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A Real-time PPG Quality Assessment Approach for Healthcare Internet-of-Things

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Abstract

Photoplethysmography (PPG) as a non-invasive and low-cost technique plays a significant role in wearable Internet-of-Things based health monitoring systems, enabling continuous health and well-being data collection. As PPG monitoring is relatively simple, non-invasive, and convenient, it is widely used in a variety of wearable devices (e.g., smart bands, smart rings, smartphones) to acquire different vital signs such as heart rate and pulse rate variability. However, the accuracy of such vital signs highly depends on the quality of the signal and the presence of artifacts generated by other resources such as motion. This unreliable performance is unacceptable in health monitoring systems. To tackle this issue, different studies have proposed motion artifacts reduction and signal quality assessment methods. However, they merely focus on improvements in the results and signal quality. Therefore, they are unable to alleviate erroneous decision making due to invalid vital signs extracted from the unreliable PPG signals. In this paper, we propose a novel PPG quality assessment approach for IoT-based health monitoring systems, by which the reliability of the vital signs extracted from PPG quality is determined. Therefore, unreliable data can be discarded to prevent inaccurate decision making and false alarms. Exploiting a Convolutional Neural Networks (CNN) approach, a hypothesis function is created by comparing heart rate in the PPG with corresponding heart rate values extracted from ECG signal. We implement a proof-of-concept IoT-based system to evaluate the accuracy of the proposed approach.

Keywords: Health Monitoring; Internet of Things; Photoplethysmogram; Wearable Electronics; Deep Learning; Convolutional Neural Networks

1. Introduction

Ubiquitous health monitoring systems are increasingly in demand to provide reactive and proactive healthcare solutions for at-risk patients as well as mitigating medical costs, errors, and workloads [5, 30]. Fortunately, techno-

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logical advancements in Internet-of-Things (IoT) systems, wearable electronics, and data analytics create significant opportunities for the development of such monitoring systems [18, 15]. These IoT-based healthcare systems can tailor various types of wearable sensors, transmission units, and remote computing resources to deliver end-to-end health solutions to users [32, 8]. In this regard, Photoplethysmography (PPG) as a non-invasive, low-cost, and convenient technique can play a significant role in IoT-based health monitoring systems to continuously provide various health parameters such as heart rate, respiration rate, and oxygen saturation.

PPG is an optical technique that indicates synchronous blood volumetric changes in the microvascular bed of tissues. Such variations in the PPG signal are associated with the oscillation of heartbeat and respiration [2]. The signal is collected by exposing light (e.g., infrared, red, and green) to the skin surface and acquiring the light reflection via photodetectors [40]. Due to simplicity and feasibility of the measurement, this technique is widely used these days in different wearable and mobile applications [29, 33, 3], and in several clinical and commercial medical devices such as pulse oximeter, smart rings, and smartwatches [23, 6, 12]. However, the PPG signal quality is highly susceptible to artifacts generated by the user's motions or surrounding resources. Unfortunately, such background noises are inevitable in IoT-based health monitoring systems, as users engage in various physical activities in different environmental conditions. For example, the signal is corrupted by hand motions in wrist-based PPG sensors although the distortion depends on the signal power and the wavelength [26]. The poor signal (i.e., low signal-to-noise ratio) leads to inaccurate vital signs extraction and erroneous decision making. Since inaccurate or incorrect assessment based on these signals may risk life-threatening consequences, such unreliable performance is unacceptable for healthcare applications. There are numerous studies in the literature to reduce the PPG signals artifacts. Several techniques have been proposed employing different signal processing, filtering, and noise cancellation methods including adaptive filters, spectral subtraction method, and Fourier series analysis [35, 43, 16, 41, 20]. Moreover, other efforts have tackled the motion artifact reduction, integrating other resources such as acceleration data to their techniques [34, 19, 42, 7, 11]. These methods could improve the signal quality and heart rate estimates, although they were unable to guarantee highly accurate results all the time, particularly when the Signal-to-Noise Ratio was too low. Consequently, they might still lead to incorrect results and false alarms.

