Computers and Electrical Engineering 92 (2021) 107065

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Deep recurrent neural network-based autoencoder for photoplethysmogram artifacts filtering☆,☆☆

Joseph Azar [a,*], Abdallah Makhoul [a], Raphaël Couturier [a], Jacques Demerjian [b]

[a] FEMTO-ST Institute, UMR 6174 CNRS, Univ. Bourgogne Franche-Comté, France
[b] LaRRIS, Faculty of Sciences, Lebanese University, Fanar, Lebanon

ARTICLE INFO

Keywords:
Wearable-based applications
Deep learning
Anomaly detection
Photoplethysmography
Health monitoring applications

ABSTRACT

Recently, the need for fast, cost-effective, convenient, and non-invasive cardiovascular analysis techniques has been the primary and most attractive reason to use photoplethysmogram (PPG). Most wearable devices on the market today can collect PPG data and enable the measurement of important features such as heart rate, respiration rate, and blood pressure, in addition to detecting irregular pulses and cardiovascular diseases. One major drawback of PPG data is their high sensitivity to motion, resulting in distorted and meaningless signals. This paper proposes a neural network-based filtering method to remove corrupted windows from the collected PPG data in an unsupervised manner. It also proposes a PPG data summarization and augmentation strategy which optimizes the network performances. Experimental results show that the proposed approach was capable of achieving 90% precision and 95% recall when processing PPG data collected from a Shimmer3 GSR+ sensor.

1. Introduction

Wearable devices and fitness tracking applications have been introduced to and used by millions of people, allowing continuous and unobtrusive tracking of individual behavior and physiological features. One of the important signals to calculate these devices' physiological features is the photoplethysmogram (PPG) signal. Photoplethysmography (PPG) is a non-invasive optical method to monitor vital signs of the body such as heart rate, heart rate variability, and blood oxygenation. The PPG waveform represents variations in blood volume and contains important and useful characteristics to analyze cycle periods, baselines, and amplitude. Fortunately, wearable health monitoring devices, including smartwatches and fitness trackers, can now capture PPG signals and allow cardiac activity monitoring by deriving from the PPG the same R–R intervals derived from the electrocardiogram (ECG).

Due to the enormous need to track chronic diseases and monitor elderly patients, ubiquitous health monitoring applications have been listed as the fastest growing segments among the various categories on the wearables market [1]. Today, current wearable devices and sensors no longer focus on basic metrics for fitness tracking, such as the number of steps taken, but also control essential physiological features. Commercial smartphones and wearable devices are currently able to measure a range of physiological parameters using PPG, such as the interval between successive heartbeats, respiration rate, and blood pressure [1].

☆ This paper was recommended for publication by associate editor Manu Malek.
☆☆ This paper is for CAEE special section VSI-swis. Reviews processed and recommended for publication to the Editor-in-Chief by Guest Editor Dr. Imran Sarwar Bajwa.

* Corresponding author.
E-mail addresses: joseph.azar@univ-fcomte.fr (J. Azar), abdallah.makhoul@univ-fcomte.fr (A. Makhoul), raphael.couturier@univ-fcomte.fr (R. Couturier), jacques.demerjian@ul.edu.lb (J. Demerjian).

https://doi.org/10.1016/j.compeleceng.2021.107065
Received 20 December 2019; Received in revised form 3 December 2020; Accepted 25 February 2021
Available online 25 March 2021
0045-7906/

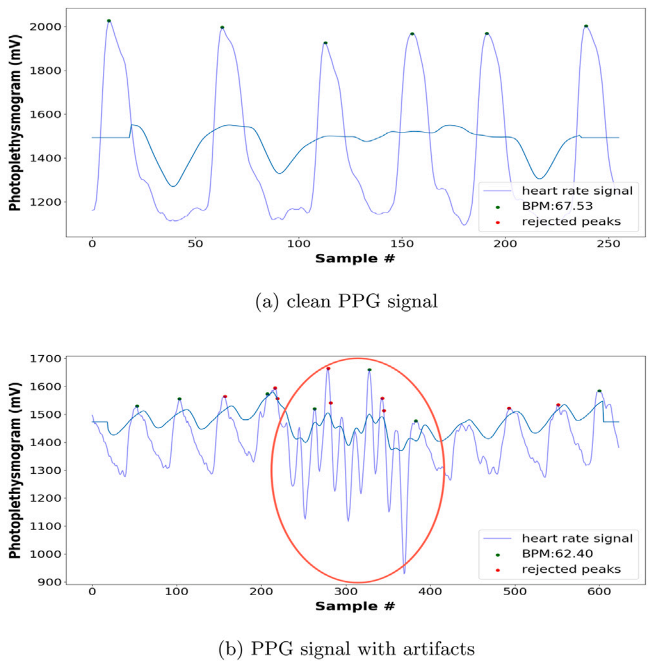


Fig. 1. Processing two PPG signals using the HeartPy library developed in [3].

One of the challenges of using PPG-based monitoring methods is the PPG signals' inaccuracy during daily routine activities and physical exercises. This restriction is based on the fact that PPG signals are highly vulnerable to hand motion artifacts and environmental noise [2]. Examples of clean PPG and PPG with artifacts are shown in Fig. 1. The estimation of heart rate variability data is strongly affected by artifacts. These artifacts' existence has consequences for anyone who relies on such data for higher-level analysis and is likely to waste storage space on meaningless data.

The aim of this paper is to address the artifacts in PPG data. The problem can be conceived as anomaly detection since the artifacts can be viewed in a PPG signal as anomalies. The difference between denoising a PPG signal and removing artifacts is important to note. An area containing artifacts such as in Fig. 1(b) is an area where features such as heart rate variability and heart rate cannot be extracted. In contrast, those features can still be extracted with confidence if the signal contains an acceptable noise level.

