Bidirectional Long Short-term Memory Neural Networks Based Electrocardiogram Biometric System

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***Abstract*—the emerging long short-term memory neural networks (LSTM) are the widely used type of recurrent neural networks (RNN). A novel ECG biometric method based on the ensemble empirical mode decomposition (EEMD) and instantaneous frequencies extracted by the Hilbert-Huang transform (HHT) is presented. Deep learning and bidirectional long short-term memory neural networks were used for classification. The performance of the system was evaluated using PTB Diagnostic ECG Database. A testing accuracy of 89.33% was achieved when the evaluation was done with the full database and an accuracy of 97.42% is achieved when the evaluation was done with 5 subjects. The main goal of this paper is to confirm the effectiveness of using instantaneous frequencies as a feature for biometric identification.**

***Index Terms*—ECG biometrics; ensemble empirical mode decomposition; Hilbert-Huang transform; instantaneous frequencies; BiLSTM**

I. Introduction

Biometrics is the science of studying and analyzing biological data for identification and authentication purposes. Biometric modalities and parameters can be divided into three major categories, physiological modalities such as fingerprint [1] and iris [2], behavioural traits like signature [3] and finally hidden modalities mainly ECG [4] and EEG [5]. In this paper we will propose a novel method that relies on the Hilbert-Huang transform (HHT) [6] which is a relatively new technique to extract the instantaneous frequencies of the electrical heart activity (ECG), then we will integrate this method into a biometric identification system, alongside the ensemble empirical mode decomposition (EEMD) for signal decomposition and a variety of recurrent neural network (RNN) which is bidirectional long short-term memory (LSTM) for classification. Unlike other neural networks and classifiers, the RNN-based algorithms do not require any prior feature extraction from the signal. ECG is a secure biometric trait as it differs from person to person; even the ECG signal of identical twins is not the same. The empirical mode decomposition (EMD) [6] is a technique that assumes that any signal is composed of multiple intrinsic mode functions (IMFs), but its major drawback is mode mixing which can be defined as the existence of multiple oscillatory modes in a single IMF. This can be avoided by using the ensemble empirical mode decomposition (EEMD) [7]. The EEMD overcome the problem of mode mixing by calculating the EMD of the original signal for a given number of times after adding white Gaussian noise of finite amplitude, then averaging all the resulted IMFs. The main contribution of this work is the use of a bidirectional long short-term memory (LSTM) recurrent neural network (RNN) to classify ECG signals based on the instantaneous frequencies of their IMFs extracted by EEMD. This is the first paper to discuss so, as far as we are aware. The rest of this paper is organised as follows: in Section 2, the proposed system is described. Section 3 discuss the experimental findings, and finally, Section 4 presents the conclusion and the prospects of this paper.

II. PROPOSED SYSTEM

In this section we will discuss the proposed system, the first step is pre-processing and segmentation, the second one is the decomposition of the segment using the EEMD and extracting the instantaneous frequencies of the 3rd and 4th IMFs and the final one is the classification using an LSTM neural network.

A. Used Database Description

The used database for this work is the publically available PTB Diagnostic ECG Database [8]. It has 549 ECG recordings from 290 different people. Each recording includes 15 simultaneously measured signals from the conventional 12 leads.

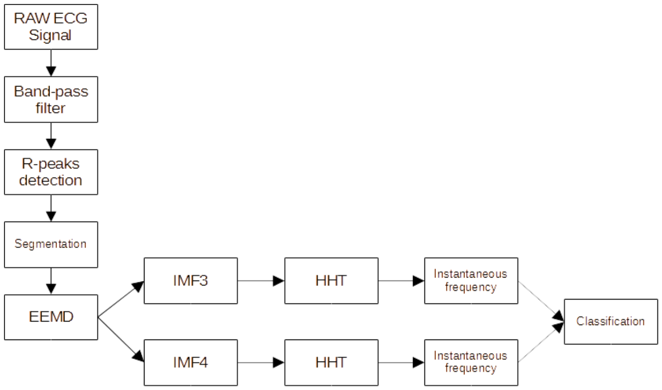

Fig. 1. General organisation of the proposed system

The records are digitalized at 1000 samples per second with 16-bit resolution over a range of ± 16.384 mV. The signals were recorded from 209 men and 81 women aged from 17 to 89. Each participant has between 1 and 5 records.