Other studies have tackled the quality assessment of bio-signals [17]. In the context of PPG studies, Elgendi [13] introduced a method to use signal quality indices for the quality assessment. The PPG signals were manually annotated in this study. A method was proposed by Sun *et al.* [39] to use morphological characteristics and variability of the signal to assess the signal quality. Another study [27] extracted four waveform features and determined the signal quality using a decision tree. Similarly, Li and Clifford [28] proposed to feed different features extracted from the signal to a neural network algorithm to determine the quality. These studies mostly classify the signal quality as "good" or "bad" according to different features extracted from the signal. However, this definition is inaccurate in the health monitoring systems, considering the reliability of the signal's outcome (i.e., health parameters) and decision makings. Let's take two different examples in this regard. A signal could be tagged as "bad" when the temporal features are distorted by motion artifact. However, the heart rate values could be detected flawlessly leveraging a robust artifact reduction algorithm; and subsequently the decision making is accurate. On the other hand, a signal could be tagged as "good" because of the superb features although pulse rate variability is erroneous because the sampling frequency is too small [10]. Therefore, the medical decisions can be invalid.

Within the IoT-based health monitoring systems, we believe a quality assessment approach is required to determine the quality of the PPG signal according to the validity and reliability of the health parameters and subsequently medical decisions. Consequently, poor data can be discarded and decision making with invalid data and misinterpretation can be prevented. In other words, *missing data can be less hazardous than unnoticed incorrect data* as there are many data imputation techniques to fill the gap [4] (e.g., repeating the imputed heart rate value vs. showing a significantly incorrect heart rate value).

In this paper, we propose a novel automatic PPG quality assessment approach for IoT-based health monitoring, focusing on the accuracy of health parameters extracted from PPG. We employ the Convolutional Neural Network (CNN) deep learning algorithm to learn a customized hypothesis function from PPG signals, labeling the signal as "reliable" or "unreliable". In the learning process, the PPG quality is specified by a set of Electrocardiogram (ECG) signals as the baseline, comparing heart rate in the PPG with heart rate in the ECG signal. Moreover, we evaluate our proposed approach on a proof-of-concept IoT-based system.

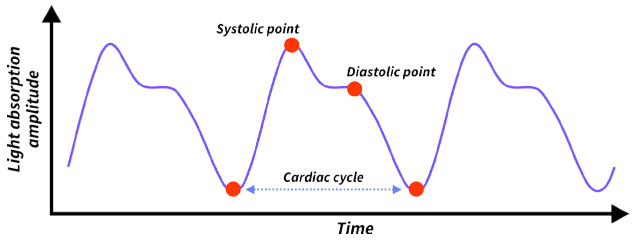


Fig. 1: A window of a filtered PPG waveform

The rest of the paper is organized as follows. Section 2 briefly outlines the background of this work. In Section 3, we present the proposed PPG quality assessment approach and our setup. The system evaluation is presented in Section 4. Finally, Section 5 concludes the paper.

2. Background

The two most widely used methods to measure the cardiac cycle and monitor heart rate are Electrocardiography (ECG) and Photoplethysmography (PPG). The ECG measures the electrical activation that leads to the contraction of the heart muscle, using electrodes attached to the body, usually at the chest. The PPG uses a small optical sensor in conjunction with a light source to measure the discoloration of the skin as blood perfuses through it after each heartbeat. Since our work focuses on PPG, in this section we summarize the background on Photoplethysmography (PPG) and Convolutional Neural Networks (CNNs).

2.1. Photoplethysmogram (PPG)

The PPG method senses the rate of blood flow by using a pulse-oximeter and measuring light absorption. Contraction of the heart causes an increase in blood pressure, so the Oxygen-rich blood is pumped through the body. Therefore, the cardiac cycle can be measured by detecting the peaks in this signal. Such a procedure can give a real-time measurement of the heart rate. A typical PPG signal is shown in Figure 1, in which the heart rate value can be calculated by the amount of time between two consecutive peaks. The signal contains two major components: the alternating current (AC) and direct current (DC) [2]. The AC component is attributed to synchronous blood variation oscillating with the heartbeats. The DC component corresponds to the various low-frequency components of blood flow such as respiration rate.

The PPG is easy to set up, convenient, simple, and economically efficient [9]. A PPG sensor includes a light source (e.g., green LED) and a light sensor placed on the skin to expose and collect the reflected light, respectively. The red and infrared lights are conventionally leveraged in finger pulse oximeter devices to obtain heart rate and blood Oxygen saturation. Moreover, the green light is mostly utilized for wearable devices such as smartwatches for heart rate detection.