The ability to detect anomalies in a data stream has become possible with the advances of deep learning and Neural Networks (NNs). Deep learning methods like Convolution Neural Network (CNN), autoencoders, and Long Short-Term Memory (LSTM) have been commonly used for anomaly detection problems [4]. This paper proposes an unsupervised deep learning architecture based on a CNN-LSTM autoencoder that can detect artifacts in a PPG signal. Moreover, it proposes a sequence summarization approach for neural networks using the discrete wavelet transform (DWT) that enhances the training speed and helps to avoid the problem of vanishing gradients, as well as a data augmentation procedure for PPG data which enables a better generalization of the model.

The rest of this paper is as follows. Section 2 discusses various works based on PPG processing in wearable applications. Section 3 gives a background information on the discrete wavelet transform and explains how an autoencoder can be used for anomaly detection. Sections 4 and 5 respectively explain the proposed data augmentation approach and deep learning architecture. Section 6 presents the experimental results. Section 7 discusses some of the open problems regarding the proposed solution and the conclusion is presented in Section 8.

2. Related work

Different research work in the literature tackled the processing and analysis of PPG data in the context of wearables and IoT. In [5], the technology of photoplethysmography and its potential applications was reviewed. This review focused on two important stages when dealing with PPG data: pre-processing and feature extraction.

Van Gent et al. did extensive work on analyzing and processing PPG. They developed the HeartPy library which works well with noisy PPG data [3]. The developed algorithm can extract the heart rate from the raw data and estimate the breathing rate. Additionally, they proposed a method that uses the R–R intervals and R-peaks to detect error/artifacts in the data [6]. In [7], the authors proposed a neural network model to enhance PPG measurements containing artifacts. The proposed approach consists of a global reference template reflecting a subject's clean heartbeat morphology prestored in the system memory. The reference template is derived through a beat quality assessment method from the current data's acceptable quality beats. The extracted template should

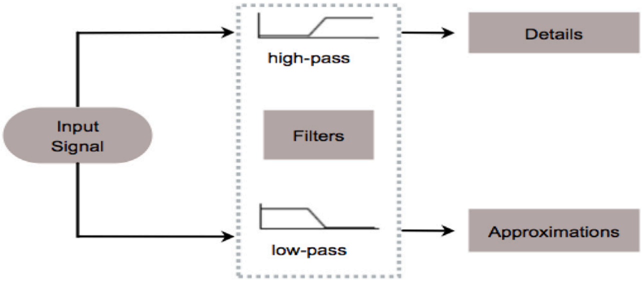


Fig. 2. Discrete wavelet transform frequency portions of signal.

reflect the subject's clean heart beats morphology for the neural network to work well. In [8], the authors used frequency-domain analysis techniques such as fast Fourier transform and band-pass filtering to process PPG data. They referred to an adaptive echo cancellation method to remove the motion artifacts from the signal. The authors in [9] proposed to use the singular spectrum analysis and a spectral subtraction technique to reduce the corruption in the signal and remove the artifacts. The authors used the artifact-related 3-D accelerometer signal as an additional information to help eliminate the artifacts. Different other approaches have been proposed in [10–14] that use independent component analysis, and Kalman smoother, wavelets, and adaptive filters to reduce the artifacts from PPG data.

Recently, deep learning methods for artifact filtering and noise reduction have gained a lot of attention in time series. An LSTM network-based architecture for automatic artifact detection in Microelectrode Recording (MER) signals was proposed in [15]. A 1-dimensional fully convolutional autoencoder was proposed in [16] for noise reduction in gravitational-wave data, and different other techniques were recently proposed in [17–19] for similar purposes.

Compared to the above approaches, the contribution of this paper consists in detecting and removing the windows where the data are meaningless and do not denoise or enhance the signal. The removal of these windows happens in an unsupervised manner without extra information from other types of data or manually crafted features.

3. Background

3.1. Discrete wavelet transform

The Discrete Wavelet Transform (DWT) allows a signal to be represented in a time–frequency domain. It divides the signal into components of low frequency (approximations) and components of high frequency (details) by using filters, as shown in Fig. 2.

The inspiration to use the DWT lives in transforming redundant samples in the temporal domain into decorrelated coefficients in the time–frequency domain, enabling the original samples to be compacted and represented with less coefficients [20–22]. This process, therefore, helps facilitate the analysis of certain original data set features.

DWT has been used in different research works for time series classification tasks [23,24]. Usually, accuracy is evaluated in accordance with other criteria when comparing several competing classification approaches. The classification algorithm's computation time (speed) is probably the second most important criterion, particularly for time series data. Since DWT produces several signal decompositions, the classification methods can be applied to the wavelet-transformed domain at a specific level. Compared to the original data, the wavelet coefficients are sets of smaller sizes, and therefore the computation speed of the classification method can be increased.

3.2. Autoencoder-based anomaly detection

An autoencoder is a particular type of neural network which copies the input values into the output values. It consists of two modules, the encoder, and the decoder. The encoder is learning a process's latent space representation. Typically, the latent features are in a smaller dimension. From these underlying features, the decoder can reconstruct the original data. The autoencoder can be used for anomaly detection problems. This is done by learning the pattern of a normal process. A given input that does not follow this pattern is then categorized as an anomaly since the model will find it different from what it has learned during the training phase. The reconstruction error is the metric used to evaluate a given input. By defining a threshold, an input vector can be labeled as an anomaly if the difference between this input's values and the output exceeds the threshold. Autoencoder-based anomaly detection can be used to process different data types, such as images and time series. Therefore it can contain convolution layers (CNN autoencoder), long short-term memory layers (LSTM autoencoder), or a combination of both (CNN-LSTM autoencoder).

