A Novel Deep Learning based Neural Network for Heartbeat Detection in Ballistocardiograph

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***Abstract*— Ballistocardiography is a revamped technology for cardiac function monitoring. Detecting individual heart beats in BCG remains a challenging task due to various artifacts and low signal-to-noise ratio, which are not well addressed by conventional approaches using intuitive or simple-form principles. Instead, we propose to employ deep learning networks to capture the characteristics of variational BCG waveforms within and across individual subjects. Particularly, we design a neural network that combines Convolutional-Neural-Network (CNN) and Extreme Learning Machine (ELM). We test the new learning method on a real BCG data set and compare it with a state-of-the-art method. We demonstrate how advanced machine learning technology can learn and detect BCG waveforms robustly.**

I. INTRODUCTION

Ballistocardiography is an unobtrusive method of cardio monitoring by sensing the mechanical movement of the body generated by heart beats. The signal carries vital information of the heart activities [1]. However, comparing to electrocardiogram (ECG), BCG signal is far more susceptible to interference and distortions. And this renders the heart-beat detection a challenging task from biomedical signal processing viewpoint.

A number of methods have been proposed for BCG heartbeat detection in the literature. Some researchers used the template matching approach [2] that essentially compares a waveform against one or a few fixed template BCG waveforms. Other researchers have proposed alternative methods including an algorithm using short-time energy [3], a k-means clustering algorithm based on finding the location of the J-peaks [4] and a dispersion maximum algorithm that aims to enhance the major BCG peaks [5]. However, existing techniques often depend heavily on the assumption of consistent, distinguishing characteristics of BCG waveform components. The assumption is questionable in view of considerable variations of BCG waveforms that may be neither consistent across individuals nor consistent over time.

We would like to note that deep learning has become a powerful tool in image processing, speech recognition and sentiment analysis. It has also been successfully applied to detection of heartbeat in electrocardiograph [6]. Inspired by the developments in the related fields, we here propose to introduce deep learning to detecting BCG heartbeats.

Particularly, a combined method consisting of 1-D Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM) is proposed. In our method, CNN is used as a feature extractor of the input BCG signal and ELM performs classification decisions.

To verify the effectiveness of our method, we construct a cross-validation test using an existing data set which comprises five subjects of two different conditions: pre-exercise and post-exercise. We examine the statistics of detection accuracy from multiple runs of the test, and compare against a recently published algorithm [5].

II. PROPOSED CNN-ELM METHOD

Our proposed CNN-ELM architecture is depicted in Fig. 1. The upper graph shows the process of feature extraction using a CNN. In this example, we consider a BCG signal at a sampling rate of 1000Hz. We take as input a 500-millisecond long BCG waveform segment. The process comprises a series of convolution, pooling and feature mapping steps (see Table. I for details). We use the back propagation algorithm to train this network. Then we take the 732-element in the first fully-connected layer as the extracted feature. The feature vector is then fed into the ELM classifier for predicting whether or not the input BCG segment contains a valid BCG heart beat waveform, or in other words, if the BCG segment contains the I-J-K complex (class label 1) or not (class label 0).

A. *Convolutional Neural Networks for feature extraction*

Convolutional Neural Network (CNN) is a state-of-the-art learning network in deep learning technology. It is widely-used in image recognition, video classification, object localization and natural language processing (NLP), thanks to the rapid development of machine learning hardware and software. Compared with traditional neural networks, CNN has two advantageous characteristics, namely, local connectivity and weight sharing. Thus, it reduces the complexity of the network model and the number of weight parameters.

A CNN structure is made up of several convolutional layers, pooling layers and fully-connected layers. In the work, we base the network design on LeNet-5 [7]. It has 7 layers excluding the output layer as defined in Table. I. Note that, because we consider only a single BCG-sensor waveform, i.e. a 1-D signal, the size of convolution kernel and some other parameters are adapted accordingly. Besides the input and output layers, the CNN has two convolutional layers (C1-C2) with ReLU nonlinear unit, two pooling layers (P1-P2) connected after C1-C2 and two fully-connected layers (F1-F2). The 732×1 dimension data is regarded as