2.2. Convolutional Neural Networks (CNNs)

Similar to how a human learns to recognize objects, a machine learning algorithm needs to be presented with an object several times before it can classify the inputs and make predictions for the incoming data. Convolutional Neural Networks, ConvNets or CNN [25] represent a class of deep learning algorithms that are organized as hierarchical feed-forward neural networks. CNNs differ from traditional neural networks through their hierarchical architecture and connectivity organization. Each layer of a CNN can be defined via three dimensions: height, width, and depth. Furthermore, neurons in each convolutional layer are not fully connected to the neurons of the next layer [24]. Classification is achieved through successive extraction of features at each layer; these features are generated by sliding filters along the input data at that layer. Finally, the ultimate output is reduced to a single vector of probability scores. CNNs enable efficient and automatic extraction of features, overcoming the tedious and possibly error-prone task of manual feature extraction, and also removing the need for an expert human-in-the-loop.

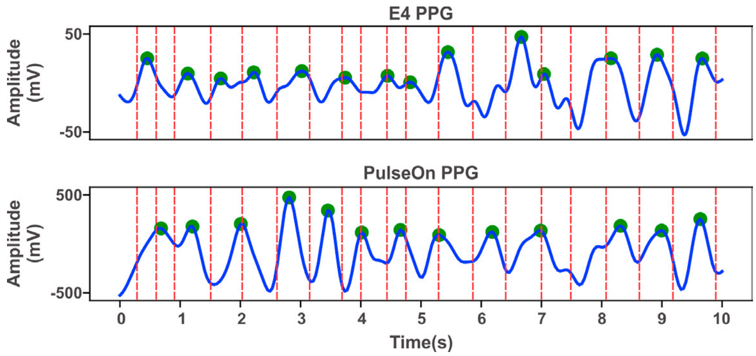


Fig. 2: 10-second windows of Empatica E4 and PulseOn PPG signals along with the ECG peak locations showing by the red dashed lines

3. PPG Quality Assessment Approach

In this section, we present how our proposed approach automatically performs the quality assessment of the PPG signal. We first outline the setup and then describe the detection approach.

3.1. Study Design and Setup

The system is designed to continuously monitor heart rate values in everyday settings. It consists of two wearable devices for PPG and one for ECG data collection. The devices are PPG-based Empatica E4 (E4) [14], PPG-based PulseOn(PO) [31], and Shimmer ECG Dev Kit (SHM) [37]. The E4 and PO are wearable wristbands enabled by a green light source. The output signal of these wrist-worn devices is a fluctuation in voltage, representing the variation in blood volume. Two views of the PPG signal collected via both devices are shown in Figure 2. In this experiment, the E4 and PO wristbands were worn tightly enough on the right and left hands, respectively. We select the Shimmer device to measure ECG signal as a gold standard to calculate heart rate values. ECG monitors the electrical activity of heart and is not prone to motion artifacts (i.e., hand movements). To prevent motion artifacts, the Shimmer device was placed on the chest along with two skin electrodes.

For this study, we carried out a continuous ECG and PPG data collection for 5 days. The sampling rates, reported by device manufacturers, are 201.3 Hz for the Shimmer device, 64 Hz for the Empatica E4, and 25 Hz for the PulseOn. Considering heart rates between 30 to 180 beats per minute, a Butterworth filter [36] was set to only pass heartbeat signals (i.e., 0.5-3 Hz). Then, a filter-based technique was utilized to extract heart rate values from the PPG signal [3]. In this technique, first, a filter was designed using the cutoff frequencies that were dynamically selected according to the peak values in the power spectral density (PSD) of the incoming signal. Second, a peak detection method was utilized to obtain the heartbeat cycles and subsequently calculate the heart rate values. The processing methods were performed using the Scipy library [21] in Python.

