Deep Convolutional Neural Network for ECG-Based Human Identification

Whitepaper by OMsignal
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***Abstract*—In this work, a deep convolutional neural network (CNN) is developed to focus on human identification problem using electrocardiogram (ECG) signals that are collected by OMsignal apparel from 33 women while doing their daily activities. The signature windows including 10 consecutive heart beats are extracted from the filtered ECG signal to be applied to the CNN model. The CNN is trained by stochastic gradient descent with a categorical cross-entropy loss function. The network performance is evaluated on validation and testing data sets. On validation and testing data sets created from different recordings of the same participants, an overall window accuracy of 95.25% and 95.95% are respectively achieved. Using majority voting classification across all collected windows, 100% of the participants with more than five ECG daily recordings are correctly identified.**

One of the main advantages of this work besides high accuracy and reliability, is to simplify the feature extraction process and to remove the need for detecting ECG signal fiducial points and extracting hand-crafted features unlike conventional methods available in the literature.

I. Introduction

ECG is a low-cost, noninvasive measure of cardiac electrical activity. ECG analysis is a standard diagnostic tool to identify different cardiac disorders. Recently, it has also become a popular and secure tool to recognize individuals besides facial geometry, fingerprints, iris and voice [1]–[3]. Comparing to common commercial biometric systems, ECG-based identification has several advantages such as greater fraud resistance, good accuracy even in abnormal cases, low sensitivity to noise and easy to acquire.

In most of the available literature, multiple features are extracted from the ECG signal fiducial points representing ECG attributes allowing to recognize the specific person using inter-subject variability [4]–[6]. However, the fiducial points detection is an error prone strategy that can be affected by changes of the signal slopes, inverted or abnormal waves, noise and artifacts.

Recently, deep learning (DL) neural networks and in particular Convolutional Neural Networks (CNN) have gained a lot of interest in multi-dimensional signal processing problems due to their strong capabilities in various applications such as object detection and classification in computer vision [7], natural language processing [8], and time-series analysis [9]–[13].

In this work, an automatic and robust deep feature learning process using a convolutional neural network (CNN) is deployed to learn intrinsic features from the raw ECG data to perform human identification without having any complicated feature engineering process. The effectiveness of the proposed algorithm is thoroughly evaluated on 33 women participating in the OMsignal MyHeart project. The participants used OM apparel to record ECG on a daily basis during six weeks. After pre-processing to remove noise and baseline wander, the filtered ECG signal is applied to the CNN. The proposed ECG-based human identification strategy using our CNN model is depicted in Fig. 1.

II. Signature Window Extraction

This section explains how the signature windows are extracted from the ECG signal. Multiple steps are defined as follows to perform signature window extraction:

- Noise reduction and baseline wander removal
- Signal normalization
- Beat segmentation

A. Noise Reduction and Baseline Wander Removal

To compensate for the effects of noise, a wavelet algorithm using the wavelet function *rbio3.7* is utilized to reduce high frequency noise effects. Moreover, the ECG signal baseline wander due to motion artifacts is removed by the use of a median filter with an order corresponding to one second.

B. Signal Normalization

Each beat in the signature window is normalized by:

- Vertical scaling: The amplitudes of signature window samples are scaled to be limited between zero and one.
- Horizontal scaling: Each beat is stretched or compressed to take up exactly 100 samples.

C. Beat Segmentation

The R peaks of an ECG waveform are detected and all non-overlapping data windows of 10 consecutive heart beats are then tested for admissibility. A signature window is constructed using 10 consecutive beats under two certain conditions, as follows:

1) The average heart rate is below 90 BPM over 10 consecutive beats of a signature window,