B. Pre-processing

In general, the ECG signal is contaminated by many types of noises [9] that can be categorized into the following groups: the power line interference that has a frequency of 50 or 60 Hz and a bandwidth of 1 Hz, The baseline wander which is a low-frequency noise (generally between 0.3 and 0.5 Hz), electrosurgical noise which is the noise resulting from the presence of other medical equipment and it varies from 100 kHz to 1 MHz. Other sources of noise include muscle contractions (also known as Electromyography noise), electrode motion artifacts, electrode contact noise and instrumentation noise resulting from the equipment used for the ECG signal acquisition. To reduce the noise from the used ECG signal and improve its equality, a 4th order Butterworth band-pass filter is used, with 1 and 40 Hz as cut-off frequencies.

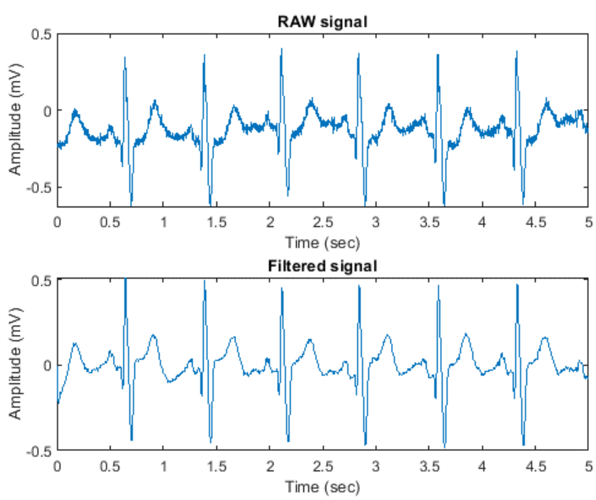

Fig. 2. A 5 seconds segment of the ECG signal before (above) and after (below) the pre-processing step

C. Segmentation

The approach used in this paper for feature extraction is completely non-fiducial. However, we need to index R-peaks throughout the signal using the Pan-Tompkins algorithms [10] in order to segment the raw ECG signal. Those peaks will be used to segment the signal into QRS waveforms.

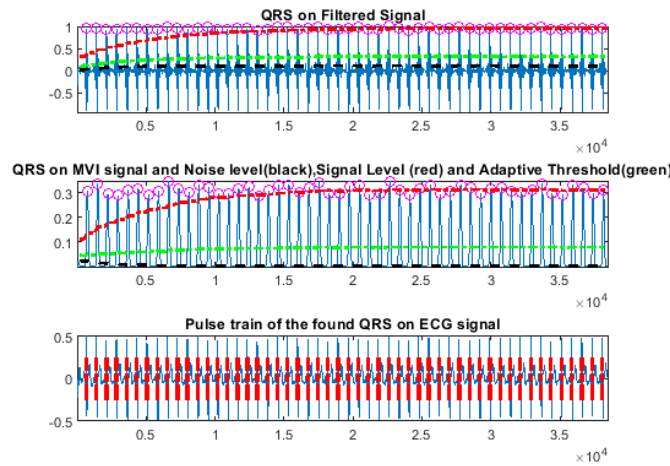

Fig. 3. Detecting R peaks using the Pan-Tompkins algorithm

Once the peaks are detected, 50 samples before and after each peak index are concatenated to create a new vector representing the QRS waveform.

