IMPROVED SYSTOLIC PEAK DETECTION IN PHOTOPLETHYSMOGRAPHY SIGNALS: FOCUS ON ATRIAL FIBRILLATION

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Abstract

Photoplethysmography (PPG) is a widely recognized non-invasive optical technique for monitoring blood volume changes. Recently, PPG signals have gained prominence in healthcare applications, including the detection of cardiac arrhythmias. Cardiac arrhythmias represent a significant global health challenge, with particular focus on identifying atrial fibrillation (AF), the most prevalent type. Accurate detection of systolic peaks in PPG signals is crucial for arrhythmia detection and other applications such as heart rate estimation and heart rate variability analysis. Despite the high accuracy of existing beat detection methods in healthy subjects, the performance in the presence of cardiac arrhythmias is lower. This study employs a deep learning method to enhance the detection of systolic peaks in PPG signals, even in the presence of AF. The model was trained on a dataset comprising 2,477 10-second PPG segments with over 37,000 annotated PPG peaks, including data from patients with AF. Our model achieved an F1 score of 97.3% on the test dataset and F1 score of 94.8% on the test dataset when considering only patients with AF.

Keywords

photoplethysmography, beat detection, systolic peak, atrial fibrillation

Introduction

Photoplethysmography (PPG) is a widely used, non-invasive optical method for monitoring changes in blood volume. In recent years, PPG signals have become increasingly popular for assessing various physiological parameters, such as heart rate (HR), blood pressure (BP), blood oxygen saturation (SpO_2), perfusion index (PI), and vessel compliance [1]. They are among the most utilized signals in wearable health assessment, aligning with the growing prevalence of smart devices and presenting a substantial opportunity to expand health monitoring to a wider population [2].

It has been found that PPG can be utilized to detect various cardiac arrhythmias [3]. Cardiac arrhythmias pose a considerable health challenge worldwide. With the emergence of wearable devices incorporating PPG, there is a chance to screen vast populations, potentially enabling the early identification of abnormal rhythms and improving prevention.

Extensive research has focused on detecting atrial fibrillation (AF), the most common cardiac arrhythmia, primarily through the analysis of irregularities in interbeat intervals (IBIs) based on detected systolic PPG peaks [4]. Therefore, accurate peak detection in PPG signals is crucial, as it helps us to better understand various aspects of heart health.

Although existing beat detectors demonstrate high accuracy in healthy subjects [5], their performance in the presence of various cardiac arrhythmias remains understudied. Research on the accuracy of PPG beat detection during AF is sparse. Väliaho et al. [6] achieved an *F1* score of 93.5% for peak detection in a cohort of patients with AF.

In this study, we are using deep learning model to detect systolic PPG peaks. By training our model on a dataset that includes healthy signals and cases of AF, we aim for accurate peak detection in both healthy and AF-affected individuals. Furthermore, we compare the results of our proposed algorithm with the PPG peak detectors from the HeartPy toolkit [7, 8].

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Dataset

In this study, we are using three independent datasets containing PPG signals from a total of 114 patients. The data include records from the publicly available CapnoBase database (University of British Columbia, Vancouver, Canada), where signals from 42 patients were acquired during elective surgery and routine anesthesia [9, 10]. The AF Perform database contains data with AF from critically ill patients, measured using a bedside monitor [5, 11, 12]. Data from the private database were measured on 53 healthy volunteers at the Department of Biomedical Engineering, Brno University of Technology, Czech Republic, using smartphone. All participants provided written informed consent, and the research was approved by the Ethical Committee of the Faculty of Electrical Engineering and Communication for Biomedical Research, Brno University of Technology.

For each PPG signal, a simultaneously recorded electrocardiogram (ECG) was available as a reference. Both PPG and ECG signals were aligned peak-to-peak and divided into 10-second segments. A total of 3,915 10-second segments were obtained, of which 52% contained AF.

Records from CapnoBase and the private database already contained reference peaks marked based on the QRS complexes present in the ECG. However, for the PPG data from AF Perform database, the peaks were manually annotated based on the QRS complexes in the ECG. Fig. 1 shows two cases of AF along with their peak-to-peak aligned ECG and PPG signals.

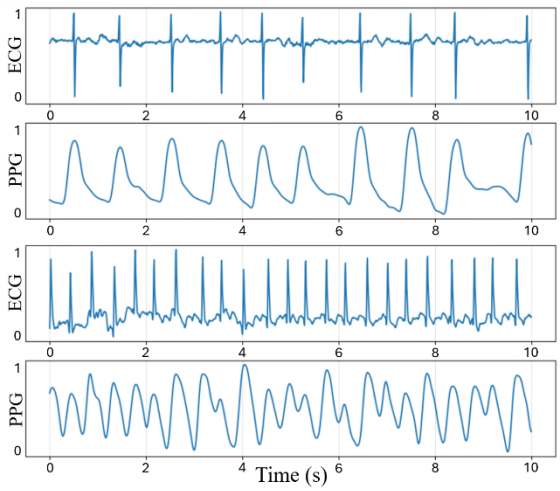

Fig. 1: ECG and PPG signals during the presence of AF.