Numerous recent works have been proposed to address anomaly detection and waveform distortions using autoencoders in physiological signals such as the ECG. In [25], the authors proposed a stacked autoencoder architecture for the detection and correction of ECG heartbeats outliers. The authors in [26] proposed a variational autoencoder parameterized by Bidirectional LSTMs for unsupervised representation learning and anomaly detection in ECG sequences. In [27], an LSTM-autoencoder was proposed for multi-sensor anomaly detection. The authors used the reconstruction model trained with normal time-series to detect anomalies in time series.

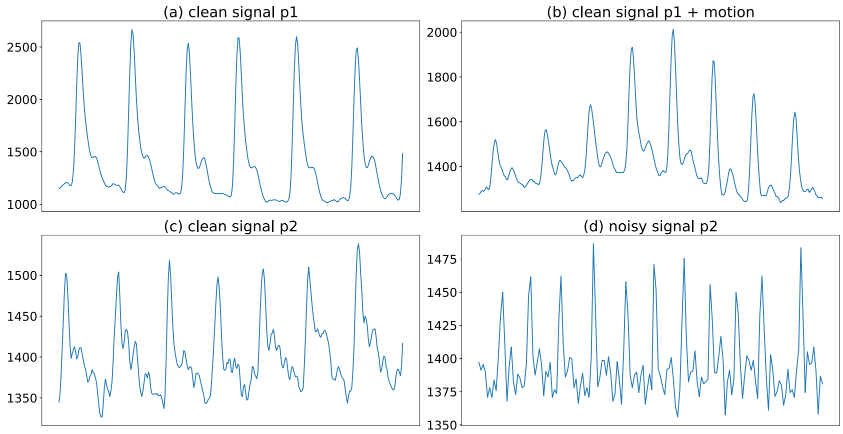


Fig. 3. Example of real world PPG signals.

4. Data augmentation

The data augmentation approach used in this paper is to apply various types of noise to the existing time series. The purpose of data augmentation is to prevent overfitting and enhance a deep learning model's generalization ability. Different data augmentation approaches have been proposed in the literature, such as in [28]. While working with medical signals such as PPG, the main challenge is to ensure that the signal produced follows the samples' temporal order and the original signal's form/shape. In other words, the peaks should still be easy to detect, and the time between two consecutive peaks should stay the same so that the same features can be derived from the newly generated data as from the original data. To make it clear, a Shimmer3 GSR+Unit was used to obtain PPG signals from two individuals in the Femto-ST laboratory. Four different PPG windows are shown in Fig. 3, two of them containing noise. Even though the signals in (a) and (c) are clean, still, the waveform is slightly different, and more significantly, the voltage magnitude is different because the signals are taken from two different persons (p1 and p2). Fig. 3(b) shows how the peaks no longer have the same magnitude when p1 gradually moves his hand. Fig. 3(d) shows the obtained signal when the sensor is poorly positioned on the finger of p2. It is important to note that all of the signals shown in Fig. 3 are meaningful and therefore, relevant information can be extracted from them. The following data augmentation approaches aim to simulate the noise and variations found in the real world PPG signals.

4.1. Gaussian and uniform noise

Uniform noise has a flat distribution that ranges between 0 and 1, which means that it is equally likely to draw all values between 0 and 1. Normally distributed noise, or Gaussian noise, has a zero-centered "bell-curve" distribution, with most values clustered to zero. Through adding and multiplying by some constants, the distribution of both uniform and Gaussian noises can be shifted and stretched. Such constants are carefully selected to keep the produced signal analyzable and meaningful, and their values depend on the application and the available data.

4.2. Scaling and magnitude-warping

The scaling approach adjusts the magnitude of the data in a batch by multiplying by a random scalar, while magnitude-warping adjusts the magnitude of each sample in this batch by convolving the data with a smooth curve that varies around one. These two approaches were inspired by the work proposed in [28]. The results of applying scaling and magnitude-warping to a PPG time series are shown in Fig. 4.

4.3. Pink and brownian noise

Pink noise, also known as fractal noise or $\frac{1}{f}$ noise, has a power spectrum that decreases as the frequency increases. Pink noise is weighted toward low frequencies, as its power decreases like $\frac{1}{f}$. The application of a vanishing frequency filter is one way to compute pink noise.

Brownian noise lowers the higher frequencies more than the pink noise. It is also known as random walk noise and is calculated by integrating random noise that is normally distributed. Brownian noise has a memory, which means that its past values influence each time point. Fig. 5 shows the results of adding pink and Brownian noise to a PPG time series. Although the shape of the time series has been affected, it is still possible to extract the relevant features.

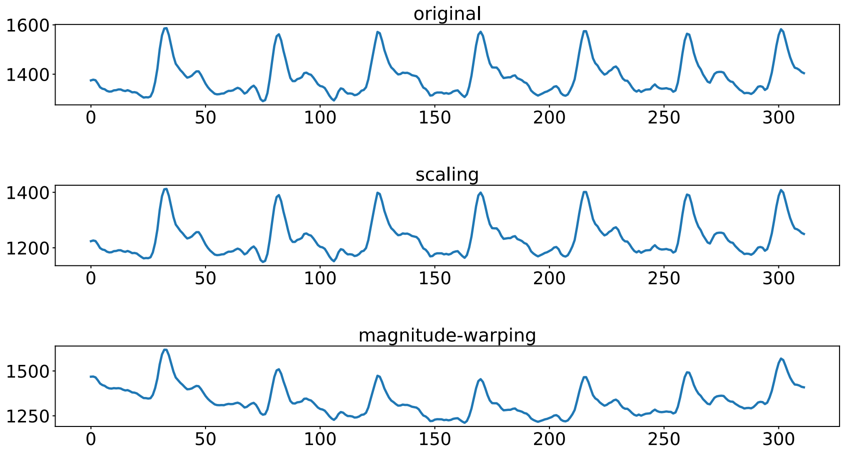


Fig. 4. Applying scaling and magnitude-warping to a PPG time series.

