The Impact of Bathtub Water Temperature on Personal Identification with ECG Signal based on Convolutional Neural Network

Jianbo Xu
Biomedical Information Technology Laboratory
The University of Aizu
Aizu-wakamatsu, Fukushima, Japan
e-mail: m5212105@u-aizu.ac.jp

Tianhui Li
Biomedical Information Technology Laboratory
The University of Aizu
Aizu-wakamatsu, Fukushima, Japan
e-mail: m5211142@u-aizu.ac.jp

Ying Chen
Biomedical Information Technology Laboratory
The University of Aizu
Aizu-wakamatsu, Fukushima, Japan
e-mail: ychen@u-aizu.ac.jp

Wenxi Chen
Biomedical Information Technology Laboratory
The University of Aizu
Aizu-wakamatsu, Fukushima, Japan
e-mail: wenxi@u-aizu.ac.j

***Abstract*—This paper explores the impact of bathtub water temperature on personal identification with ECG signal using convolutional neural network. Ten volunteers' ECG records are collected with lead-III at low temperature of bathtub water (38±0.2 ℃ in average) and high temperature of bathtub water (42±0.5 ℃ in average) environments, respectively. Each record is about 5±1 minutes at low temperature and 4±1 minutes at high temperature. In the data preprocessing stage, we denoise the original ECG signal and segment the QRS complex on a beat-by-beat basis. Then, we perform two interpolation calculations based on the QRS segmentation and convert the QRS complex into a binary image one by one. When we use the ECG signals which are collected at low temperature to train and test the CNN model, the identification rate is 82.67%. However, if we use the ECG signal collected at high temperature to test this trained CNN model, the identification rate is only 13.33%. Conversely, when we use the ECG signal collected at high temperature to train and test the CNN model, the identification rate is 85.50%. However, if we use the ECG signal collected at low temperature to test this trained CNN model, the identification rate is only 12.17%. Thus, we notice that the different bathtub water temperature has an important impact on the ECG signal patterns and it is feasible to perform personal identification by convolutional neural network with ECG signal collected during bathing at the same temperature.**

Keywords—Bathtub water temperature, impact, electrocardiogram, drowning accidents, healthcare, personal identification, convolutional neural network, binary image

I. INTRODUCTION

Nowadays, bathing has been not only an important habit but also a culture for Japanese people. However, many old people whose ages are more than 65 years old easily have drowning accidents during bathing, especially among the old people with heart diseases. According to an investigation, the number of drowning accidents in the Japanese daily bathing at home has been increasing these years [1]. Figure 1 shows the detailed information of the drowning accidents.

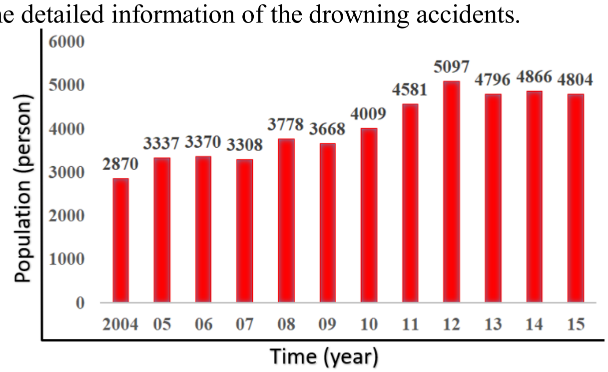

Figure 1. Changes of the drowning accident in a bathtub at home.

Many bathtubs can't automatically give an alarm when the drowning accidents are happening. Therefore, we hope to develop a smart bathtub device with two important functions: the first function is that it can perform long-term tracking of the ECG during daily bathing; the second function is that it can show the health condition based on ECG before one person entering a bathtub and give the alarm urgently once the ECG waveform changes greatly during bathing. So we should know who is in the bathtub when we perform long-term tracking of the ECG. Thus, how to implement personal identification with ECG is the primary problem we need to solve. The previous papers explored the feasibility of using finger ECG for authentication [2] and long-term tracking of the ECG during bathing for daily stress monitoring [3], some papers explore the impact of ECG and body temperature on health [4-11]. This paper explores the impact of different bathtub water temperatures on personal identification with ECG signal by convolutional neural network.

ECG shows the process of heart electrical activity on the skin. It exists in all the living creatures with heart, which is usually used for medical diagnostic purposes in the clinical.

A normal ECG waveform includes 3 important parts, they are P wave, QRS complex and T wave [12-18]. Among them, the QRS complex includes more discriminative information. Many previous papers proposed personal identification using the QRS complex [19-22].

In our experiment, we segment all QRS complexes from the raw ECG signal and then convert them into binary images. All the binary images are used to train and test the convolutional neural network.