3.2. Methodology

We propose a machine learning-based method to assess the PPG signal quality. We train a classifier in this regard to distinguish between reliable and unreliable signals. For the training dataset, an automatic method is utilized to label the collected PPG signals as reliable or unreliable. The automatic method is performed in the system as follows. First, the PPG signal is synchronized in time with our gold standard ECG reference. Second, we employ a sliding window strategy to segment the signal into windows of 60 seconds that have a 50% overlap with each other. Third, the signal's amplitude in each window is normalized to enhance the peak detection (i.e., heart rate extraction). Then, the windows (i.e., PPG signal) are labeled by comparing the average heart rate value of each window with the corresponding heart rate value from the ECG reference. The PPG signals along with the labels are fed to the proposed classification method.

The PPG Quality Assessment has been proposed in different studies using traditional machine learning algorithms [28, 38]. However, such algorithms need proper features to perform the classification. In these works, feature

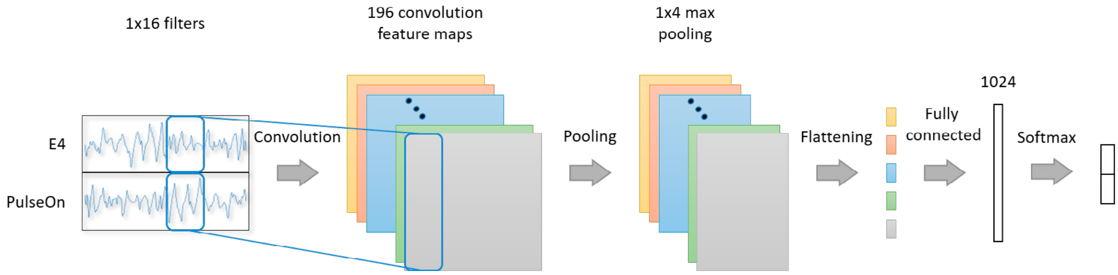


Fig. 3: CNN architecture used for the PPG Quality Assessment

values are extracted from the signal at first. Then, feature selection and dimensionality reduction are applied. Even though, such features might indicate the signal quality according to the variations in temporal and frequency domains, they cannot reflect the accuracy of signal's outcome. Therefore, a reliable and automatic method is needed to perform the feature extraction process. We believe deep networks are effective in this regard. One can feed the network with the data directly and discard the challenging feature extraction process, as extracting feature can be automatically done in the architecture itself. One of the most successful deep architectures is Convolutional Neural Networks (CNN) [25, 24]. CNN can extract features from the 1D signals (PPG signals in our case) and handle the entire feature engineering part. CNN consists of hierarchical layers for feature extraction. First layers extract basic features from the signal although higher layers obtain more complex features.

We here design a CNN method to perform PPG quality assessment. Figure 3 shows the overall architecture of our CNN computational pipeline. The inputs are 60-second windows of PPG signals. The processing begins with 196 convolutional filters with the size of 1×16. Each convolution layer takes inputs from the previous layers to convolve with several kernels and pass the result to the next layers. We leverage a non-linear activation function in this method. Among all the conventional activation functions, we tend to choose the rectified linear unit (ReLU), as its gradients are non-saturation and accelerates the convergence of the stochastic gradient descent in comparison with sigmoidal and hyperbolic tangent [24]. ReLU units are applied to the 196 feature maps. A pooling layer is then used to reduce the dimensionality, increasing the invariance of the features. Taking the maximum value and average value of the data are two conventional choices to pool feature maps from the previous layers. We select max-pooling of size 1×4 due to its sensitivity to existence of some patterns in pooled regions.

The pooling layer is subsequently passed to a flattering operation (see Figure 3) which unifies all the outputs and stacks them together. It makes a feature vector which is passed to the network classifier. The flattened feature vector is then followed by a fully-connected layer with 1024 neurons. The fully-connected layer performs the classification part. To minimize overfitting, a dropout technique with the rate of 0.05 is used. Finally, a softmax layer predicts output class probability distribution over two reliable and non-reliable classes, using the inputs from the fully connected layer. In our setup, Tensorflow computation library [1] is used for training the model and evaluation. The network's parameters are optimized with Adam [22] optimization method. Then, binary cross-entropy loss as a loss function on the softmax output is used. With l_2-norm regularization of CNN weights, the goal of training our model which is minimization of cross-entropy loss function is satisfied. In each iteration from a given training set of PPG, we randomly pick up the segments that injects enough noise to each gradient update, while achieving a relative speedy convergence.