The dataset was partitioned into training, validation, and testing subsets (Table 1). All these subsets contain data from all databases, while ensuring that data from individual patients remain segregated across training, validation, and test sets.

Table 1: Number of subjects, 10s PPG segments, and PPG reference beats for the training, validation, and test sets.

Dataset	Subjects	10s segments	Peaks
Training	68	2,477	37,163
Validation	23	719	8,804
Test	23	719	9,743

The label vector for each recording was created based on reference peak marks. Samples within a 0.1 s (equivalent to 12 samples) proximity to both the left and right sides of the peak annotations were identified as belonging to the PPG peak class (with a value of 1), whereas all other samples were classified as non-PPG peaks (with a value of 0). The input to the network was the PPG signal and its corresponding label vector.

Methods

In this study, we employed a deep learning technique with U-Net architecture to detect systolic peaks in PPG signals. The U-Net architecture consists of an encoder and a decoder and resembles the shape of the letter "U". The U-Net was originally developed by Ronnenberger et al. [13] for image segmentation. However, for this task, all layers were modified to operate in a one-dimensional form. The input to the model is 10-second-long PPG segment (1,250 samples) and a label vector (1,250 samples). The network output is an array of size 2×1,250, corresponding to the PPG peak probability and non-PPG peak probability for each analyzed segment.

Preprocessing

All signals were resampled to 125 Hz and divided into 10-second segments. To ensure robustness and minimal preprocessing, the signals were detrended and normalized to a range from 0 to 1. Data augmentation was then performed for each record by adding additive Gaussian noise.

Neural Network Architecture

In this study, we adopted the U-Net architecture proposed by Koscova et al. [14]. This architecture comprises four reduction blocks and four expansion blocks. The difference between the mentioned architecture and our architecture is the different number of filters in the convolutional layers and the size of the kernels in the convolutional layers. The number of filters in each convolutional layer was set to 16, 32, 64, 128, and 256. The last layer in the network was a convolutional layer with a softmax activation function. The output consists of two mentioned probability classes.

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To train the model, we employed the Adam optimization algorithm with a learning rate of 0.001. The total number of epochs used for training was 31, with a batch size of 8. The loss function was based on the Dice Coefficient. Training was performed in Python (version 3.12.6) using the PyTorch library.

Postprocessing

The output from the model consisted of two probability classes with a length equivalent to the input signal. Specifically, the probabilities for class 1 (indicating the presence of a peak) were selected as the final output. If the probability exceeded the threshold of 0.97 and persisted for a duration of 12 samples (both determined based on the validation set), it was identified as the peak region. The final peak position was then determined to be the center of this peak region (Fig. 2).

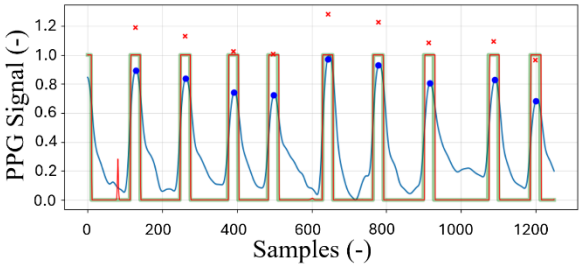

Fig. 2: Label vector (green), probability of class 1—output from the network (red signal), and final positions of the detected peaks (blue dots).

Accuracy assessment

The detector performance was evaluated using sensitivity (*Se*), positive predictive value (*PPV*), and *F1*-score (*F1*). *Se* represents the proportion of correctly detected peaks relative to the total number of reference peaks. *PPV* indicates the proportion of correctly detected peaks among all detected peaks. *F1* is the harmonic mean of the *Se* and *PPV*. A peak was considered correct if its position fell within a tolerance of ±10 samples of the reference beat.

Results

Table 2 presents the model performance (*F1*, *PPV*, and *Se*) for the training, validation, and test sets. Additionally, model performance was evaluated solely on data containing AF.

Subsequently, the results from the proposed method were compared with the Elgendi's and Bishop's detectors from the HeartPy Toolkit, Python Heart Rate Analysis Toolkit, designed to handle PPG data [7, 8]. The same metrics and tolerance of ± 10 samples from the reference beat were used to evaluate the performance of these detectors. A comparison between the proposed method and these detectors is presented in Table 3.

