Pulse Wave Analysis of Photoplethysmography Signals to Enhance Classification of Cardiac Arrhythmias

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Abstract

Photoplethysmography (PPG) has recently gained increasing interest for less obtrusive long-term cardiovascular monitoring. As for cardiac arrhythmia (CA), most research and available PPG devices have focused on the detection of atrial fibrillation (AF), the most common CA. However, other less studied CAs can induce errors in standard AF detectors.

To address the PPG-based detection of both AF and non-AF CAs, we investigate novel features, extracted by pulse wave analysis (PWA), that provide insight into the morphology of individual pulses. Their discriminative power was evaluated based on the RELIEFF algorithm for feature selection, and we compared performance metrics for CA classification with and without PWA features.

The classification accuracy using ridge regression was increased by 0.4%, from 75.6% to 76.0%, when using PWA features on top of temporal and spectral features. Likewise, the classification of non-AF CAs was globally improved.

These results show the potential of extracting measures about individual pulse morphologies to improve detection of various CAs.

1. Introduction

The continuous monitoring of cardiovascular functions in everyday life is now facilitated by photoplethysmography (PPG) technology. Numerous commercial wearable devices, such as smart watches, integrate PPG technology and make continuous heart function monitoring widely available. In this context, consumers will benefit from this technology for the prevention and early detection of cardiac arrhythmias (CA) as this represents an alternative to current screening methods [1], such as ambulatory electrocardiography (ECG) devices. Ambulatory ECG recordings are usually limited to a maximum of 2 weeks, devices are cumbersome, and ECG electrodes can cause skin irritations. PPG-based devices are easier to use in everyday life, which is advantageous for the long-term monitoring of CAs. CAs can be intermittent and sometime asymptomatic in their early stage and difficult to diagnose when monitoring is performed only over a short period of time.

Numerous studies investigated the potential to discriminate between normal sinus rhythm (SR) and atrial fibrillation (AF) from PPG signals recorded at the wrist, with very encouraging results [2]. However, the expression of other CAs can present characteristics that resemble those of AF and thus lead to wrong classification of pure SR-vs-AF detectors [3]. Only a few studies investigated the detection of AF against other CAs. Some of them make use of meaningful features often combined with machine learning classifiers to detect atrial flutter [4], ventricular tachycardia [5] or premature contractions [6]. Liu et al. [7] stand out by using a deep learning method to classify six different classes of CAs. All these studies have in common that they exploit the morphological characteristics of individual pulses.

We propose to classify several types of CAs by using pulse wave analysis (PWA) [8] to characterize the morphology of individual pulses. To this end, PWA features were added to features based on inter-beat interval (IBI) timeseries traditionally used for rhythm analysis and most AF classifiers. We hypothesized that these novel PWA features will help improve AF detection performances in the presence of various types of CAs: premature atrial/ventricular contractions (PAC/PVC),

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ventricular tachycardia (VT), atrial flutter (AFL), atrioventricular reentrant tachycardia (AVRT) and atrial tachycardia (AT).

2. Material and Methods

2.1. Data

The dataset consisted of simultaneous ECG, PPG and acceleration measurements in 42 patients referred for catheter ablation at Lausanne University Hospital. The study was approved by the local ethics committee (CER-VD, study number 305/15). The ECG was measured with a gold-standard 12-lead device and the PPG and 3-axis acceleration signals were acquired by a wrist bracelet developed at Swiss Center for Electronics and Microtechnology (CSEM).

2.2. Preprocessing

PPG and ECG signals were first aligned based on detected pulse time series from both signals. PPG signals recorded at 25 Hz were processed by a second-order Butterworth bandpass filter between 0.5 and 12 Hz. Signals were segmented into 11'985 non-overlapping windows of 30 s. After isolating individual pulses for PWA feature extraction, PPG signal were resampled to 100 Hz and the first and second derivatives were computed.

2.3. Artefact rejection

Windows were rejected based on acceleration signals, pulse detection frequency, and signal quality. 237 windows were rejected from analysis based on the norm of the difference in acceleration between two successive samples: $\boldsymbol{n} = \left\|\boldsymbol{a}(t_j) - \boldsymbol{a}(t_{j-1})\right\|_2$, where $\boldsymbol{a}(t)$ is a 3-dimensional acceleration signal. A window was rejected if the average of $\boldsymbol{n}$ was above a threshold, $\overline{\boldsymbol{n}} > 0.3\ G$. In addition, windows were excluded when the number of heartbeats was lower than 15 leading to the exclusion of 2’011 and 1’428 windows due to too few heartbeats in the ECG and PPG, respectively. This procedure of exclusion often indicated ECG signals of very low quality and ensured that time domain features were computed based on a sufficient number of PPG pulses. In our dataset, a pressure cuff periodically corrupted measured PPG signals by obstructing blood flow in the arm. Therefore, additional 5’654 windows were rejected based on a perfusion index indicating the absence of pulsation in the PPG signal.