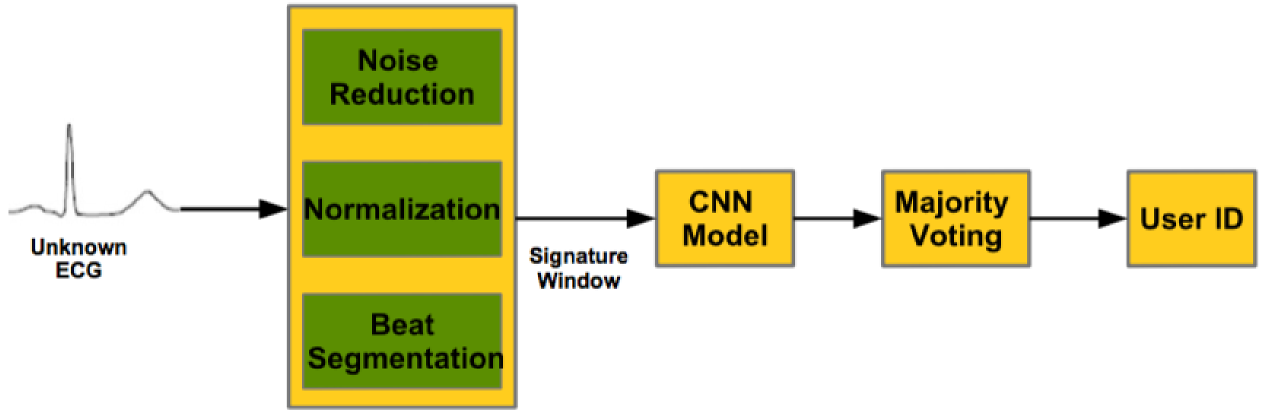

Fig. 1. The overall structure of the ECG-Based Human Identification System using our proposed CNN model.

2) There are at least five beats where the Pearson product correlation coefficient of each one of the five beats with the 10 beats average beat is greater than 0.98.

An example of a signature window after all prepossessing steps is displayed in Fig. 2.

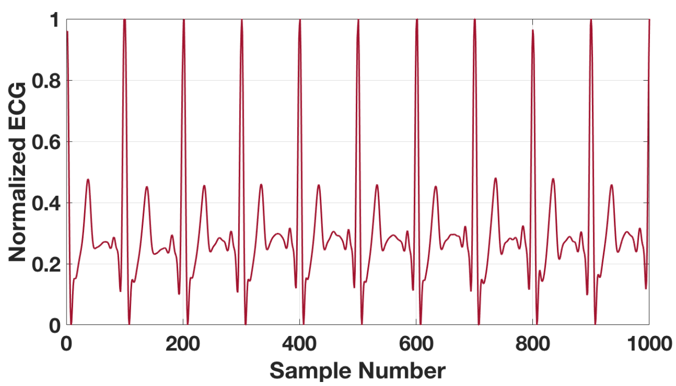

Fig. 2. An example of a signature window after all pre-possessing steps that is applied to the CNN.

III. Convolutional Neural Network Design

Convolutional neural networks (CNN) were initially developed in the 1980s by K. Fukushima [14]. It is the first deep learning approach whose hierarchical layers are trained robustly by means of the stochastic gradient decent algorithm. It is also a popular method for feature extraction and time-series classification.

In this work, a deep CNN structure is designed to perform the human identification task for 33 participants of OMsignal MyHeart project using their ECG signature windows that are extracted in Section II. The CNN is composed of a batch normalization applied on an input window, multiple convolutional layers followed by max-pooling layers, a certain number of fully connected layers as well as a softmax output layer. Batch normalization and dropout layers are also applied after each set of convolutional and max-pooling layers to avoid over-training [15].

TABLE I. The structural and learning parameters for the optimized CNN during the training mechanism.

Parameters	Value
Learning Rate	0.01
Kernel Size	15
Pooling Size	5
Number of Neurons in Fully Connected Layer	400
Batch Size	256
Iteration per Epoch	256
Stopping Epoch	105

The network parameters are trained via the stochastic gradient descent algorithm with the categorical crossentropy loss function. The exponential linear unit (*elu*) and *tanh* are respectively used as the activation functions of convolutional and fully connected layers. The overall structure of our proposed CNN is depicted in Fig. 3. Also, our proposed CNN structural and learning parameters are indicated in TABLE I.