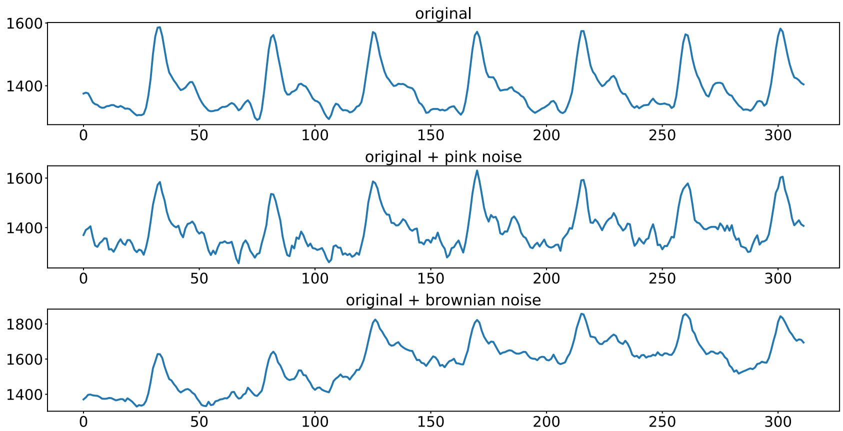


Fig. 5. Adding pink and Brownian noise to a PPG time series.

5. Our proposed neural network model

In this paper, we propose the use of a hybrid model, namely CNN-LSTM autoencoder, to detect the artifacts in a signal in an unsupervised manner. Given that PPG data are time series and do have a temporal structure, an interesting approach is to use a model based on LSTM. Furthermore, CNN layers have been used as a front end to the LSTMs and serve for feature extraction. If input sequences are very long, such as a PPG trace of hundreds of time steps, LSTMs can be difficult to use. The first problem of dealing with long sequences is the very long time required to train the model. Additionally, the backpropagation through long input sequences can lead to vanishing gradients and, in turn, an unlearnable model. The first step in this paper's proposed solution is to address the issue of long input sequences. Note that the goal is to check that a PPG data window is clean or contains artifacts, and that a window can contain hundreds to thousands of data points. The approach taken is sequences summarization using the Discrete Wavelet Transform (DWT). In natural language processing, where input sequences are words, and summarizing sequences have been used, it might be possible to eliminate all words from input sequences above a defined word frequency. Instead of removing samples from the data, the use of the DWT will introduce a more compact version of the signal to the neural network. It can be viewed as a summary of the original signal with fewer data points. For example, if we take a PPG signal with a length of 312 as shown in Fig. 6, applying one-level decomposition will result in a set of 156 approximation coefficients and 156 detail coefficients. Then another decomposition can be applied to the approximations obtained, resulting in 78 approximation and detail coefficients. The model will then be trained on the approximation coefficients, and the details will be discarded. As a result, the learning speed could be improved, and the problem of the vanishing gradient avoided.

The proposed architecture takes as inputs a fixed-length vector with shape $\langle S, T, 1\rangle$, where S is the number of data windows in a mini-batch, and T is the number of samples in each data window. Note that the data are standardized before being initialized to the model. The encoder part is made up of a 1D convolution layer with a kernel size of 5 and 320 feature maps, followed by a 1D max pooling layer with a pool size of 4 and a dropout layer with a rate of 40%. The output of the convolution layer is then flattened and fed into a bidirectional LSTM layer with 256 units, followed by a second dropout layer. Bidirectional LSTMs help to get the

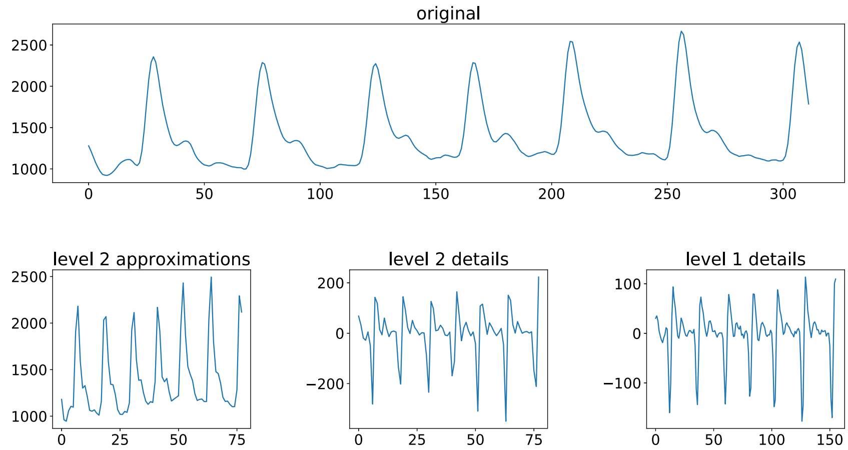


Fig. 6. Example of the two-level decomposition of a PPG signal.