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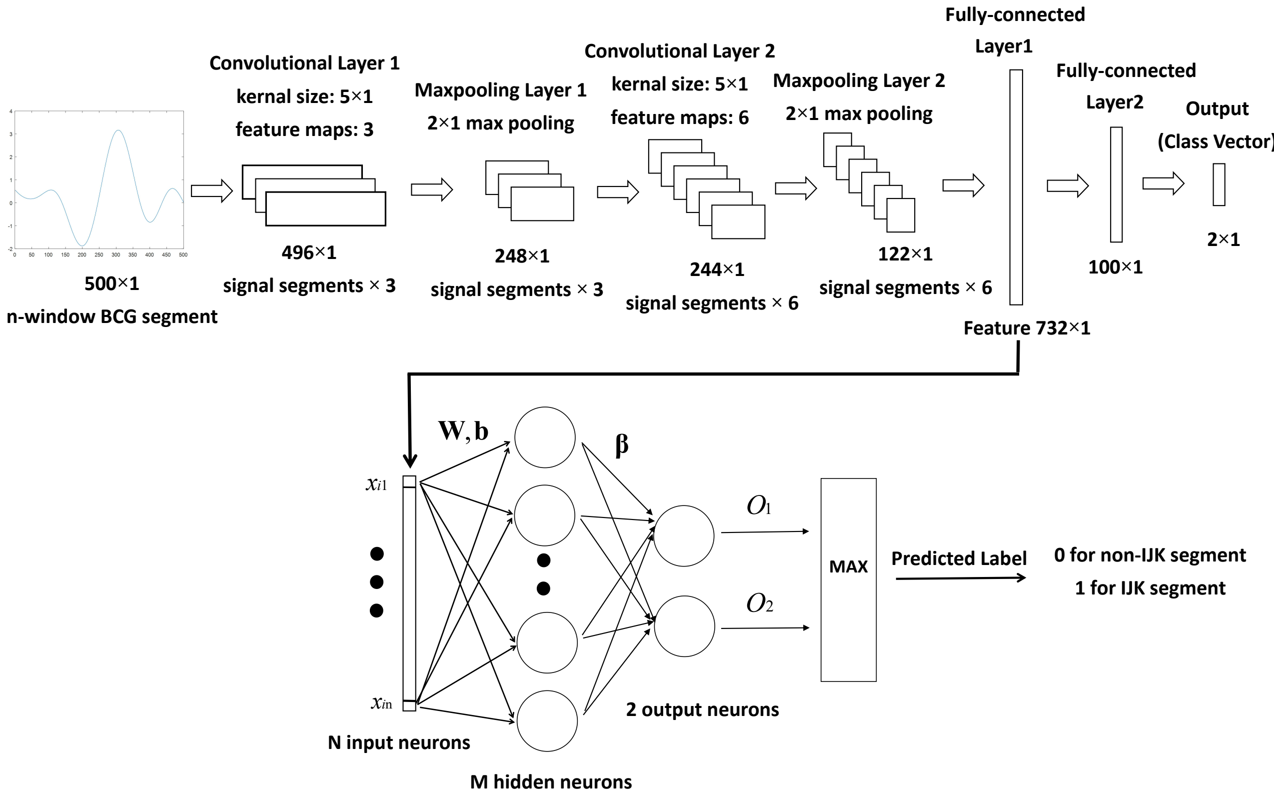

Fig. 1. Structure of our proposed CNN-ELM method

the extracted feature vector to be used in the subsequent classification processing by the ELM.

TABLE I
PROPOSED CNN-ARCHITECTURE.
NOTE: LAYER TYPE: C-CONVOLUTIONAL, P-POOLING, F-FULLY-CONNECTED.

Layer	No.Filter	Unit Type	Kernal Size	Strides	Output Size
Input					(500,1,1)
C1	3	ReLU	(5,1)	(1,1)	(496,1,3)
P1		Max	(2,1)	(2,1)	(248,1,3)
C2	6	ReLU	(5,1)	(1,1)	(244,1,6)
P2		Max	(2,1)	(2,1)	(122,1,6)
F1		ReLU			732
F2		ReLU			100
Output		Logistic			2

B. Extreme Learning Machine for BCG signal classification

ELM is a straightforward single-hidden-layer feed-forward neural network (SLFN) with a learning algorithm proposed in [8]. Compared with other traditional neural networks, it has the following features. Firstly, ELM algorithm takes random weights between the input layer and hidden layer. Secondly, ELM has a simple feed-forward neural network mechanism. It has been demonstrated that ELM has certain advantages in terms of fast learning and generalization performance.

ELM-based BCG signal classification/detection consists of the following two steps: (1) Construct the BCG signal classifier: The feature extracted by CNN is the input training matrix and the category matrix of the training samples is regarded as the output matrix. (2) Perform BCG signal classification for a test sample: The feature matrix of the test sample is regarded as the ELM classifier input and the output is the BCG segment category: non-IJK segment labeled as 0 and IJK segment labeled as 1. The specific steps of the ELM-based signal classification method are described as follows:

(1) Given the training dataset of the BCG signal segments $\{(\mathbf{x}_i, \mathbf{t}_i) | \mathbf{x}_i \in R^n, \mathbf{t}_i \in R^m, i = 1, 2, ...N\}$, hidden layer output function $g(\mathbf{w}, b, \mathbf{x})$, the number of hidden nodes L and test samples $\mathbf{y}$.

(2) Randomly assign the parameters of hidden layer nodes $(\mathbf{w}_i, b_i)$, $i = 1, 2, ...L$.