D. Decomposing into IMFs with EEMD

The segmented signal is then decomposed into multiple IMFs using EEMD. The used EEMD settings [11] during this analysis process are 0.1 noise standard deviation and 100 ensemble trials (N).

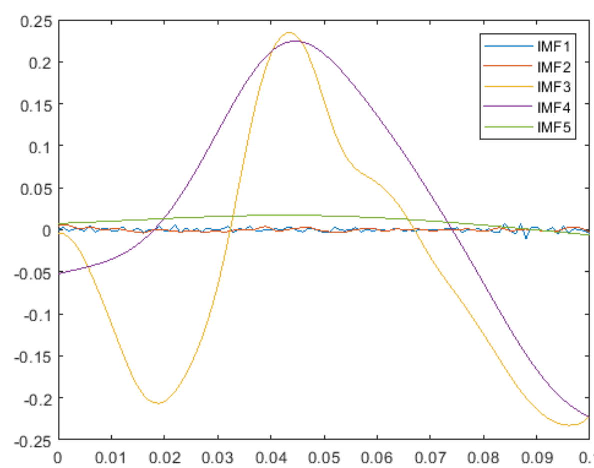

Fig. 4. Example showing the used IMFs alongside the ignored ones

The applied EEMD is calculated according to the following algorithm:

1) Define the parameters: number of ensemble trials, noise standard deviation, and set m=1.
2) Add white Gaussian noise to the input signal.

$$s_1(t) = s(t) + w(t) \tag{1}$$

3) Apply the EMD to the signal with added noise to decompose it to multiple IMFs.
4) Check if m¡N, then m=m+1 and repeat the second and third steps with different white Gaussian noise. If m = N jump to the next step.
5) Calculate the ensemble mean of the N trials for each IMF.

$$IMF_j(t) = \frac{1}{N}\sum_{i=1}^{N} IMF_{i,j}(t) \tag{2}$$

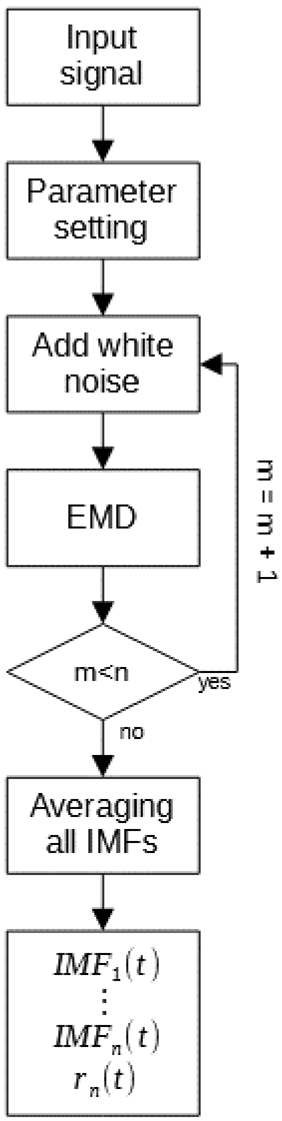

Fig. 5. EEMD algorithm

E. Hilbert-Huang Transform and Instantaneous Frequencies

The traditional signal analysis techniques are based on the assumptions of the linearity and the non-stationarity of the data. However, most of the real-life signals are non-stationary, for this reason, in the last few years researcher are working to develop new methods that are more suitable for non-stationary time-series data analysis. One of the recently developed techniques is the Hilbert-Huang transform. The main objective of the HHT is to explore the time-frequency domain of the studied signals and to express its non-stationarity by extracting the instantaneous frequencies and the instantaneous amplitudes by using the Hilbert spectral analysis. In this study, the instantaneous frequencies are extracted by applying the HHT to each segment extracted from both the 3rd and 4th IMFs obtained using the EEMD technique. The instantaneous frequency can be given by the following formula:

$$\omega_i(t) = \frac{d\theta_i(t))}{dt} \tag{3}$$

The instantaneous frequencies of each ECG segment are then given as input vectors to the bidirectional LSTM cells.