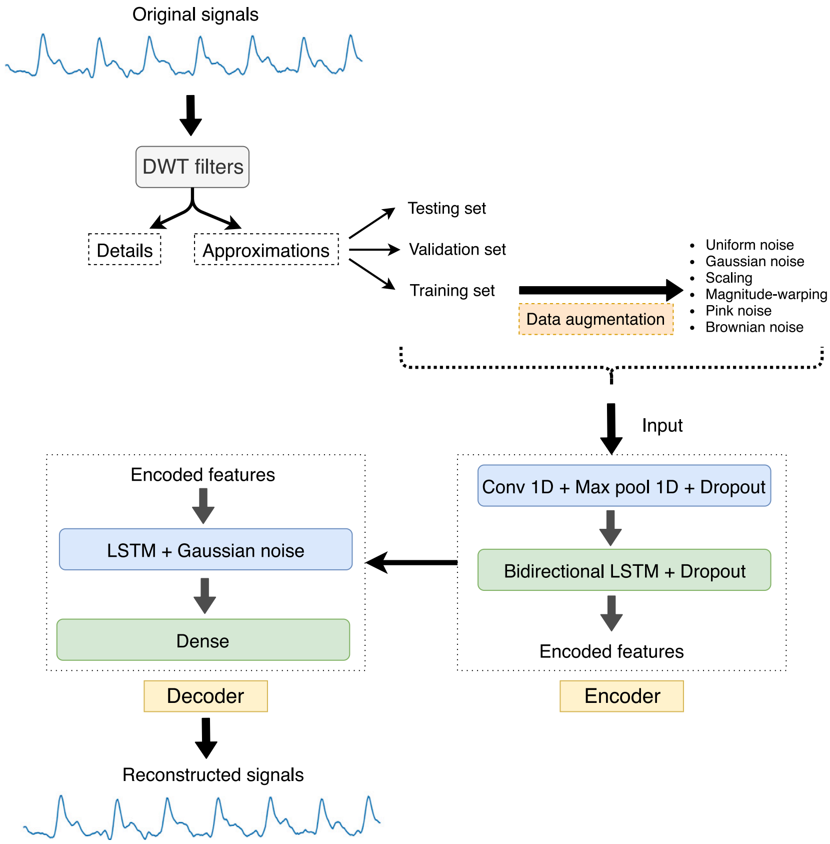


Fig. 7. Proposed neural network approach for unsupervised PPG artifacts detection using CNN-LSTM Autoencoder.

most out of the input sequence by stepping through input time steps in both the forward and backward directions. The decoder part consists of an LSTM layer with 192 units followed by a Gaussian noise layer for regularization and a time distributed dense layer. The linear activation function has been used for the output dense layer and the Rectified Linear Units (ReLu) for the convolution and LSTM layers. Additionally, the He normal initialization [29] was used for weights initialization, the mean squared error was used as a loss function, and Adam as optimizer with gradient clipping to avoid exploding gradients. Fig. 7 illustrates the proposed approach used for unsupervised PPG artifacts detection. Note that the data augmentation described in Section 5 is applied to the training set after applying the wavelet transform on the original signals and splitting the resulting approximations into training, validation, and testing sets. Then the model is trained only on clean PPG signals and tested on mixed PPG signals.

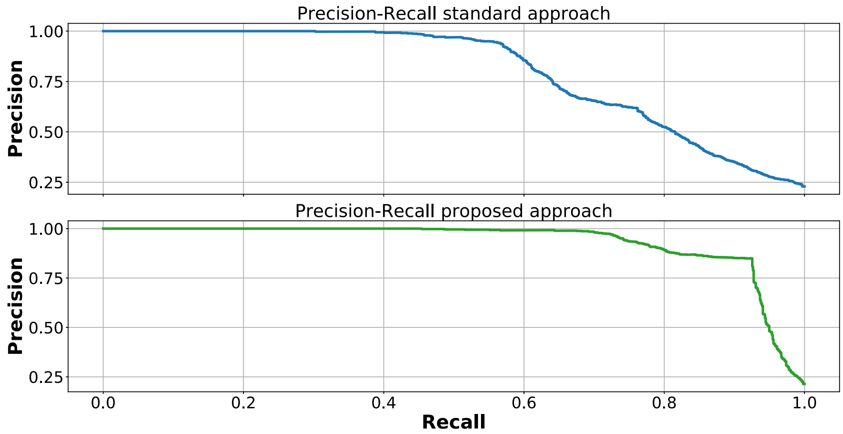


Fig. 8. Precision and recall for different threshold values.

6. Experimental results

The PPG data set was collected from two doctoral students using Shimmer3 GSR+Unit with a sampling frequency of $Fs = 52$ Hz in the Femto-ST laboratory department DISC, Belfort, France. The data is collected in a controlled environment where the students are asked to move their hands gradually or to adjust the PPG sensor to generate a signal noise (or signal noises?). Likewise, they were told to walk or move their hands quickly to get meaningless windows in the signal. An overlapping sliding window was used to split the collected data set into batches, resulting in a training set containing 10,212 batches of clean PPG and 3149 batches of artifacts, a validation set containing 4358 batches of clean PPG and 1369 batches of artifacts, and a test set containing 150 unlabeled windows of clean PPG and artifacts.

In the experimentation, two strategies are considered. The first is to use PPG recording windows of 3 s ($Fs \times 3 = 156$ samples), so the model's input will be a tensor of shape $\langle S, 156, 1\rangle$. The second strategy is the proposed one, which takes larger PPG recording windows of 6 s (312 samples) and then applies two-level decomposition on these windows to reduce their length. As a result, the model's input will be a tensor of shape $\langle S, 78, 1\rangle$. Notice that the windows size selection and the number of decompositions are based on empirical testing; these factors may differ from one application to another. The main challenge here is that it is quite common to have problems with underflow/overflow during the early stages of the training by taking windows of large time steps. The argument to be made is that the proposed summarization step allows working with larger windows (more than 4 s windows), which is more effective in capturing meaningless windows in the signal while trying to avoid the problems encountered with long input sequences and reducing the training time. This can be achieved because the summarization step decreases the size of the input sequences while retaining the same details in the larger sequences. The data augmentation process has been applied to the second strategy only in order to assess its advantage on the final output. The computations were performed on an NVIDIA Tesla Titan X GPU.

In order to determine how beneficial it can be to train the model on wavelet approximations and to augment the data compared to the standard approach, the Precision vs. Recall and Receiver Operating Characteristic (ROC) curves were used. Precision defines the number of positive class predictions (artifacts) that actually belong to the positive class. Recall defines the number of correct positive class predictions made out of all positive examples in the data set. Precision and recall metrics serve as alternatives to the accuracy metric defined as the total number of correct predictions divided by the total number of predictions provided that the classes are imbalanced in this data set. The ROC curve illustrates the trade-off between the true positive rate and the false-positive rate for a model using different thresholds. The Precision vs. Recall curve illustrates the trade-off between the true positive rate and the positive predictions for a model using different thresholds. Note that high precision is associated with a low false-positive rate, and high recall is associated with a low false-negative rate. The thresholds in the curves are the autoencoder reconstruction error, and the desired outcome is a model with high scores for both metrics (high precision and high recall).

