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Beat-by-Beat ECG Monitoring from Photoplythmography Based on Scattering Wavelet Transform

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ABSTRACT

The electrocardiogram (ECG) is a popular measurement scheme to assess and diagnose cardiovascular diseases. ECG devices use gel material and electrodes that may cause skin irritation and discomfort during long use, which restricts the long-term use of these devices. On the other hand, Photoplethysmography (PPG) is an optical approach used to estimate the skin blood flow using photons. Recently, the relationship between the PPG and ECG has been recognized and there are early stage attempts to reconstruct the ECG signals from PPG signals that can lead to giving up electrodes and skin irritating and uncomfortable materials. However, these recent researches suffer from the sensitivity to the PPG signal quality, shifting, and scaling. Therefore, it is restricted with constrained PPG signals. In this paper, we propose an ECG reconstruction system that is independent of PPG scaling and shifting. The proposed system is based on scattering wavelet transform (SWT) as a feature domain along with the deep learning network. Using SWT helps deep learning networks to learn the non-linear relationship between ECG and PPG even with small datasets. Also, the proposed system is based on beat-by-beat ECG estimation rather than signal-based which leads to the learning of local features rather than global features. Based on the presented simulation results, the proposed system with beat-by-beat SWT features extraction outperforms the other feature domains; Time, DCT, and DWT domains.

1. INTRODUCTION

Cardiovascular diseases are the leading cause of global death in the world. According to the World Health Organization, the world's biggest killer is ischemic heart disease, responsible for 16% of the world's total deaths [1]. Electrocardiogram (abbreviated as EKG or ECG) is a recording of the electrical activity of the heart. Since it has been invented in 1902, ECG has become the most used cardiovascular diagnostic procedure and is a fundamental tool of clinical practice [2]. People are asked to monitor their ECG signals for many reasons, such as to check their general health, diagnose a medical condition, and monitor a medical condition before surgeries. Currently, ECG monitoring is performed by clinical laboratories using special devices with special preparation (in case of effort or effortless ECG monitoring). In this monitoring, the patients relate to several electrodes with some special Gel. Patients may feel discomfort and/or pain itching or skin irritation at the electrode's positions. It is considered one of the most important attributes of continuous health monitoring required for identifying those who are at serious risk of future cardiovascular events or death. Many modern wearable ECG systems have been developed in recent decades [3]. They are simpler and more reliable than before, weighing only a fraction of a pound. Unfortunately, it suffers from some limitations as the material used to provide good signal quality with the electrode may cause skin irritation and discomfort during long use, which restricts the long-term use of the devices. On the other hand, PPG is a noninvasive circulatory signal related to the pulsatile volume of blood in tissues [4]. PPG is easy to set up compared with ECG, more convenient, more economical, and nearly ubiquitous in clinics and hospitals in the form of finger/toe clips and oximeters and has increasing popularity in the form of consumer-grade wearable devices that offer continuous and long-term monitoring capability and do not cause skin irritations.

There is a vast amount of research is being conducted with the goal of developing wearable devices capable of continuous ECG monitoring and feasible for daily life use by continuously measuring PPG signal and reconstructing ECG signal from it as Photoplethysmogram (PPG) is considered a close alternative to ECG, which contains valuable cardiovascular information. For instance, studies have shown that several features extracted from PPG [5] are highly correlated with corresponding metrics extracted from ECG [6]. Yet, through recent advancements in smart watches, smartphones, and other similar wearable and mobile devices, PPG has become the industry standard as a simple, wearable-friendly, and low-cost solution for continuous heart rate (HR) monitoring for everyday use. However, PPG suffers from inaccurate HR estimation and several other limitations in comparison to conventional ECG monitoring devices [4-8] due to factors like skin tone, diverse skin types, motion artefacts, and signal crossovers among others. Moreover, the ECG waveform carries important information about the cardiac activity. As a result, ECG is consistently being used by cardiologists for assessing the condition and performance of the heart. Based on all the previous studies, there is a gap between the need for continuous wearable ECG monitoring and the available solutions in the market.