IV. CNN Performance Evaluation

In this section, the performance of our trained CNN with the topology displayed in Fig. 3 is investigated. For this purpose, the recorded signature windows are categorized into training, testing and validation data sets. In each epoch, a batch of 256 samples is selected from the training data set for which the CNN model is trained and this procedure is repeated 256 times. By the end of each epoch, the categorical accuracy is calculated for training and validation data sets. The model is saved when it reaches either the highest accuracy or the lowest loss values on validation data.

In this work, participants are required to provide at least five ECG recordings in different days. However, since the collected data is not enough for a few of the participants who joined our study recently, the proposed CNN model performance is investigated for two categories: users with more than five days

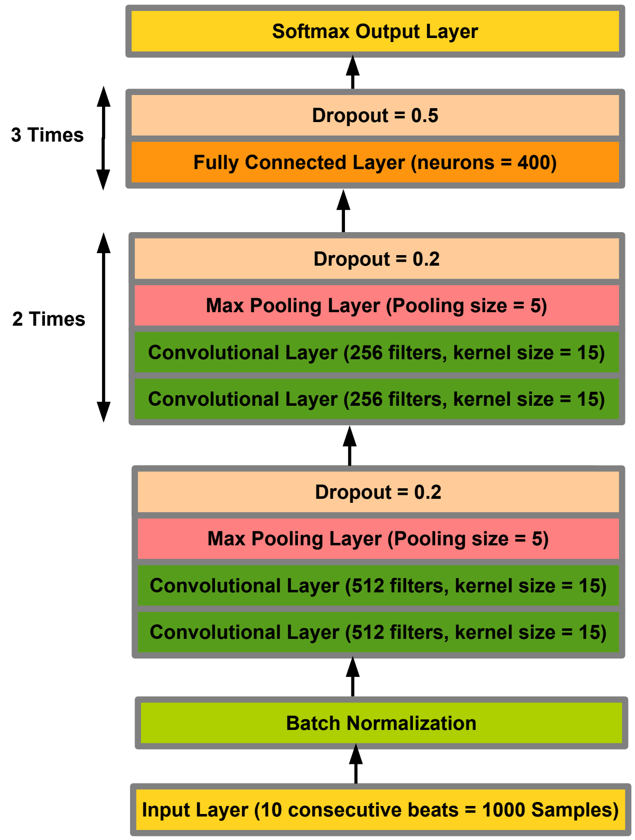

Fig. 3. The overall structure of our proposed CNN to solve the ECG-based human identification problem.

recordings (Group A) and those with less number of daily recordings (Group B).

Two accuracy metrics, namely window accuracy and subject accuracy are obtained to evaluate our proposed CNN model performance in identifying MyHeart participants. The window accuracy is the rate of correctly identified signature windows out of our total number of extracted signature windows for all the users in each data set. Also, the subject accuracy defines the rate of accurately identified participants. The subject is identified using a majority voting mechanism in which an ID with more than 50% of votes is assigned to the subject. The overall window and subject accuracy values are indicated for training, testing and validation data sets in TABLE II. The accuracy metrics are separately calculated for two groups A and B.

The window accuracy rates are also calculated for validation and testing records of any individual subject. The results are displayed in Tables. III and IV associated with Group A and B.

According to our CNN simulation results indicated in Tables. II, III and IV, group A in which the users have a sufficient number of ECG daily recordings reaches higher accuracy rates as compared to Group B. Having more number of ECG daily recordings enables one to capture the variation of user

TABLE II. THE OVERALL WINDOW AND SUBJECT ACCURACY RATES ASSOCIATED WITH TRAINING, TESTING AND VALIDATION DATA SETS COLLECTED FROM MYHEART PARTICIPANTS IN GROUPS A AND B.