4. Experimental Results

In this section, we evaluate the proposed approach in terms of accuracy of the signal quality assessments. The PPG signals in this setup are measured using two different devices, i.e., Empatica E4 and PulseOn. Heart rate values are extracted from the signals, and labeling of the windows (i.e., reliable or unreliable) is carried out by comparing the obtained heart rates with the ECG heart rates. For the collected 5-day data, the Mean Absolute Error (MAE) for the Empatica E4 and PulseOn are 8.21 and 12.41, respectively, measuring the distance between the PPG heart rate values and the ECG ones. The binary labels are specified using a threshold for the distance between both heart rate values. We select 10 beats per minute distance as the threshold in this evaluation. Therefore, the window is considered as reliable when the distance between its heart rate and ECG heart rate is less than 10 beats per minutes.

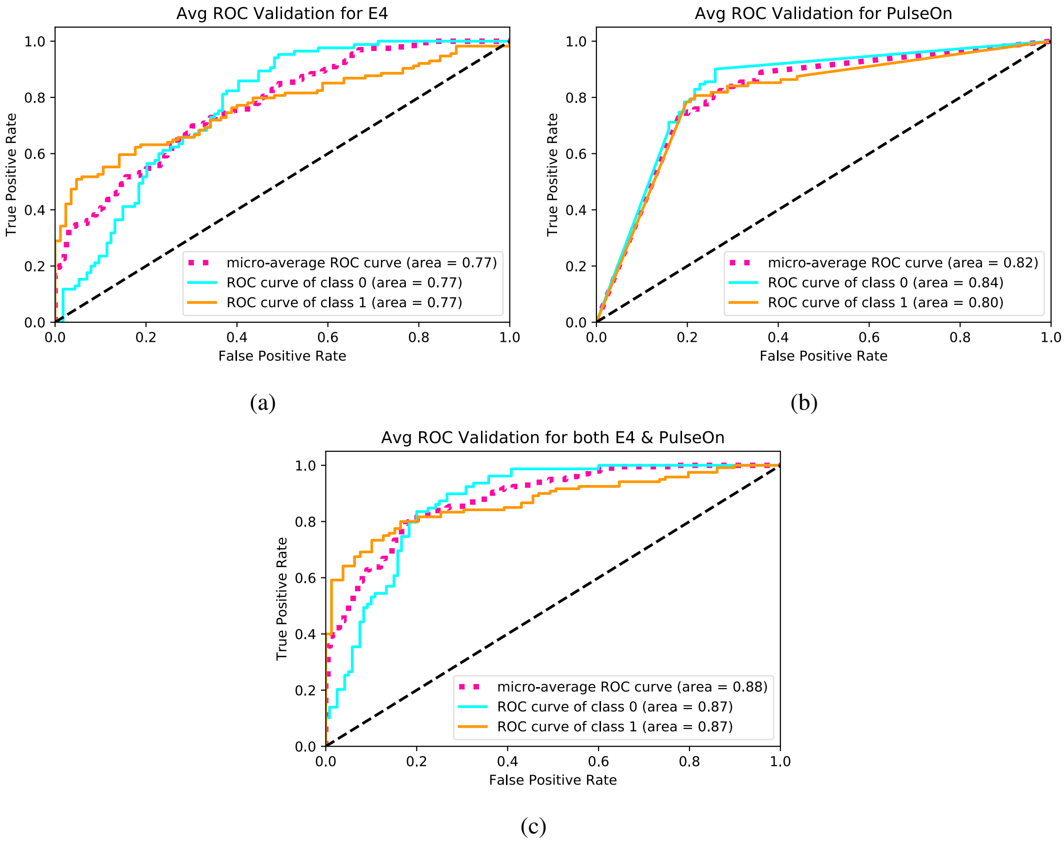


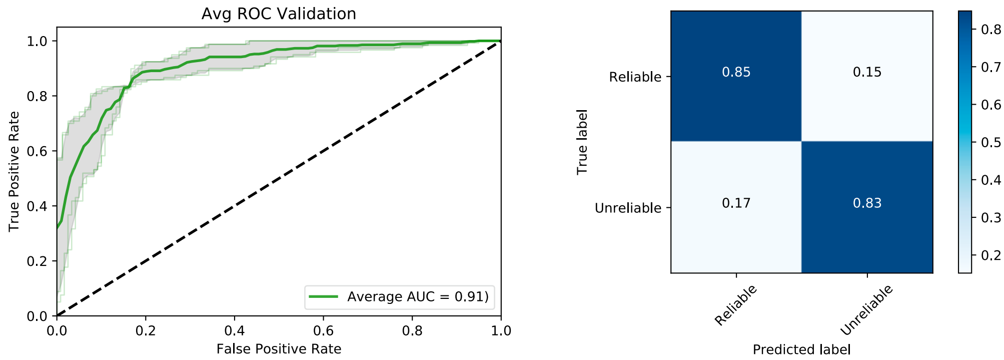
Fig. 4: Average ROC of the sensors (a) Empatica E4, (b) PulseOn, and (c) both Empatica E4 and PulseOn

To evaluate the proposed method, three different datasets as "Empatica E4 data", "PulseOn data" and "Empatica E4 and Pulseon data" are selected for the training process. In this regard, three models are trained to indicate the performance of the proposed approach in case of different training datasets. Then, we evaluate the models on 1440 60-second windows of PPG signals as the test data. The performance of the proposed method are shown in Figures 4 and 5, and Table 1.

The Receiver Operating Characteristic (ROC) curves of the three models are indicated in Figure 4. Moreover, Area Under Curve (AUC) per each class and contiguous flattened array (micro-average) of both reliable and unreliable classes are shown for the three classifiers. AUC values are respectively 0.77, 0.82, and 0.88 for the classifiers trained with "Empatica E4 data" (Figure 4a), "PulseOn data" (Figure 4b), and "Empatica E4 and PulseOn data" (Figure 4c). The AUC of the third model is higher that the other two classifiers. Recall that the test data is selected from the both Empatica E4 and Pulseon datasets. Consequently, the classification accuracy is increased if the model is trained using both PPG sources.

Moreover, the CNN architecture is evaluated using different values for the dropout rate. This evaluation is performed to mitigate overfitting in the model. The average ROC curve of the third model (green line) along with the standard deviation (gray area) is shown in Figure 5a. The average AUC is 0.91 and remains almost the same for all the dropout rates, indicating accuracy changes are insignificant with different dropout values.