The rest of the paper is organized as follows: Section 2 discusses the related works, Section 3 presents the proposed SWT-based ECG monitoring system, Section 4 introduces the experimental results, and finally the paper is concluded in Section 5.

2. RELATED WORKS

By taking the benefit of the correlation between the two signals there are inspirations to not only the ECG parameters but also reconstruct the ECG waveform from the PPG measurement. ECG generation is proposed in much research in the literatures [9-13]. However, some of them are not related to the proposed work where ECG is artificially generated for other purposes. In literature [9], synthesizing ECG with generative adversarial networks (GANs) is studied using bidirectional Long Short-Term Memory-Convolutional Neural Network (LSTM-CNN) architecture to generate ECG from Gaussian noise. In literature [10], personalized GAN (PGAN) is proposed to generate patient-specific fake synthetic ECG waveforms from input noise. In literature [11], the synthesis of ECG waveforms is proposed to improve emotion classification accuracy where synthetic ECG was used to augment the available ECG data. Another study is performed by generating ECG from input noise to augment the available ECG training set to improve the performance for arrhythmia detection [12]. With respect to the specific problem of PPG-to-ECG transformation, to the best of our knowledge, there are two research tried to solve this problem [13, 14]. Synthesizing ECG with GANs was first studied in literature [13], where bidirectional LSTM-CNN architecture was proposed to generate ECG from Gaussian noise. This work used linear regression with the discrete cosine transformation (DCT) technique to map each PPG cycle to its corresponding ECG cycle. First, onsets of the PPG signals were aligned to the R-peaks of the ECG signals, followed by a de-trending operation to reduce noise. Next, each cycle of ECG and PPG was segmented, followed by temporal scaling using linear interpolation to maintain a fixed segment length. Finally, a linear regression model was trained to learn the relation between the DCT coefficients of PPG segments and corresponding ECG segments. In spite of several contributions, this study suffers from a few limitations: First, the model failed to produce reliable ECG in a subject independent manner, which limits its application to only previously seen subject's data. Second, often the relation between PPG segments and ECG segments is not linear, therefore in several cases, this model failed to capture the non-linear relationships between these two domains. Third, no experiments have been performed to indicate any performance enhancement gained from using the generated ECG as opposed to the available PPG (for example a comparison of measured HR). CardioGAN [14] is a solution for generating ECG signals from input PPG signals to aid with continuous and reliable cardiac monitoring. This method takes 4-second PPG segments and generates corresponding ECG segments of equal length. Self-gated soft-attention is used in the generator to learn important regions, for example the QRS complexes (ventricular depolarization) of ECG waveforms. Moreover, a dual discriminator strategy is used to learn the mapping in both time and frequency domains. Further, they evaluate the merits of the generated ECG by calculating HR and comparing the results to HR obtained from the real PPG. The analysis shows a clear advantage of using CardioGAN as more accurate HR values are obtained as a result of using the model. The works done in the ECG estimation from PPG [13, 14] suffer from the sensitivity to the shifting and/or scaling of the test PPG signal. On the other hand, the scattering wavelet transform is shown as an effective tool for feature extraction for classification [15]. Scattering wavelet is shown to be insensitive to the signal scaling and shifting. Therefore, it is a powerful feature domain. Motivated by the discussion and regarding the previous works for ECG estimation, our main contributions in this paper are:

- Unlike the previous work [14], we propose to estimate ECG on a beat-by-beat basis rather than a signal basis.
- Unlike the work done in the study of Zhu et al. [13], we used the scattering wavelet domain rather than the time domain to make the system more robust against scaling and shifting.

SWT is used as a feature domain to extract features that are insensitive to scaling and shifting rather than using time domain (TD) [14], DCT [13] domain, or discrete wavelet transform (DWT) domain that are sensitive to scaling and shifting.