Fig. 8 shows that a better balance between recall and precision could be achieved by the proposed approach. If the model is trained on three seconds PPG windows with no data augmentation, the model will have a precision of less than 0.4 in order to achieve a recall greater than 0.9 while the model was able to have a precision of 0.9 with a recall greater than 0.9 when trained on six seconds compacted PPG windows with data augmentation. During the experiments, it was noticed that the larger the data window, the easier it was for the model to detect anomalies since large PPG windows contain more features and enable the model to learn more about the regular shape of PPG signals. The improved results of the proposed approach can be explained by the fact that we can allow the model to learn the patterns and shape of larger windows of PPG data from a summarized version by using the discrete wavelet transform.

Fig. 9 shows that the proposed approach has a higher area under the ROC curve (AUC) than the standard approach. Note that a model with an AUC higher than 0.5 is better than a random classifier. Selecting a threshold that gives a true positive rate greater than 0.9 and a false positive rate close to 0 is possible when using data augmentation.

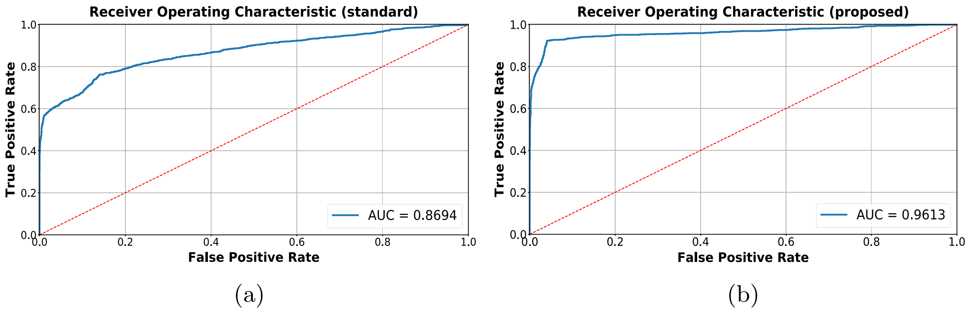


Fig. 9. Receiver operating characteristic curves for the standard and proposed approaches.

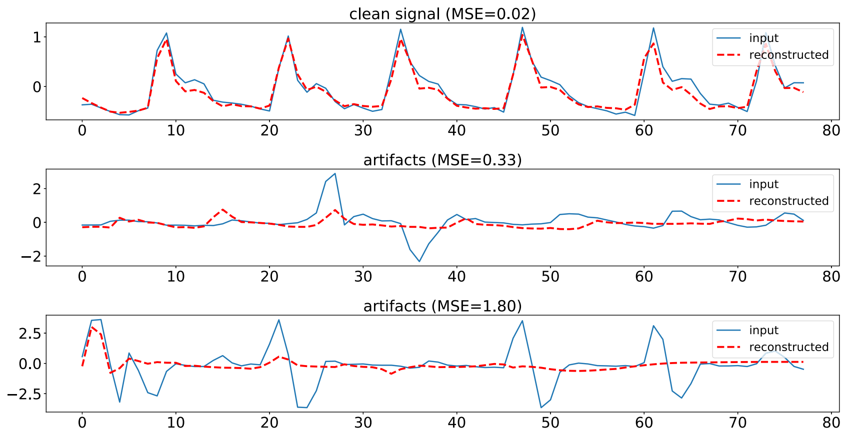


Fig. 10. Examples of mean squared error obtained when clean PPG signals and artifact signals are reconstructed.

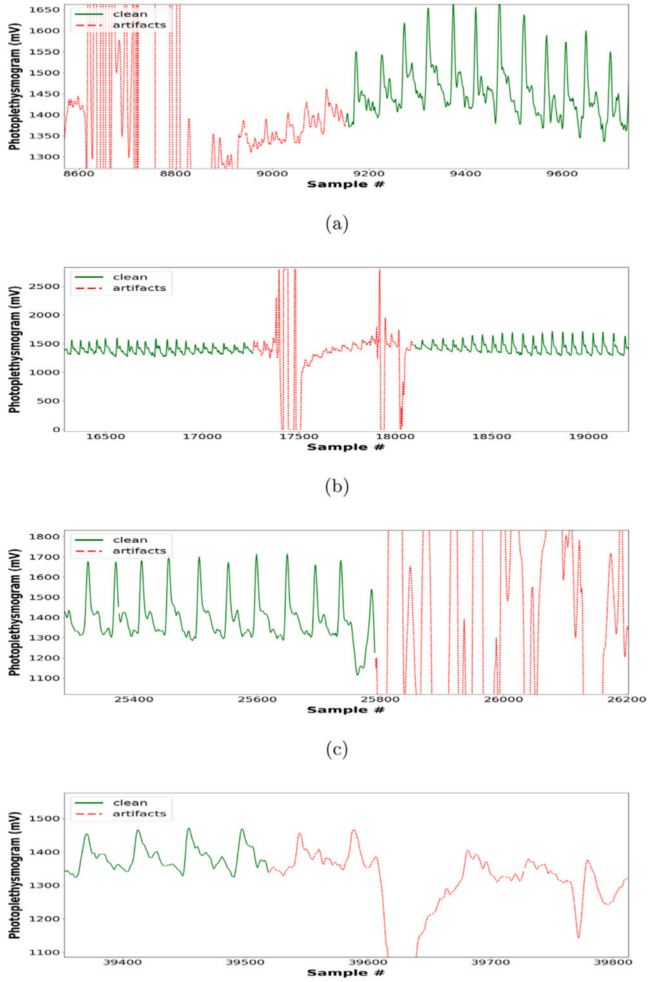
In order to define whether or not a PPG signal is valid, the cut point was defined as 0.06; this threshold is based on the last training loss value obtained during the training. If the mean squared error between the reconstructed signal and the input exceeds this threshold, then this signal is marked as a meaningless PPG signal. Fig. 10 shows the reconstruction of one clean PPG signal and two irrelevant signals. The mean squared error when the signal is clean is 0.02, while it exceeds the threshold value for the other two signals. It was noticed that there was a reconstruction error greater than 0.1 in most PPG signals with artifacts.