Group A			
Overall Accuracy	Training	Validation	Testing
Window Accuracy	0.9976	0.9700	0.9714
Subject Accuracy	1.0000	1.0000	1.0000
Group B			
Overall Accuracy	Training	Validation	Testing
Window Accuracy	0.9965	0.7845	0.7777
Subject Accuracy	1.0000	0.7143	0.8571

TABLE III. ACCURACY RATE FOR MYHEART PARTICIPANTS IN GROUP A, MEASURED FOR THEIR VALIDATION AND TESTING ECG RECORDS.

Subject ID	Validation Accuracy Rate	Testing Accuracy Rate
1	0.9444	0.8591
2	0.9789	0.9970
3	0.9611	0.9375
4	0.9907	0.9952
5	0.8936	0.9819
6	0.9619	0.9570
7	0.8433	0.9634
8	0.8792	0.8466
9	0.9996	1.0000
10	0.9939	0.9928
12	0.9989	0.9992
13	0.8627	0.9777
14	0.9934	0.9613
15	0.9612	0.9886
16	1.0000	1.0000
17	0.9546	0.8255
18	0.8777	0.9600
19	0.9845	0.9888
21	0.9867	0.9948
22	0.9793	0.9949
25	0.9854	0.9299
27	0.9553	0.9884
28	0.9908	0.9377
29	0.9802	0.8333
31	0.9857	0.9897
33	0.9817	0.9824
Mean	0.9586	0.9570

TABLE IV. ACCURACY RATE FOR MYHEART PARTICIPANTS IN GROUP B, MEASURED FOR THEIR VALIDATION AND TESTING ECG RECORDS.

Subject ID	Validation Accuracy Rate	Testing Accuracy Rate
11	0.9325	0.9601
20	0.6158	0.4657
23	0.9968	0.9684
24	0.9924	0.9281
26	0.8893	0.8852
30	0.2157	0.9259
32	0.2881	0.9096
Mean	0.7044	0.8633

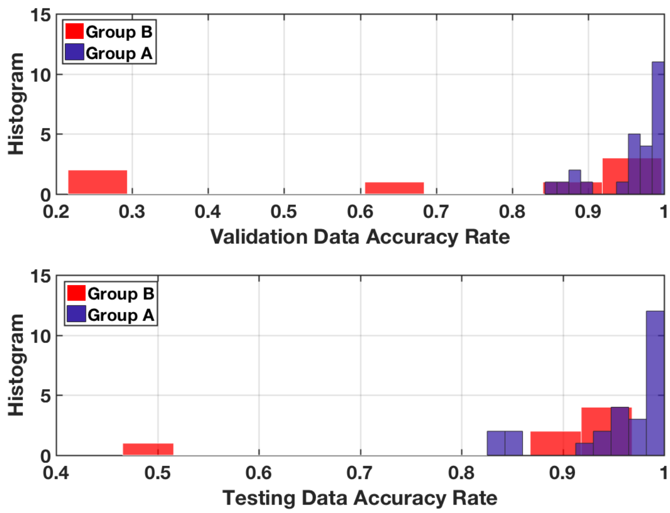

Fig. 4. The histogram of accuracy rates corresponding to Groups A and B, for validation data set (top) and testing data set (bottom)

signature during a longer time and to reach a more accurate model to identify that user. To compare the overall accuracy of our proposed CNN model for validation and testing data sets, Fig. 4 represents the histogram of accuracy rates corresponding to Groups A and B.

V. CONCLUSION

In this work, a deep CNN architecture is proposed as a feature learning and classification methodology to solve ECG-based human identification problem with no need to detect fiducial points and to extract hand crafted features. The proposed CNN network is capable of operating with filtered ECG time-series signals to extract and down-sample features through computing convolutions among the input vectors with their associated weights as well as determining the maximum outputs among the adjacent neurons. The proposed methodology enables one to identify people with a fairly high accuracy per signature window, which makes it a suitable approach for human identification and authentication systems.

Moreover, the promising performance of this ECG-based human identification system provides encouraging evidence that OM apparel provides a high quality ECG signal that if combined with machine learning algorithms will enable one to find subtle patterns useful for multiple applications such as authentication system, cardiac activity monitoring applications and arrhythmia detection.

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