Personal Identification by Convolutional Neural Network with ECG Signal

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***Abstract*—This paper proposes a novel approach for personal biometric identification with Convolutional Neural Network (CNN) based on the electrocardiogram (ECG) signals that are measured during bathing, aiming at exploring a feasible way to avoid or reduce the drowning accidents during daily bathing. After we perform denoising and QRS segmentation on the raw ECG signal, the preliminary experimental results showed that the best and robust identification rate is 97.20% for 10 individuals only with 5 epochs. When the proposed method was tested on a public ECG Database, the identification rate is as high as 98.70%. This work provides with strong evidence that ECG signals can be useful for personal identification.**

Keywords—electrocardiogram, bathing, drowning accidents, personal identification, convolutional neural network

I. INTRODUCTION

Bathing is a part of daily life in Japan, almost every Japanese home has a bathtub. In a bathing room, the thermal load from the bathing water and the carbon dioxide density is much higher than outside. When a person enters a bathtub, the ECG will change greatly. During daily bathing in the Japanese home, the drowning accidents have been increasing these years, especially among the children, the elderly, and people with heart diseases. The details are shown in Figure 1.

As we all know, the state of ECG could reflect one's health status precisely, a smart alarm system based on ECG will help to reduce the drowning accidents, therefore, how to implement personal identification with ECG and carry out long-term tracking of the ECG status variability during daily bathing are the most important functions of the system.

To date, there are many traditional subject identification methods such as fingerprint, signature, face, retinal structure,

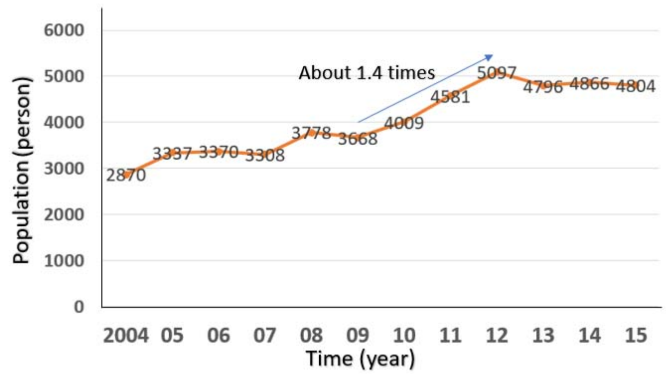

Fig. 1. Changes of the drowning accidents in a bathtub at home [7].

and voice, etc [1-6]. However, according to the property of the biometric characteristic and the application environment, each of the above biometric methods has its advantages and weaknesses. For example, the fingerprint is easy to be copied, the signature is easy to be imitated, the face can be counterfeited by 3D model, and the voice can be easily recorded by recording equipment. On one hand, many present biometric recognition systems are only based on one feature of the traditional biometric. On the other hand, these features can generally be seen with our eyes, so the security vulnerabilities are increasing with the development of the advanced forgery techniques. However, some emerging approaches such as DNA and ECG that can make up the shortcomings of the traditional biometric techniques [8-11], which have been the research focus. The DNA and ECG have some common characteristics, of which the most important ones are: universality-they exist in all the living creatures; distinguishability-there are no two identical DNA or ECG in the world; invisibility –it is extremely difficult to be forged [12-17]. Their applications are increasingly widespread and they have been playing an increasingly important role in the civilian, commercial and government aspects, especially the DNA analysis, which has been used in the governmental applications for criminal and forensic investigations. This paper mainly focuses on the ECG.

ECG is the cardiac electrical activity of the heart measured on the body surface. Because it presents in all living individuals and contains many unique and discriminative characteristics of a biometric [18-20], it is thoroughly used for medical diagnostic purposes. The typical ECG signal features on a normal heartbeat are shown in Figure 2.

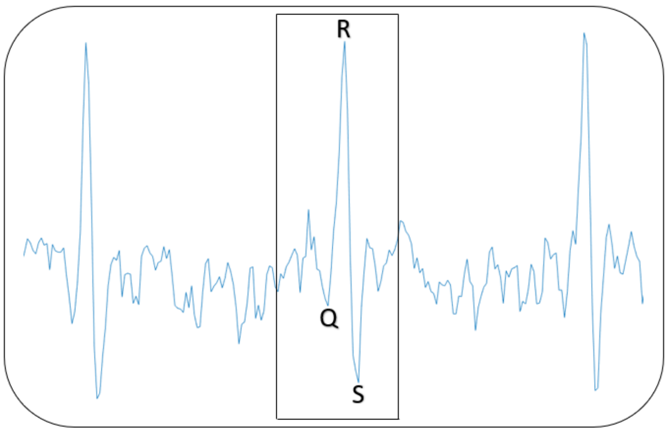

Fig. 2. ECG waveform includes a complete QRS complex.