3. THE PROPOSED SWT-BASED ECG MONITORING SYSTEM

The proposed system depends on photoplethysmography signals and uses deep learning models to determine the ECG signals on a beat-by-beat basis. Specifically, the proposed system consists of two phases: namely, the learning phase and the testing/prediction phase. A block diagram for the whole proposed system is shown in Figure 1. The learning phase consists of signal-based data cleaning, signal segmentation, per-beat data cleaning, beat normalization and beat-by-beat DL training. On the other hand, the prediction phase consists of signal segmentation, beats normalization and scaling and ECG prediction. These stages are described in detail in the following sections.

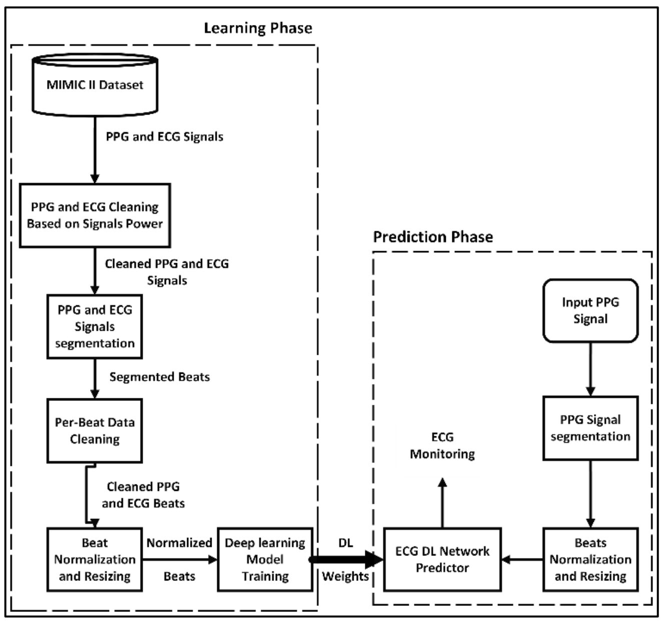


Figure 1. The block diagram for the whole system

3.1 Learning phase

The input to this phase is the MIMIC II dataset that contains contact PPG and the corresponding ECG. In this phase, the database passes through the following steps:

3.1.1 PPG cleaning based on signal power

In this stage, both PPG and ECG signals are inspected without any segmentation. The main idea resides in viewing both signals in the frequency domain where both signals have to exhibit similar spectral construction as follows. Both PPG and ECG signals are arising from the same pulsating source which is the heart. So, PPG and ECG signals can be considered quasi-periodic signals with identical fundamental frequencies. Hence, the estimated heart rate (HR) from the PPG signal has to coincide with that estimated from the ECG signal. Also, physiological limits impose upper and lower bounds on the HR ranges. Often, the estimated fundamental frequency F_0 determines the estimated heart rate. Hence, the constraints on HR imply corresponding constraints on the spectral shape. Moreover, thanks to the semi-periodicity of PPG/ECG signals, most of the signal power has to be concentrated around the fundamental frequency and its harmonics with a very narrow bandwidth of 0.2 Hz [16]. The ratio of the power of the in-band signal to the power of the out-band signal is calculated by Eq. (1).

$$Q_{\mathrm{SNR}} = \frac{\int_{f_0-\Delta f}^{f_0+\Delta f} \hat{P}_f \mathrm{df} + \int_{2f_0-\Delta f}^{2f_0+\Delta f} \hat{P}_f \mathrm{df} + \int_{3f_0-\Delta f}^{3f_0+\Delta f} \hat{P}_f \mathrm{df}}{\int_{\Omega} \hat{P}_f \mathrm{df} - \left(\int_{f_0-\Delta f}^{f_0+\Delta f} \hat{P}_f \mathrm{df} + \int_{2f_0-2\Delta f}^{2f_0+2\Delta f} \hat{P}_f \mathrm{df} + \int_{3f_0-\Delta f}^{3f_0+\Delta f} \hat{P}_f \mathrm{df}\right)} \quad (1)$$

where $\hat{P}_f$ represents spectral power density measured over the cardiac band (Ω), Ω=[0.5−8]Hz, f_0 is the fundamental frequency and Δf is the in-band around the fundamental frequency.