Since one window can be rejected by more than one criterion, a total of 6’754 windows were rejected from analysis.

2.4. Labels

Individual ECG pulses were labeled by an expert. 1'084 windows were rejected for reasons including missing labels, presence of cardiac pacing or noisy ECG measurements. This resulted in 4'147 windows remaining for analysis. As a window can contain different pulse labels [3], windows were labeled based on the most frequent pulse label, referred as the primary label. Windows containing more than 4 premature contractions have been given the primary label “frequent ectopic beats”. Windows were finally given one of the 3 class labels: *SR* (primary labels: “sinus rhythm”, “sinus bradycardia”, “sinus tachycardia”), *AF* (primary label: “atrial fibrillation”) or *non-AF* (primary labels: “atrial tachycardia”, “ventricular tachycardia”, bigeminy”, “atrial flutter”, “atrioventricular reentrant tachycardia”, “frequent ectopic beats”).

2.5. Feature extraction

Time domain features of heart rate variability (HRV) were computed based on IBI time series contained in windows. The following features are implemented as defined in [4]: Shannon entropy (ShEn), normalized root mean square of successive differences (nRMSSD), percentage of differences of successive IBIs that exceed 40 or 70 ms (pNN40, pNN70), sample entropy (sampEn) and coefficients of sample entropy (CoSEn) of embedding dimensions 1 and 2, turning point ratio (TPR), minimum, maximum, mean and standard deviation (std) of IBI time series. In the frequency domain, Horjth mobility and complexity, spectral entropy (specEn) and spectral purity index (SPI) were extracted from PPG signals.

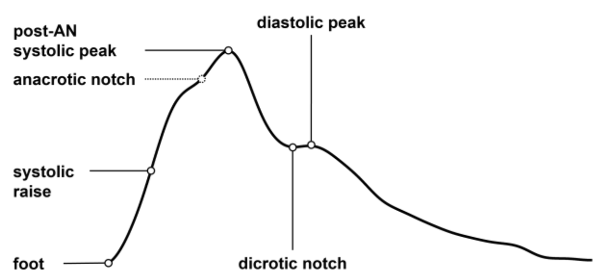

Figure 1. Example of individual PPG pulse with associated PWA features (with AN for anacrotic notch) used for characterizing pulse morphology. Anacrotic notch is designated by a dashed line because it does not actually exist on this example pulse.

PWA features were extracted from individual PPG pulses by detecting specific extrema in the signal and its derivatives. Figure 1 shows the pulse foot, the systolic raise, the anacrotic notch (AN), the post-AN systolic peak, the dicrotic notch and the diastolic peak. Individual PPG pulses were normalized such that the timing of the pulse foot and its amplitude were equal to zero, and the maximum amplitude to one. PWA feature time series were then evaluated in the time domain similarly to IBI time series by computing their ShEn, nRMSSD, sampEn, CoSEn, TPR, mean and standard deviation.

2.6. Feature Selection

In total, 13 temporal features, 4 spectral features and 140 PWA features were extracted. Because numerous additional PWA features might be irrelevant to the classification task, feature selection was applied. Features were first whitened, and missing values were replaced by zero because depending on the pulse morphology, certain PWA features can be absent. The Fisher score [9] was then applied (with a number of neighbors equal to 100) to determine the discriminative power of every feature. It allowed to limit the number of features by selecting the 100 best ranked features. It also provided insights into the discriminative power of individual PWA features.

2.7. Classification

To choose the most appropriate type of classifier and optimize its hyperparameters, cross-validation was used. To this end, the dataset was divided into 5-folds so that all windows from a given patient were in the same fold and that different class labels were equally represented in every fold. Different classifiers were tested: ridge regression, random forest, K-nearest neighbors and SVM (with linear, RBF and sigmoid kernel).

Classification performances were then evaluated by performing leave-one-group-out classification, that means training the chosen classifier on all patients except one that was used as the test set and repeating this for every patient. Accuracy, sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) are reported for every class of arrhythmia and on average.