(3) Calculate the hidden layer output matrix $\mathbf{H}(\mathbf{w}_1, ...\mathbf{w}_L, b_1, ..., b_L, \mathbf{x}_1, ...\mathbf{x}_L) =$

$$\begin{bmatrix} g(\mathbf{w_1} \cdot \mathbf{x_1} + b_1) & \cdots & g(\mathbf{w_L} \cdot \mathbf{x_1} + b_L) \\ \cdots & \cdots & \cdots \\ g(\mathbf{w_1} \cdot \mathbf{x_N} + b_1) & \cdots & g(\mathbf{w_L} \cdot \mathbf{x_N} + b_L) \end{bmatrix} \quad (1)$$

Ensure that the row of $\mathbf{H}$ is full. In the above formula, $\mathbf{w}$ is the input weights between input layer and hidden layer, b is the biases of hidden layer, $\mathbf{x}$ is the input of training dataset, N is the number of training samples and $g(x)$ is the activate function.

(4) Calculate the optimal weight $\boldsymbol{\beta}$: $\boldsymbol{\beta} = \mathbf{H}^{+}\mathbf{T}$.

(5) Calculate the output of testing samples $\mathbf{y}$:

$$o = \mathbf{H}(\mathbf{w}_1, ...\mathbf{w}_L, b_1, ..., b_L, \mathbf{x}_1, ...\mathbf{x}_L)\boldsymbol{\beta} \quad (2)$$

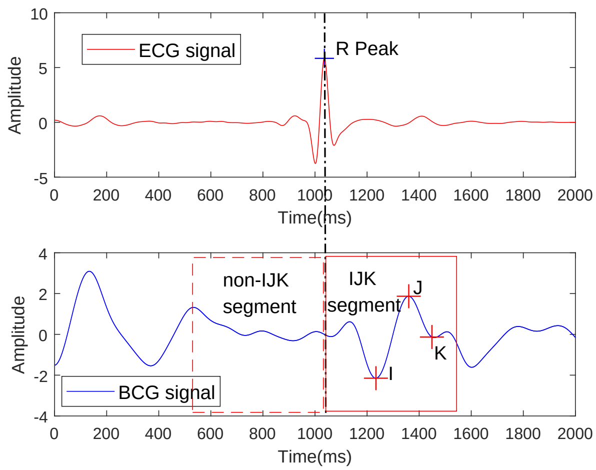

Fig. 2. The extraction of non-IJK and IJK segments in BCG according to ECG signal in one heartbeat.

(6) Execute the BCG signal classification for testing samples, and the maximum value of the ELM output vector determines the prediction of the BCG signal class.

$$Sort(y) = \max_{1 \leq i \leq m} (o_i) \quad (3)$$

III. Experiment and Results

A. Data collection and preprocessing

The data collection was described in details in our earlier publication in [9], and here is a brief summary. We attached two fiber-optics BCG sensors to an arm-chair (while only the bottom one being used in this work) and one-lead ECG electrode (V1) to the recruited human subjects. The sensors and electrodes were connected to a neurophysiological signal amplifier from Neuroscan Inc., for simultaneous time-sampling and digitization. Data were obtained from five healthy male adults on a volunteering basis. Each of them contributed two sessions of data: pre-exercise and post-exercise.

After manual screening and rejection as reported in [9], we obtained a total of 4607 valid heartbeat samples.

B. Signal segmentation and processing

An example of the collected concurrent BCG and ECG signals is shown in Fig. 2. After deliberation and manual verification, we chose two time intervals with respect to each ECG R peak: the 500-millisecond time interval leading to R is taken as a non-IJK sample; the 500-millisecond time interval post R is then an IJK sample. Therefore, a total of 4607 non-IJK samples and 4607 IJK samples are available for testing algorithms.

In order to evaluate our proposed method in comparison with a reference algorithm [5], we need to study the characteristics of the output values from the two methods.

(1) As for our proposed CNN-ELM method, for each sample (BCG signal segment), we can obtain an output value calculated by Equation 2. So that we can obtain 4607 non-IJK segment values and 4607 IJK segment values in total.

(2) As for Dispersion-Maximum Algorithm method [5], we use the peak of each segment to represent a segment (see Fig.3). The value in the dashed line box represents the corresponding non-IJK segment and the value in the solid line box represents the corresponding IJK segment.

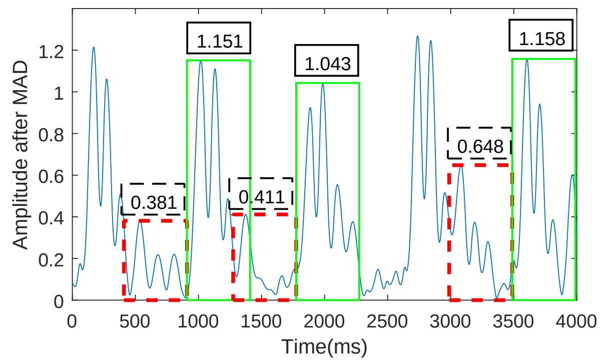

Fig. 3. Signal processed by moving mean absolute deviation.