3.1.2 Beat segmentation

In the beginning, the cleaned dataset is passed through two stages filtering process. In the first filter, the signals are passed through a band-pass filter in the cardiac frequencies [0.8 Hz - 5 Hz]. Then the filtered signal is segmented into beats to deal with each beat individually. The signals are segmented based on the detection of local minimum locations. Figure 2 shows the local minimum locations for the filtered signal. Therefore, the time interval between each two consecutive minimums is defined as the beat interval (BI). The beat interval is an important feature of the beats. Therefore, BI will be used with PPG values in the case of the time domain.

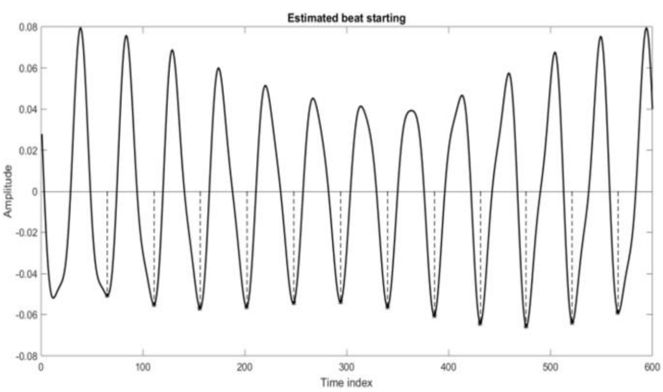


Figure 2. The detected local minimum locations of the filtered signal

3.1.3 Per-beat data cleaning

After beat segmentation, some of these beats are distorted beats. Beats are cleaned (valid beats are selected) to be used in the training process based on some metrics related to the general distinct shape of PPG patterns. These metrics are beat intervals, skewness value and correlation with the fundamental PCA component. Figure 3 provides an example of segmented beats. This figure contains different beats that are valid and invalid. Some invalid beats are due to the existence of multi systolic beats (as shown in beats in blue and yellow). Beats in solid black and dashed black have a single systolic peak and a single notch therefore they are valid beats. The skewed beat in green is invalid as well. The three following criteria [16] are used to select valid beats and reject the others:

1. Beat interval (BI): the standard range of the heart rate is [40 bpm-180 bpm] which corresponds beat interval in the range [0.33-1.5] second. Therefore, we use only beats with beat intervals in the range 0.33≤BI≤1.5.

2. Beat Skewness quality index (SQI): the Skewness measures the asymmetry of the PPG beats compared to the standard beat. The normal beats have positively skewed shapes.

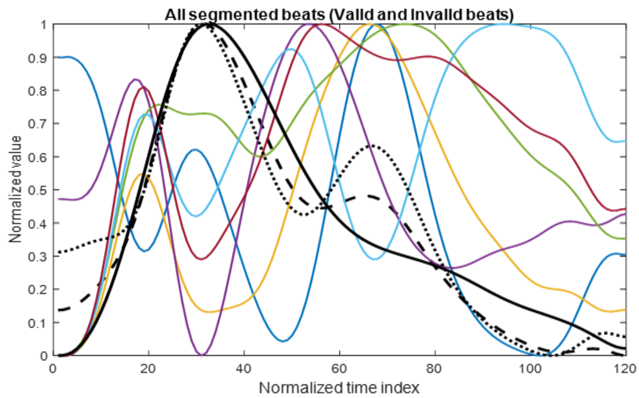


Figure 3. Segmented beats

It is also can be called the right-skewed beat. A tail is referred to as the tapering of the curve differently from the data points on the other side if the given beat is shifted to the right and with its tail on the left side, it is a negatively skewed beat. It is also called a left-skewed distribution. The skewness value of any distribution showing a negative skew is always less than zero. SQI can be calculated by Eq. (2).

$$SQI = \frac{\sum_{i=1}^{N} (Y_i - Y^{\sim})^3 / N}{\sigma^3} \quad (2)$$

where, Y_i is the i-th beat's ponit, $Y^{\sim}$ is the mean of the beat, σ is the standard deviation, and N is the number of beat's points. In this work, we restrict our beats with only positive SQI. Moreover, the high positivity of SQI leads to long tailed beat which is nota normal beat. In our work, we use valid beats with 0≤SQI≤1.

