approximate linear an non-linear functions.

Our first attempt to detect extrasystoles in the PPG signals was carried out in the study [16], however, signal database was relatively small (9 signals). It was also discovered, that the previous algorithm had limitations in detecting successive extrasystolic pulses e.g. bigeminy (every second beat is extrasystolic).

The limitation of present study is that signal annotations were not performed by the doctors. It should also be noted that the late and interpolated extrasystoles in the PPG can not be detected, because hemodynamic changes are insignificant and pauses are very short or absent, however these extrasystoles are quiet rare [17].

The aim of the further research is to develop robust arrhythmia (e.g. atrial fibrillation) detection method and adapt it for the use in the embedded wearable PPG based screening system.

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