The trained model was tested on the test set containing a mix of clean and irrelevant PPG windows. The test set is unlabeled, so a visual assessment was needed to verify the model's efficacy. Fig. 11 displays four different parts taken from the test set. The green zone is where the model predicted the signal as clean and the red zone as artifacts. From the figures, it can be seen that the model can efficiently predict the irrelevant PPG windows where it is difficult to extract important features. This paper, in addition to summarizing data, proposed a data augmentation process for medical time series collected from wearable devices and sensors to increase the amount of training data and make the model more robust to noise.

7. Discussion

The target problem of this work is the problem of artifacts and meaningless windows present in PPG signals. The key drawback of such work is the small amount of training data that represent the meaningful PPG windows, even though they contain noise. It is hard to predict how the noise would ultimately impact the signal, given the multiple factors that can result in a noisy signal, such as the sensor's bad positioning. From the preliminary experiment referred to as the standard approach (Fig. 9a), it can be found that the precision–recall trade-off is not optimal. The results showed that the proposed data augmentation and summarization approaches helped achieve better results using deep learning by introducing different types of noise (Fig. 9b). Note that the waveform of the signal can vary from one person to another due to various reasons, such as sensor placement. Therefore, the data augmentation step helped to introduce more variations of PPG windows to the model.

Many problems regarding the proposed solution could be further addressed. For example, a sampling frequency of $Fs = 52$ Hz was considered in the experiments. However, greater sampling frequency $Fs > 500$ Hz could be used in reality, which results in very long sequences and may affect the performance of the deep learning model. In that case, more wavelet decomposition could be applied to better summarize the data. Another problem that could be addressed is the problem of false positives, as seen in Fig. 8. It can be noticed that the precision value drops to 0.9 when the recall bypasses 0.85, which means that several PPG windows could be falsely predicted as artifacts.



(a)

(b)

(c)

(d)

Fig. 11. Four windows taken from the test set showing the prediction results obtained from the trained model.

8. Conclusion

This paper proposed a deep learning model for automatic motion artifacts detection from photoplethysmography. Before training the model, two major steps were taken that helped to achieve better results. First, a data summarization step was applied to the input data through the discrete wavelet transform to reduce the sequences' length and avoid vanishing gradients. As a result, summarizing large windows can allow the model to learn the same patterns while processing fewer data points; the model can learn patterns better from large data windows than small ones.

Finally, a CNN-LSTM autoencoder architecture was proposed to detect and discard irrelevant windows in photoplethysmogram signals to avoid analyzing and processing meaningless data. This paper's findings show that the proposed approaches to data summarization and augmentation helped improve the performance of the neural network and were able to achieve 90% precision and 95% recall. The proposed method in this paper can be generalized for various types of medical time series such as electrocardiogram (ECG) data in addition to periodic sensory data.

In our future work we intend to compare the proposed deep learning architecture with other architectures and explore the generative adversarial network for artifact filtering. Also, collecting more data with different sampling rates and conducting various experiments may help obtain better results and decrease false positives.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is partially funded with support from the Hubert Curien CEDRE, France programme n40283YK and the EIPHI Graduate School, France (contract ‘‘ANR-17-EURE-0002’’). Computations have been performed on the supercomputer facilities of the ‘‘Mésocentre de calcul de Franche-Comté’’.