3. Beat correlation quality index (CQI): the correlation with a standard beat can help restrict beats to be within a valid range. However, the correlation should be not strict that is CQI should be more than 0.3 to insure rejecting highly deviated beats.

3.1.4 Beat normalization and resizing

The segmented PPG beats are normalized to be in the range [0-1] by using Eq. (3).

$$S_n = \frac{S - min\ (S)}{max(S) - min\ (S)} \tag{3}$$

where S_n is the normalized signal and S is the un-normalized signal. The normalized beats are then normalized in time so as to be with a fixed length (120). The time interval is used as a feature besides the normalized beats in case of the time domain.

3.1.5 Deep learning model training

Using LSTM sequence-to-sequence regression, the ECG beats are estimated from the corresponding PPG features. Four feature domains are tested including the time domain, DCT domain, DWT domain and SWT domain. In the time domain, the beat interval information is included with the input sequence. Each feature domain has its advantages as follows: the time domain includes the beat interval and the behavior of the PPG which is related to the behavior of the ECG in the time domain. However, the time domain features require a huge dataset and complex network to extract the deep features directly from the PPG beats in the time domain. On the other hand, the DCT feature domain compresses the beats features in a small number of points which can help in reducing the input size with less deformation. However, in this study, we used the full length DCT features for a fair comparison. The main drawback of this feature domain is that error prediction of the DC and low frequency components may lead to destructive results in the ECG prediction. The DWT domain has combinational features that are time and frequency which make it suitable for ECG estimation. However, it suffers from the sensitivity to the signal shifting and scaling that is usually happen with the PPG sensors. Therefore, it may lead to errors due to scaling and shifting. Unlike DWT, SWT doesn't suffer from the effect of the shifting and scaling of the PPG beats. So, SWT is suitable to be used as a feature extraction to help the LSTM network learn the relationship between PPG and ECG.

3.2 Prediction phase

Table 1. Network specifications

Number of Signals	158094
Signal Length	120
Number of Channels	4×1 Layer array
Layer specifications	1. Sequence input with 120 dimensions 2. LSTM with 50 hidden units 3. Two fully connected layer 4. Regression Output mean-squared-error
Learning Rate	0.005
Number of Iterations per Epoch	191
Optimization function	L2-Norm
Optimization method	ADAM

Table 2. Input and output data size in the two used scenarios for different domains

Domain	Time	DCT	DWT	SWT
Input size	121 × 1	120 × 1	120 × 1	120 × 1
Output size	120 × 1	120 × 1	120 × 1	120 ×1

The input to this phase is the PPG signal. In this phase, the PPG signal passes through the following steps: signal segmentation and beat normalization and beat-by-beat ECG prediction. The network specifications are tabulated in Table 1. Also, the size of the input and output data from the LSTM network is tabulated in Table 2 for different cases. The outputs of all the cases have the same size as they are the ECG signal. However, in case of time, the input size is different compared to that of the other cases this is because in the case of the time domain the beat interval is included (120 + 1). However, in the cases of the frequency domain, only the frequency domain coefficients are used as input to the network (120).

4. EXPERIMENTAL RESULTS

4.1 Dataset

Physionet's MIMIC II data collection (Multi-parameter Intelligent Monitoring in Intensive Care) [17] gives the combined PPG-ECG data required to feed the learning models. The datasets collection are introduced in a compiled version with a better display in the study [18]. However, an examination of that data set reveals that it still contains a significant number of faulty PPG and ECG signals. That data set will be used to create a jointly cleaned PPG-ECG dataset to feed deep learning-based BP estimate algorithms. This data collection includes 12,000 records of various lengths. ABP (invasive arterial blood pressure in millimeters of mercury), PPG (photoplethysmograph from fingertip), and ECG (electrocardiogram from channel II) signals are captured at Fs=125 samples per second in each record. However, we're just interested in the PPG signal and the ECG label that goes with it. Records are divided into pieces of 1024 samples in length for effective processing and filtering. We've accumulated 30,660 in records. Only PPG signals can be pre-processed using any boosting approach (such as band-pass filtering in the [0.8-5] Hz frequency range) as long as their morphological form is not changed. The ECG signal, on the other hand, cannot be tampered with since any attempt to improve its quality alters its magnitude, which indicates the ECG parameters. PPG beats will also be adjusted during the beat segmentation step, but comparable ECG beats will be left alone. Without any filtering capability, heavily distorted ECG signals or beats must be discarded.