C. Statistical analysis and results

For these values of non-IJK segments and IJK segments, in terms of statistical approaches, it is necessary to determine probability distribution functions (PDFs) and cumulative distribution function (CDF) of the variable values. Then, we need to set a threshold for the minimum empirical error according to Equation 4. The processing results of two methods can be seen in Fig. 4 and Fig. 5.

Denote the non-IJK segment values by x_1 and the IJK segment values by x_2. We suppose that $mean(x_2) \geq mean(x_1)$, and there is a threshold x_{set} to determine if an unknown segment is IJK ($x >= x_{set}$) or non-IJK ($x < x_{set}$). The minimum error is then

$$error_{min} = \min\{1 - P(x_1 \leq x_{set}) + P(x_2 \geq x_{set})\} \quad (4)$$

where $P(x \leq x_{set})$ is the probability that an arbitrary value x is less than or equal to x_{set}.

Now consider a cross-validation approach to evaluation of performance. Specifically, we select 5000 BCG signal segments randomly as the training data and the other (4214) samples as testing data (Folder 2). This training-test process is repeated 30 times, where we evaluate our method as well as the Dispersion-Maximum Algorithm [5] and obtain the result as summarised in Table. II. The table illustrates the minimum empirical classification error rate by either our CNN-ELM method or the Dispersion-Maximum. The result shows that the CNN-ELM produced far less errors. Especially, the accuracy on the

IV. Discussion

In this paper, a neural network architecture for BCG signal classification is proposed, where CNN extracts the deep features of BCG I-J-K complex and ELM performs classification. Unlike conventional BCG detection methods, our method does not assume a fixed pattern or prominent peaks in the BCG complex. Compared with the dispersion-maximum

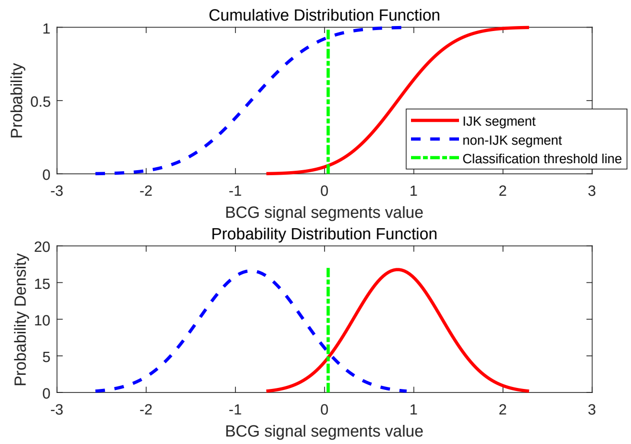

Fig. 4. One example of the result of our proposed method presented using PDF and CDF figures. The dashdot line in the figure is the classification threshold which has the minimum Percentage of error: 11.88%

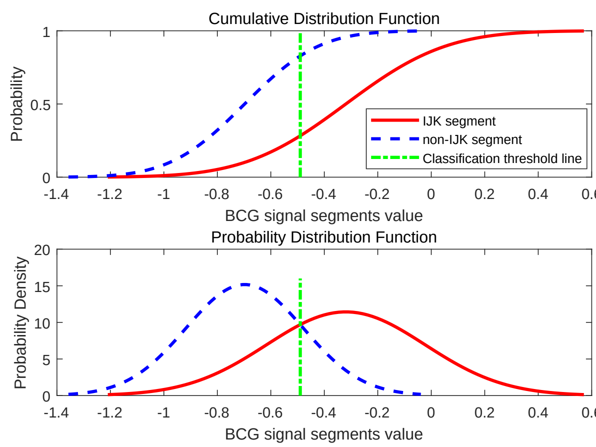

Fig. 5. One example of the result of the comparion method presented using PDF and CDF figures. Percentage of error: 47.22%

algorithm, our proposed method achieved a reduction of error rate by more than 30% on average.

While this work considers classification of clearly labeled BCG and non-BCG waveforms as labeled using the ECG R-peak, our future work will look into continuous processing and detection where the inter-beat structure will be important as well as the intra-beat BCG characteristics.

TABLE II
MINIMUM CLASSIFICATION ERROR RATE (USING SUBJECT-INDEPENDENT DETECTION MODELS).

Algorithm	Folder 1 (5000 training samples)	Folder 2 (4214 testing samples)
CNN-ELM	1.36%	12.47%
Dispersion-Maximum [6]	43.21%	45.46%

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