There are 3 main waveforms in a normal ECG signal, named P wave, QRS complex and T wave respectively. The P wave is generated by the start and end of the atrial depolarization of the heart; the QRS complex is generated by the ventricular depolarization; the T wave is generated by the ventricular repolarization. Because of the heart position and chest geometry as well as other pathological condition, the shapes of these complexes differ from person to person. For example, in clinical diagnosis, the shape of the QRS complex could reflect the status of the heartbeat, whether it is normal or arrhythmias. Since the QRS complex includes more discriminative information than P wave and T wave in a typical ECG signal, some previous published papers used the QRS complex to perform personal identification [21-24], which has become a suitable biometric modality in medium and high security access.

This paper proposes a novel method that utilizing CNN combined with the QRS segments on the ECG signals measured during bathing, to perform personal identification. We use the ECG data from the existing Database ECG-ID [25] to evaluate the performance of the trained CNN model.

II. Material and Method

A. Data collection and preprocessing

The ECG signal in the bathtub is recorded using three non-contact electrodes, which are placed on the bathtub wall close to right hand, left hand and right foot respectively. The electricity is transmitted through water to electrodes. We use cord to connect the measuring ECG amp box with AD box and oscilloscope. AD box and PC is connected by LAN, and PC is used to save data. Details of the system are shown in Figure 3.

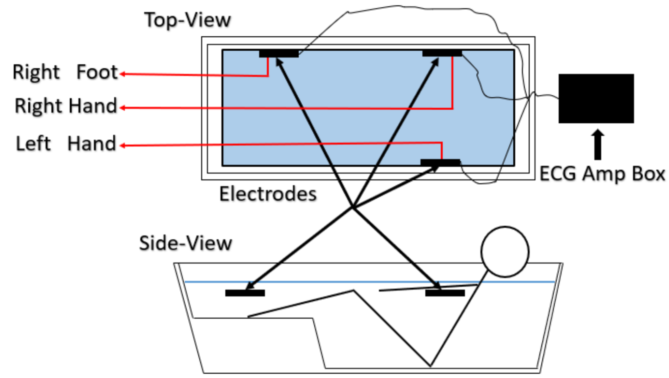

Fig. 3. The data collection system in our laboratory.

The focus of this study is on using bathtub ECG for identification at home, so the average family member will not be greater than 10. We include 10 healthy volunteers in our preliminary experiment, including men and women aged between 20-25 years old. Each ECG record is about 15 minutes, with a sampling rate of 100 Hz. Firstly, we normalized the original signals; Secondly, baseline drift and noise are removed; Thirdly, template matching method is applied to perform R peaks detection. Finally, QRS complexes are segmented. The number of the QRS complexes we segmented is between 1200 and 1500. The details are shown in Figure 4 and Figure 5.

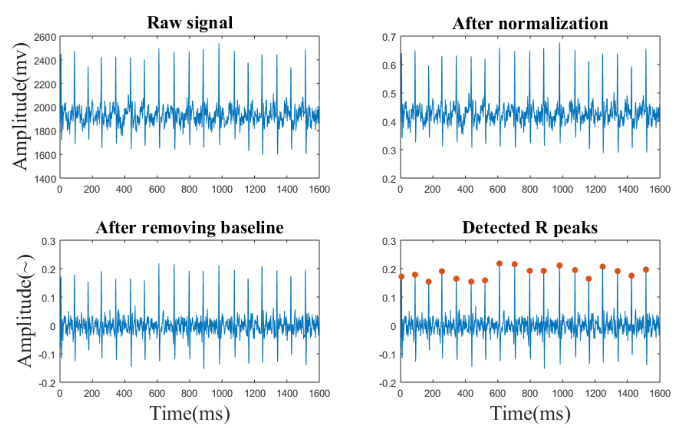

Fig. 4. An example of ECG signal processing.

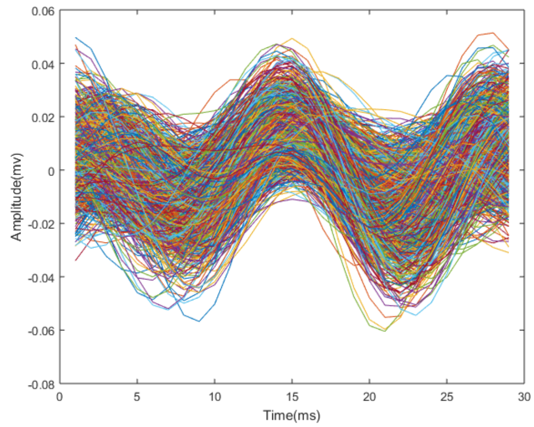

Fig. 5. An example of QRS waveform segmentation result.