4.2 Results and discussion

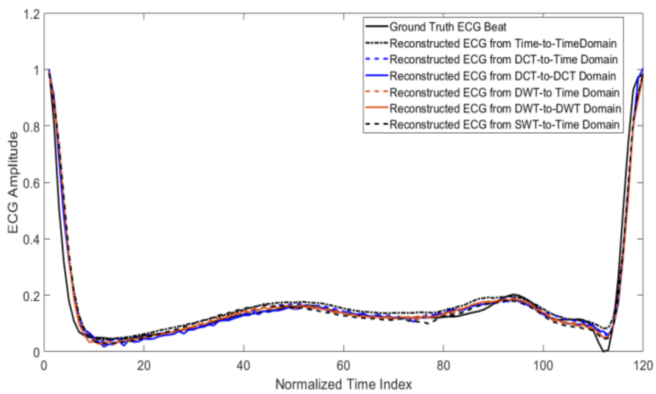
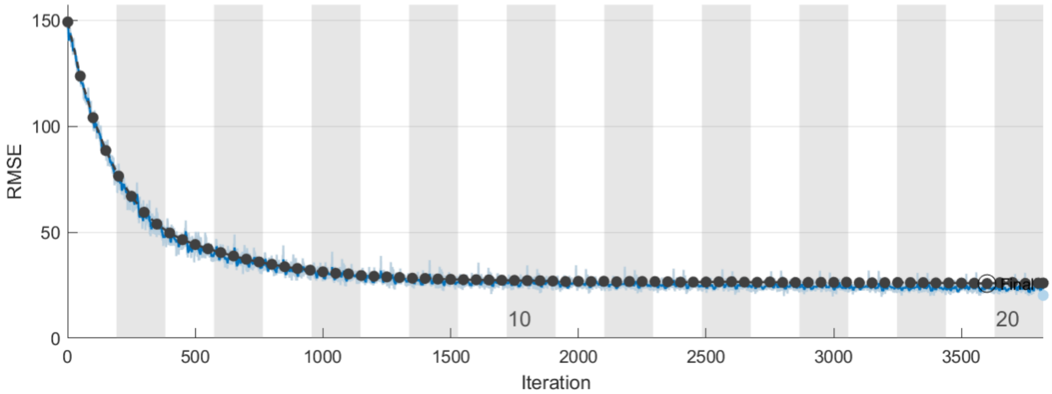


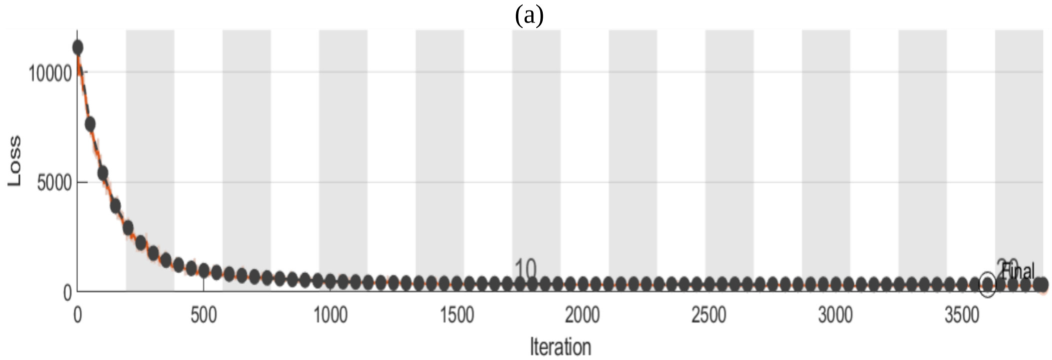
Figure 4. Estimated ECG beats from PPG beats using different transformations