3. Results

3.1. Feature selection

The scores assigned by the RELIEFF algorithm to the 18 best scored features are shown in Figure 2. The best features are CoSEn and SampEn of embedding dimensions 1 and 2, pNN40, pNN70 and ShEn of IBI time series. Most traditional HRV features based on IBI timeseries are among the best ranked features, as well as spectral entropy (specEn), ranked 8th, which is based on the PPG signal. The best ranked PWA features are the TPR of the time of waves *a* and *d* (see [8]) and the systolic raise ranked 10th, 12th and 13th. The TPR of the amplitude of the dicrotic notch and the next pulse's foot are ranked 14th and 17th.

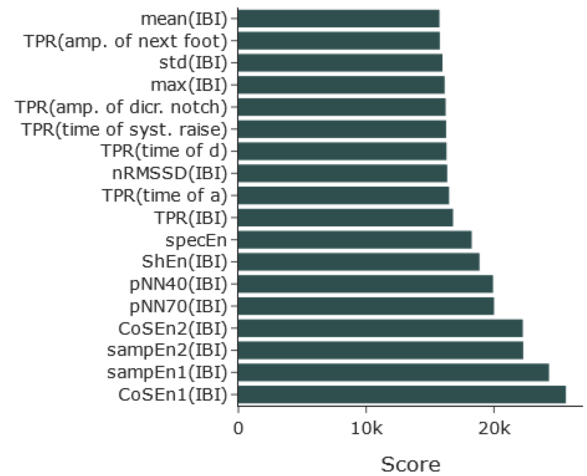

Figure 2. Feature score of the 15 best features ranked by the RELIEFF algorithm.

3.2. Classification

During the 5-fold cross-validation process, ridge regression with $\alpha = 29$ has been chosen as classification model without PWA features, and $\alpha = 2$ has been chosen while adding the 9 best ranked PWA features. Although the accuracies were slightly better with random forest than ridge regression models, the high variance of accuracies across folds led us to prefer the simplest model.

Table 1. The classification accuracy (Acc), sensitivity (Sens), specificity (Spec), positive predicted value (PPV) and negative predictive value (NPV) of each class (SR, AF, non-AF) are reported in percent (%), both with and without PWA features. The reported average is balanced such that every class has equal weight.

Class label	PWA	Acc	Sens	Spec	PPV	NPV
SR	no	81.9	79.4	87.9	94.0	64.4
	yes	82.1	79.6	87.8	93.9	64.6
AF	no	89.8	86.5	90.3	55.5	97.9
	yes	89.8	87.5	90.2	55.5	98.1
non-AF	no	79.5	52.7	85.2	42.9	89.5
	yes	80.0	53.1	85.7	44.0	89.6
class average	no	83.7	72.9	87.8	64.1	83.9
	yes	84.0	73.4	87.9	64.5	84.1

When performing leave-one-group-out cross-validation on the entire dataset the global accuracy is 75.6% without and 76.0% with PWA.

In more details, Table 1 reports performance metrics for each class of arrhythmia. Notably, AF classification sensitivity increased from 86.5% to 87.5%, and specificity decreased by 0.1% but remains high (90.2%). The benefit of PWA features is clearer when classifying non-AF CAs since all metrics were improved.

4. Discussion

This study shows that additional information about the morphology of individual PPG pulses extracted with PWA is beneficial for the classification of non-AF CAs. PWA features also make AF detection more sensitive, while keeping specificity relatively high which is important to limit the number of false alarms.

Nevertheless, the size of our dataset is limited, and a larger number of arrhythmic events is necessary to draw more significative conclusions. The high variability of accuracy scores when performing cross-validation suggested to prefer the leave-one-out-group method rather than the standard train-test split for the evaluation of performances. In addition, random forest classifiers showed better balanced accuracy scores on average during the hyperparameter tuning step, but the very high variability of scores across folds clearly indicated overfitting. This is the reason why ridge regression models have been preferred.

Moreover, the extraction of PWA features might suffer from the 25 Hz sampling rate of the PPG signals. In our future work, PPG signals recorded at 100 Hz sampling rate will certainly favor PWA features over spectral features that are less affected by low sampling frequencies.

Finally, non-AF CAs were grouped in a single class while their hemodynamic expression can be quite different. This has the advantage of limiting the complexity of the classification task, but it also reduces the contribution of this approach. In our future work, we plan to separate ventricular and supraventricular arrhythmias similarly to Liu et al. [7]. A second step could consist in detecting premature contractions pulse by pulse, similarly to Han et al. [6], instead of labelling a window as non-AF when it contains several premature contractions.

5. Conclusion

The classification performance of CAs via PPG has been marginally improved when numerous morphological features extracted by PWA were added to the classification model. More arrhythmic episodes and higher quality PPG signals are needed to investigate this approach in detail.

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