III. RESULTS AND DISCUSSION

To evaluate the proposed method we have used the publicly available PTB Diagnostic ECG database; it contains data from both diseased and healthy subjects. It is a large dataset that contains ECG data collected from 290 different subjects measured from 12 leads as discussed in section II.A. Only the signals obtained from lead I are used for training in our application, as single lead signals are proved to be sufficient for biometric identification [12]. In this paper, a novel method to classify and analyze the ECG signals based on the instantaneous frequencies of their IMFs is proposed. We start the experiment by applying a fourth-order band-pass filter with 1Hz and 40Hz as cut-off frequencies in order to eliminate noises. The second step is using the Pan-Tompkins algorithm to detect the R-peaks of the ECG and segment the signal around those peaks as they are the most prominent ones, the dimension of each segment is 101 samples. After segmentation we decompose each segment into IMFs by applying the EEMD, calculating the EEMD of the whole signal (before segmentation) takes days of execution. Hence, it is desirable to segment the signal to get a reasonable execution time (a few hours). Now we extract the instantaneous frequencies of the 3rd and 4th IMFs of each segment by applying the Hilbert-Huang transform. After the pre-processing, the segmentation and the extraction of the IMFs and instantaneous frequencies, we move to the classification phase. The recordings were randomly separated into 70% of training data, 20% of testing data and 10% of validation data. The classification is done using Bidirectional LSTM which is a variety of RNN; we chose LSTM over other types of neural networks as it is the most suited for classifying signals based on time-series data [13]. We have used two bidirectional LSTM layers for this experiment; the dimension of the hidden units in both layers is set to 100.

TABLE I
LAYERS OF THE PROPOSED NEURAL NETWORK

#	Layer
1	Sequence input with 2 dimensions
2	BiLSTM with 100 hidden units
3	BiLSTM with 100 hidden units
4	20% dropout
5	Fully connected layers
6	Softmax
7	Classification output (cross entropy)

We set the learning rate at 0.001 and the mini-batch size at 150. All of the code implementations are done in MATLAB R2021a and a PC with the following characteristics: Intel i3 M370 processor @ 2.40 GHz, Intel HD integrated GPU and 4GB RAM. The obtained training accuracy is 100% and the test accuracy is 89.33% when classifying all the patients from the database, while an accuracy of 97.42% is achieved when the algorithm is evaluated using 5 subjects. This obtained test accuracy outperforms some of the recent models proposed by researchers as shown in Table II.

TABLE II
COMPARATIVE TABULATION WITH OTHER STATE-OF-THE-ART TECHNIQUES

Authors	**Database**	**Acc. (%)**
Chan et al., 2008 [14]	Private	89
Chee-Ming Ting et Salleh, 2010 [15]	MIT-BIH	87.50
Zhang et al., 2017 [16]	MIT-BIH	91.1
	VFDB	86.6
Lynn et al., 2019 [17]	ECG-ID	98.60
	MIT-BIH	98.40
Narayana et al., 2022 [18]	MIT-BIH ECG-ID	99
Proposed method	PTBDB	89.33
	PTBDB (5 subjects)	97.42

IV. Conclusion

In this paper, we proposed a novel non-fiducial method that relies on the HHT to extract the instantaneous frequencies of the ECG signal, and then we integrated it into a biometric identification system alongside the EEMD for signal decomposition and LSTM for classification The proposed method proves that the instantaneous frequencies of IMFs extracted by the EEMD from the electrical heart activity are reliable and can be used as features when used for biometric identification. The Instantaneous frequencies were directly fed to the neural network. The proposed method shows an acceptable performance with an 89.33% as accuracy rate when tested with the full database. In future works, we will focus on improving the system accuracy by extracting more significant frequency features and investigating how the method performs when tested with different and diverse databases.

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