In this section, the ECG beats are estimated from the corresponding PPG beats by using the LSTM network with a 120×1 sequence regressor output layer. As the output represents a sequence and as we are interest in the time series ECG, there are Six possible training combinations for ECG estimation with different feature domains. These combinations are: 1) using time domain (TD) for PPG beats with BI and TD for the ECG beats, 2) using DCT for PPG beats and TD for ECG, 3) using DCT for PPG beats and DCT for ECG and then using IDCT for comparison and evaluation, 4) using DWT for PPG beats and TD for ECG, 5) using DWT for PPG beats and DWT for ECG and then using IDWT for comparison and evaluation, and 6) using SWT for PPG beats and TD for ECG.

Table 3 shows the RMSE and MAE for the estimated ECG beats with different cases and different feature domains. As expected, using SWT outperforms the other feature domains. Figure 4 shows the plot of the reconstructed ECG beats with different feature domains and different cases. As shown from this figure, the estimated ECG beat by using SWT-TD is highly related and correlated to the ground truth ECG beat. Figure 5 shows the convergence for the loss function and the RMS error for the training and validation stages. This figure shows that the SWT-TD case converges after 20 epochs.



(a)



(b)

Figure 5. (a) The RMSE convergence for the training and validation steps in case of the SWT domain, (b) The Loss function convergence for the training and validation steps in case of the SWT domain

Table 3. Comparison between different transformations

ECG Beats	Time	DCT		DWT		SWT
	TD+BI-TD	DCT-TD	DCT-DCT	DWT-TD	DWT-DWT	SWT-TD
RMSE	0.1101	0.1104	0.1050	0.1033	0.1013	0.1006
MAE	0.0928	0.0932	0.0872	0.0858	0.0836	0.0828

5. CONCLUSION

In this paper, we presented a beat-by-beat ECG signal estimation system. The ECG beats are estimated from PPG beats. The proposed system is based on deep learning with scattering wavelet as a feature domain. The main advantage of using SWT is that it is independent of shifting and scaling. Therefore, it can detect the ECG signal regardless of the shifting or scaling of the PPG signal. Different feature domains are compared to show the effectiveness of the scattering wavelet to estimate the ECG beats. Unlike the work done in the literature, we proposed ECG estimation in a beat basis rather than in a signal basis. Based on the presented simulation results, using beat-by-beat SWT outperforms other schemes that are beat-by-beat time domain, beat-by-beat DCT domain, and beat-by-beat DWT domain. The limitation of the proposed method is that inaccurate signal segmentation may lead to invalid beats. This in turn leads to beats rejection and therefore incomplete ECG signal. In future work, an extension for the segment -by-segment ECG reconstruction rather than beat-by-beat can overcome the limitation of inaccurate signal segmentation.

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NOMENCLATURE

ABP	Arterial blood pressure
BI	Beat interval
CNN	Convolutional neural network
CQI	Beat correlation quality index
DCT	Discrete cosine transform
DL	Deep learning
DWT	Discrete wavelet transform
ECG	Electrocardiogram
GAN	Generative adversarial network
HR	Heart rate
LSTM	Long short-term memory
PGAN	Personalized GAN
PPG	Photoplethysmography
SQI	Beat skewness quality index
SWT	Scattering wavelet transform
TD	Time domain

Greek symbols

Ω	Cardiac frequency band, Hz
σ	Standard deviation
Δf	The in-band around the fundamental frequency.

Subscripts

f_0	The fundamental frequency
N	Number of beat's points
$\hat{P}_f$	spectral power density
Q_{SNR}	The ratio of the power of the in-band signal to the power of the out-band signal
S	Un-normalized PPG signal
S_n	Normalized PPG signal
$Y^{\sim}$	The mean of the beat's points
Y_i	i-th beat's point