B. *CNN model and data structure*

When design the CNN model, we use the back-propagation algorithm to train a network, the CNN model parameters are shown in Table 1:

Table 1: The parameters of the CNN model

Layer	Remark	Activation Function
Input	20*28 nodes	-
Convolution	20 convolution filters (9*9)	ReLU
Pooling	1 mean pooling (2*2)	-
Hidden	100 nodes	ReLU
Output	10 nodes	Softmax

Data structure settings: Every QRS segmentation result is represented by a n*29 two-dimensional matrix, and n is the number of segmented QRS complex. We randomly rearrange the order of each row, and the 10 mean QRS waveforms based on segmentation are shown in Figure 6.

In order to train our CNN model and estimate its performance reasonably, we set 500 training data and 100 test data for every identification subject.

For each individual, we choose the first 28 columns of the QRS segmentation matrix to get an n*28 matrix. Then we choose its 1st to 20th row as the first data set and choose its 2nd to 21th row as the second data set. Until we get 600 data sets, the first 500 data sets are taken as the training data and the last 100 data sets are taken as the test data. Using the same method, we can get the other 9 individuals' data sets. Eventually, all the training data and test data are put together, so the final training data is represented by a 20*28*5000 3D matrix and the test data is represented by a 20*28*1000 3D matrix.

We use the following system structure to perform personal identification, and the details are shown in Figure 7.

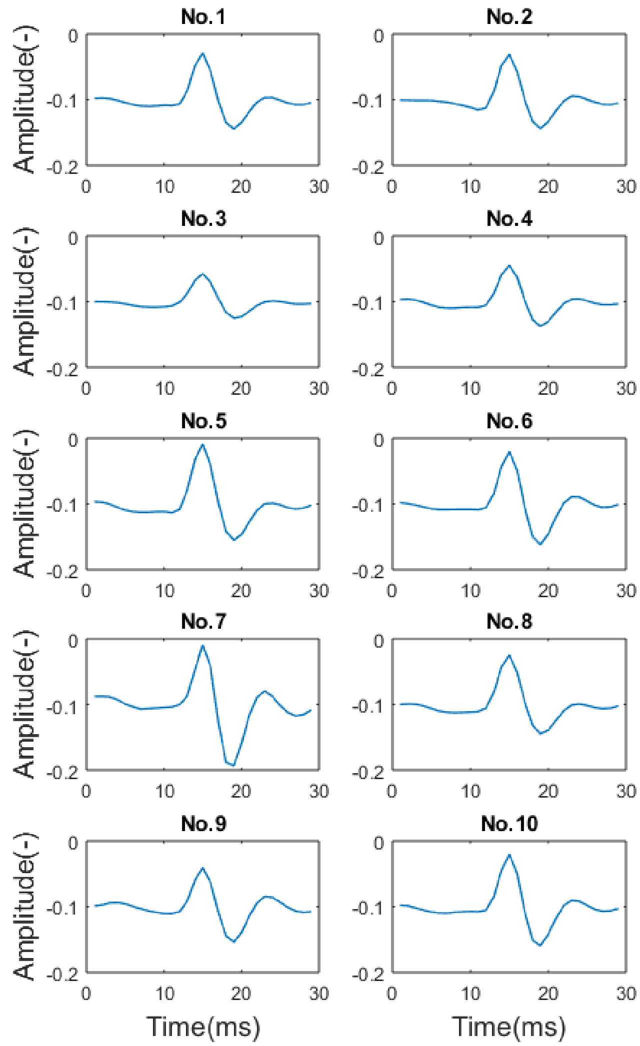

Fig. 6. The 10 mean QRS waveform.

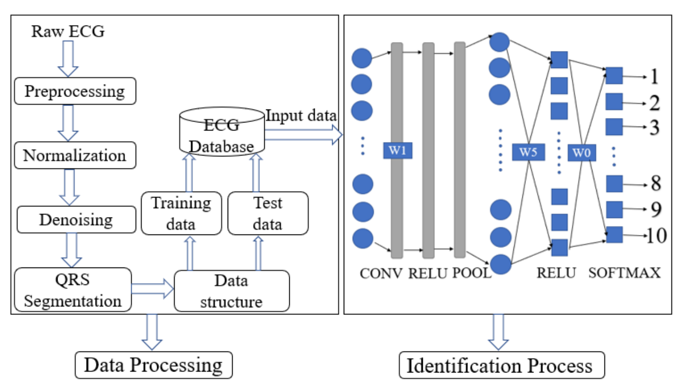

Fig. 7. Architecture of the biometric system for personal identification.