References

[1] Pantelopoulos A, Bourbakis NG. A survey on wearable sensor-based systems for health monitoring and prognosis. IEEE Trans Syst Man Cybern 2010;40(1):1–12. http://dx.doi.org/10.1109/TSMCC.2009.2032660.
[2] Castaneda D, andMohammad Ghamari AE, Soltanpur C, Nazeran H. A review on wearable photoplethysmography sensors and their potential future applications in health care. Int J Biosens Bioelectron 2018;4(4):195–202.
[3] van Gent P, Farah H, van Nes N, van Arem B. Heartpy: A novel heart rate algorithm for the analysis of noisy signals. Transp Res 2019;66:368–78. http://dx.doi.org/10.1016/j.trf.2019.09.015.
[4] Kwon D, Kim H, Kim J, Suh SC, Kim I, Kim KJ. A survey of deep learning-based network anomaly detection. Cluster Comput 2019;22(1):949–61. http://dx.doi.org/10.1007/s10586-017-1117-8.
[5] Elgendi M. On the analysis of fingertip photoplethysmogram signals. Curr Cardiol Rev 2012;8(1):14–25.
[6] van Gent P, Farah H, van Nes N, van Arem B. Analysing noisy driver physiology real-time using off-the-shelf sensors: Heart rate analysis software from the taking the fast lane project. J Open Res Softw 2018;7(1):32.
[7] Singha Roy M, Gupta R, Chandra JK, Das Sharma K, Talukdar A. Improving photoplethysmographic measurements under motion artifacts using artificial neural network for personal healthcare. IEEE Trans Instrum Meas 2018;67(12):2820–9. http://dx.doi.org/10.1109/TIM.2018.2829488.
[8] Cennini G, Arguel J, Akşit K, van Leest A. Heart rate monitoring via remote photoplethysmography with motion artifacts reduction. Opt Express 2010;18(5):4867–75. http://dx.doi.org/10.1364/OE.18.004867.
[9] Askari MR, Rashid M, Sevil M, Hajizadeh I, Brandt R, Samadi S, Cinar A. Artifact removal from data generated by nonlinear systems: Heart rate estimation from blood volume pulse signal. Ind Eng Chem Res 2019.
[10] Bacà A, Biagetti G, Camilletti M, Crippa P, Falaschetti L, Orcioni S, Rossini L, Tonelli D, Turchetti C. CARMA: A robust motion artifact reduction algorithm for heart rate monitoring from PPG signals. In: 2015 23rd European Signal Processing Conference (EUSIPCO). 2015, p. 2646–50. http://dx.doi.org/10.1109/EUSIPCO.2015.7362864.
[11] Kim B, Yoo SK. Motion artifact reduction in photoplethysmography using independent component analysis. IEEE Trans Biomed Eng 2006;53(3):566–8. http://dx.doi.org/10.1109/TBME.2005.869784.
[12] Lee B, Han J, Baek HJ, Shin JH, Park KS, Yi WJ. Improved elimination of motion artifacts from a photoplethysmographic signal using a Kalman smoother with simultaneous accelerometry. Physiol Meas 2010;31(12):1585–603. http://dx.doi.org/10.1088/0967-3334/31/12/003.
[13] Raghuram M, Venu Madhav K, Hari Krishna E, Ashoka Reddy K. Evaluation of wavelets for reduction of motion artifacts in photoplethysmographic signals. In: 10th International Conference on Information Science, Signal Processing and their Applications (ISSPA 2010). 2010, p. 460–3. http://dx.doi.org/10.1109/ISSPA.2010.5605443.
[14] Ram M, Madhav KV, Krishna EH, Komalla NR, Reddy KA. A novel approach for motion artifact reduction in PPG signals based on AS-LMS adaptive filter. IEEE Trans Instrum Meas 2012;61(5):1445–57. http://dx.doi.org/10.1109/TIM.2011.2175832.
[15] Hosny M, Zhu M, Gao W, Fu Y. A novel deep LSTM network for artifacts detection in microelectrode recordings. Elsevier; 2020,
[16] Ormiston R, Nguyen T, Coughlin M, Adhikari RX, Katsavounidis E. Noise reduction in gravitational-wave data via deep learning. 2020, arXiv preprint arXiv:2005.06534.
[17] Lee SS, Lee K, Kang G. EEG Artifact removal by Bayesian deep learning & ICA. In: 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE; 2020, p. 932–5.
[18] McIntosh JR, Yao J, Hong L, Faller J, Sajda P. Ballistocardiogram artifact reduction in simultaneous EEG-fMRI using deep learning. IEEE Trans Biomed Eng 2020.
[19] Ban B, Ryu D, Lee M. Deep Learning Method to Remove Chemical, Kinetic and Electric Artifacts on ISEs. 2020.
[20] Azar J, Habib C, Darazi R, Makhoul A, Demerjian J. Using adaptive sampling and DWT lifting scheme for efficient data reduction in wireless body sensor networks. In: 2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). 2018, p. 1–8. http://dx.doi.org/10.1109/WiMOB.2018.8589093.
[21] Azar J, Darazi R, Habib C, Makhoul A, Demerjian J. Using DWT lifting scheme for lossless data compression in wireless body sensor networks. In: 2018 14th International Wireless Communications Mobile Computing Conference (IWCMC). 2018, p. 1465–70. http://dx.doi.org/10.1109/IWCMC.2018.8450459.
[22] Azar J, Makhoul A, Couturier R, Demerjian J. Robust IoT time series classification with data compression and deep learning. Neurocomputing 2020.
[23] Tzanetakis G, Cook P. Musical genre classification of audio signals. IEEE Trans Speech Audio Process 2002;10(5):293–302. http://dx.doi.org/10.1109/TSA.2002.800560.
[24] Subasi A. Epileptic seizure detection using dynamic wavelet network. Expert Syst Appl 2005;29(2):343–55. http://dx.doi.org/10.1016/j.eswa.2005.04.007.
[25] Karpinski M, Khoma V, Dudvkevych V, Khoma Y, Sabodashko D. Autoencoder neural networks for outlier correction in ECG-based biometric identification. In: 2018 IEEE 4th International Symposium on Wireless Systems Within the International Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS). IEEE; 2018, p. 210–5.
[26] Pereira J, Silveira M. Unsupervised representation learning and anomaly detection in ecg sequences. Int J Data Min Bioinform 2019;22(4):389–407.
[27] Malhotra P, Ramakrishnan A, Anand G, Vig L, Agarwal P, Shroff G. LSTM-Based encoder-decoder for multi-sensor anomaly detection. 2016, arXiv preprint arXiv:1607.00148.
[28] Um TT, Pfister FMJ, Pichler D, Endo S, Lang M, Hirche S, Fietzek U, Kulic D. Data Augmentation of Wearable Sensor Data for Parkinson's Disease Monitoring using Convolutional Neural Networks. 2017, CoRR abs/1706.00527. arXiv:1706.00527.
[29] He K, Zhang X, Ren S, Sun J. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. 2015, CoRR abs/1502.01852. arXiv:1502.01852.

Abdallah Makhoul is a Full Professor in Computer Science at University of Franche-Comte and a member of the computer science department (DISC) of FEMTO-ST institute. From 2009 to 2019, he has been an Associate Professor at University of Franche-Comte. His research interests include distributed algorithms, Internet of Things (IoT), Wireless Sensor Networks and Programmable Matter.

Raphael Couturier is a Full Professor at University of Franche-Comte (UFC), France.

Jacques Demerjian has received his Ph.D. degree in Network and Computer Science from TELECOM ParisTech (ENST-Paris) in 2004. Dr. Demerjian is a Full Professor at the Faculty of Sciences at the Lebanese University in Lebanon. His main research interests include Human–Computer Interaction, Streaming Data Quality and Summarization, Mobile Cloud Computing, VANET, Body Sensor Network, Data Mining and Wired and Wireless Network Security.