Figure 5b shows the normalized confusion matrix of the third experiment, applying the third model on the test dataset. As indicated, the proposed method could correctly estimate the "Reliable" and "Unreliable" classes %85 and %83 of the times, respectively. Table 1 presents precision, recall, F1-score and support values of the two classes. Micro-average and macro average of the model are also indicated in the table. Our results show an acceptable performance for the proposed CNN-based approach, through which a binary decision is delivered to indicate PPG signal quality in a real-time manner.



(a) Average ROC for validation

(b) Normalized confusion matrix

Fig. 5: Average ROC validation and normalized confusion matrix for the third model on the test set.

Table 1: The precision, recall, F1-score, and support results of the proposed CNN method of both classes alongside with micro avg, macro avg

	precision	recall	F1-score	support
Unreliable	0.7674	0.8354	0.8000	79
Reliable	0.8850	0.8333	0.8584	120
micro avg	0.8342	0.8342	0.8342	199
macro avg	0.8262	0.8344	0.8922	199

5. Conclusion

PPG is a simple optical technique utilized in various wearable devices to continuously acquire health parameters such as heart rate. Such a technique is highly susceptible to environmental noises, particularly motion artifacts. In this work, we presented an automated PPG quality assessment approach for IoT-based health monitoring systems, focusing on the accuracy of the health parameters extracted from the PPG. Using our approach, unreliable signals could be removed to prevent false decision making. We leveraged a CNN approach to determine the PPG signal quality according to the extracted heart rate values. In the training process, the PPG signal was automatically labeled as reliable and unreliable by comparing the PPG signal against an ECG signal, as a gold standard for heart rate measurements. The hypothesis function was created by feeding the PPG signals to the model. We tested our algorithm by implementing a proof-of-concept IoT-based system. Our results indicated an acceptable performance for the proposed approach to distinguish between reliable and unreliable PPG signals. The precision and recall of the approach were 0.89 and 0.83 in our experiment, respectively.

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