Table 2: Results of the proposed PPG peak detector.

Dataset	*F1* (%)	*PPV* (%)	*Se* (%)
Training	97.7	97.8	97.8
Validation	97.1	95.1	99.2
Test	97.3	97.6	97.1
Test (AF)	94.8	96.1	94.0

Table 3: Results of PPG peak detectors from HeartPy.

Dataset	*F1* (%)	*PPV* (%)	*Se* (%)
Bishop (test)	93.4	97	89.5
Elgendi (test)	95.1	97.2	93.2
Bishop (test AF)	91.3	95.8	86.9
Elgendi (test AF)	93.2	95.7	91.2

Discussion

Our proposed method achieved better results on the test dataset (*F1* = 97.3%) compared to detectors from the HeartPy library (Bishop's *F1* = 93.4%, Elgendi's *F1* = 95%). Furthermore, it is worth mentioning that *Se* increased by approximately 4% compared to Elgendi's detector and by almost 8% compared to Bishop's detector.

Our method achieved better results on the test dataset containing only AF records (*F1* = 94.8%) compared to Bishop (91.3%) and Elgendi (93.2%).

In Fig. 3, there is an example of PPG peak detection using our algorithm (blue dot), Elgendi's (green square), and Bishop's (blue plus) algorithms. The annotations (ground truth) are marked with a red cross. The signals were the same as those shown in Fig. 1.

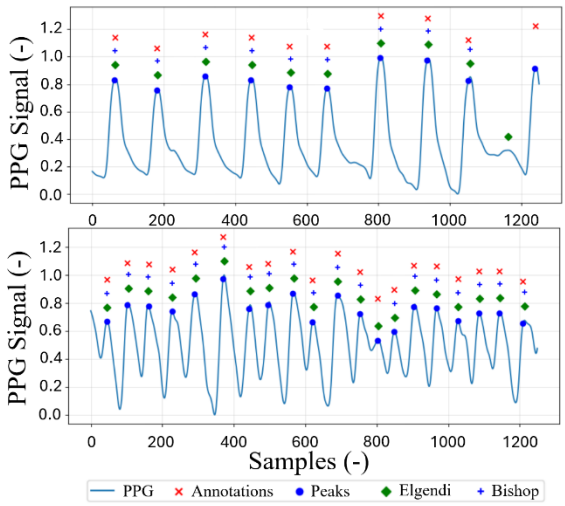

Fig. 3: Comparison of PPG peak detectors; red cross: annotations, blue dot: our detector, blue plus: Bishop, green square: Elgendi.

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Based on the analysis of our results, we found that false negatives often occur because the reference peak is located at the beginning/end of the 10-second segment. However, the output probability (class 1) does not yet have sufficient duration (12 samples) to meet the criteria to be considered a peak by the proposed algorithm (Fig. 4). This limitation will be simply resolved in future studies.

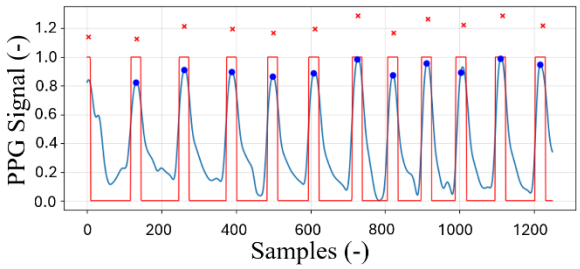

Fig. 4: Undetected PPG peak at the beginning of the segment; output probability to class 1 (red), detected PPG peaks after post-processing (blue dots).

A limitation of this study was the small number of patients (114). In future research, we aim to train the model on a database containing data from more patients with various cardiac arrhythmias beyond AF. For example, the accurate detection of premature atrial contractions and premature ventricular contractions could subsequently lead to the reliable classification of individual beats and thus to the classification of various types of arrhythmias.

Conclusion

This paper addresses the challenge of detecting systolic peaks in PPG signals, which can be challenging in the presence of various arrhythmias. We proposed a method for systolic PPG peak detection, achieving an *F1* score of 97.3% on a dataset containing signals from both healthy and AF individuals, and an *F1* score of 94.8% on a dataset containing only AF patient data. In comparison with other methods discussed in our paper, our proposed method achieved better results in both cases.

These results demonstrate the potential for clinical application, particularly for enhancing the accuracy of arrhythmia detection. Accurate identification of systolic peaks in PPG signals is crucial for reliable arrhythmia diagnosis, and our method could contribute to improved diagnostic tools for AF as well as other arrhythmias that depend on precise PPG peak detection. However, a limitation of this study was the number of patients involved. In future, we aim to expand the dataset to include a larger number of patients and incorporate additional cardiac arrhythmias.

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