III. EXPERIMENT RESULTS

Now, we use the designed biometric system to perform personal identification. In the output layer, we calculate the output probability of each subject by the Softmax Activation Function. The output of the Softmax is a 10*1 matrix, of which the every element represents the probability of the every identification subject respectively. If the row of its biggest element in the matrix equals to the label of the input data, then we increase the precision by one. At last, we divide the final precision by the number of test data. This result is the final personal identification rate.

At the beginning, when we use the designed CNN model to implement data training and data inference, we can't always get good results as we expect. When we check the Training-Set and the Test-Set, we find that the first 500 training data belong to person one, and the second 500 training data belong to person two, and the other training data and the inference data are also arranged in such a format. This means that everyone's training data and inference data is strictly concentrated. Then we randomly rearrange the order of the Training-Set and Test-Set. Eventually, we get the expect result after we execute data training and data inference again. The detail is shown in Figure 8 and Table 2.

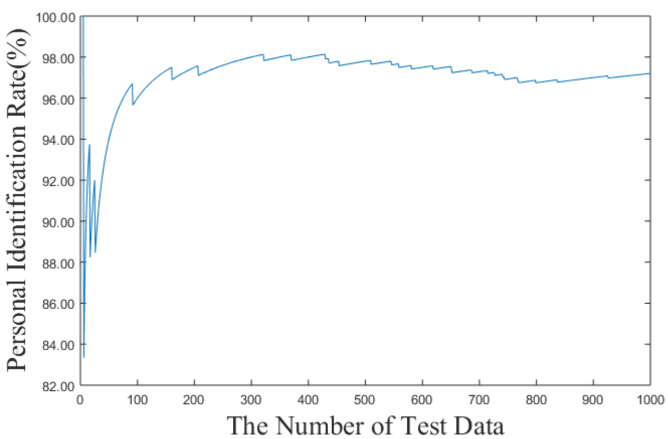

Fig. 8. The accuracy of the personal identification.

IV. DISCUSSION

In this paper, we have proposed using the Convolutional Neural Network to implement the personal identification based on ECG signal measured during bathing. In our first experiment, no matter how we change the learning conditions, we can't get the expected result. When we examine the output of the 'Softmax' activation function, all of its element is '0.1', which means that the output of the Softmax is not convergent.

Then we check the data structure, and we find that, in the training data matrix, the 1^{st} to 500^{th} training data belong to individual one, and the 501^{th} to 1000^{th} training data belong to individual two. That is to say every individual's training data is strictly concentrated on.

Next, we randomly rearrange the order of the training data and test data, however, the experiment results are still very poor. Although the output of Softmax is convergent, the effect of the convergence is not obvious. In our third experiment, we try to normalize the data once again based on the QRS segmentation results. This time we get the experiment results as expected. Then we repeat this experiment several times under the same conditions. The best and robust personal identification rate is as high as 97.20% with only 5 training epochs, which is higher than that in [26-33]. But when we make all the data to be strictly concentrated on again, no matter whether we normalize the data based on the QRS segmentation results or not, the experiment result is still the same with the first time.

Thus, we notice that if every individual's training data is strictly concentrated on when the identification subjects are more than 2, such a characteristic of data structure will mislead the CNN model to an extreme while deep learning is performed. If you want to get a better result by CNN when you perform deep learning, it is better to randomly arrange the order of the training data.

In addition, what need to be emphasized is that all the data was normalized twice during our experiment. The first normalization is based on the raw data, aiming at reducing the computational cost and storage space. The second normalization is based on the QRS segmentation result.

In the future work, we will focus on developing more optimized denoising methods and designing more complicated and advanced CNN models, and trying to explore more efficient and accurate personal identification system based on other ECG features.

Table 2: The misidentification information of each subject in test stage.

Subject	Number of misidentification	Error rate(%)
1	0	0.00
2	27	2.70
3	1	0.10
4	0	0.00
5	0	0.00
6	0	0.00
7	0	0.00
8	0	0.00
9	0	0.00
10	0	0.00
total	28	2.80

V. Conclusion

In this paper, we designed a biometric system for personal identification. Under the dual requirements of test accuracy and computational cost, it has been demonstrated to be efficient and robust. We recommend that the system should be used in the following two applications during the daily bathing at home: perform long-term tracking of the variability of the ECG status for healthcare and reduce the drowning accidents.

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