II. Material and Method

A. Data Collection and Preprocessing

All the ECG records are collected with 3 leads, this paper only uses the data from the first lead between right arm and left arm. 3 non-contact electrodes are placed on the bathtub wall close to right arm, left arm and left foot respectively. The electricity on the skin transmit to electrodes by water. The ECG Amp box and oscilloscope are connected by wire, the oscilloscope and PC are connected by LAN, PC is used to save the ECG records. The schematic of the data collection system is shown in Figure 2.

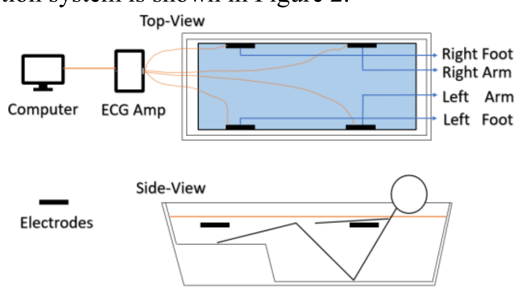

Figure 2. ECG collection system.

This paper focuses on exploring impact of bathtub water temperature on personal identification with ECG signal during daily bathing at home. The average number of family member will not be greater than 10. So, 10 healthy subjects are included in our preliminary experiment, whose ages are in the range of 20-25 years old, including male and female. Every volunteer collects 2 ECG records, each record is about 5±1 minutes at high temperature (42±0.5 ℃ in average) and 4±1 minutes at low temperature (38±0.2 ℃ in average), with the sampling rate as 100 Hz.

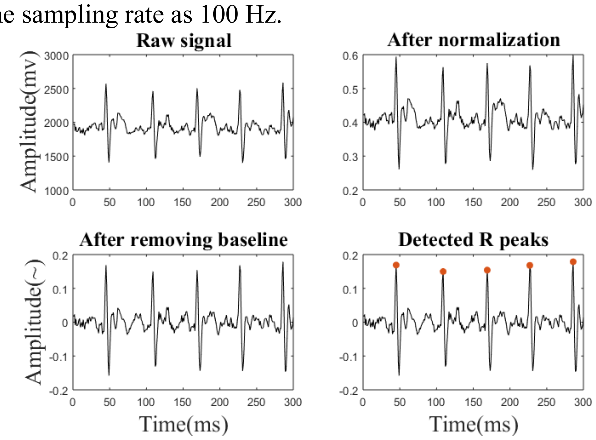

Figure 3. An example of ECG signal processing.

In the data preprocessing stage, we normalize the raw ECG and remove the baseline drift and noise. Then, all the R peaks of the QRS complex are detected using the template matching method. At last, we segment the QRS complexes. The number of QRS complexes of each person are different with each other, with the range from 360 to 568. An example of the result after each preprocessing is shown in Figure 3.

B. Data structure a CNN Model

Data structure: We use a 2D matrix to represent the QRS. Its size is n×29, n is the number of the QRS complexes, 29 represents every segmented QRS complex includes 29 sampling points. 10 average QRS complex after QRS segmentation are shown in Figure 4.

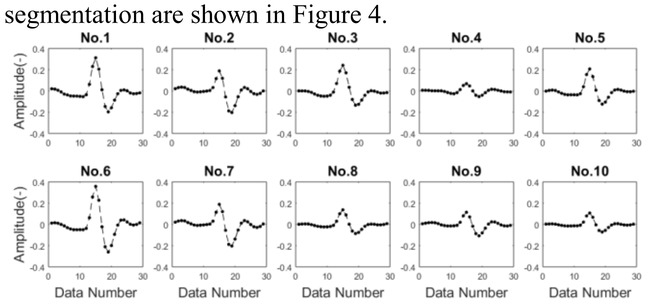

Figure 4. Average QRS complexes after QRS segmentation.

In our experiment, we use 300 training data and 60 test data for each subject.

For each individual, we randomly rearrange the row order of the 2D matrix. Then, we convert every QRS complex into a binary image. Because the sampling rate is 100Hz, every QRS segmentation is a 1×29 row vector. First, we insert every mean of the neighboring element based on the 1×29 row vector, and it forms a 1×57 row vector. We repeat this step again, and get a 1×113 row vector and name it $A_{1\times113}$.

Then, we convert it into a binary image by the following steps: first, we definite the pixel of the binary image as 112×112 pixels and initialize a 112×112 matrix $B_{112\times112}$ with all the elements set as zero; second, calculate the distance delta between the maximum and minimum values of $A_{1\times113}$ and the size delta1 of the unit distance which is represented by each pixel; third, calculate the distance between each element $A_{1\times113}(1,k)$ and the minimum value $\min(A_{1\times113})$ separately, and divide this distance by delta1, then round the result, if the final result num1 is 0, we change it into 1, this result unm1 represents the row in the binary image matrix of every element in $A_{1\times113}$; at last, we let $B_{112\times112}$ (num1,k) be 1 and turn matrix $B_{112\times112}$ upside down.

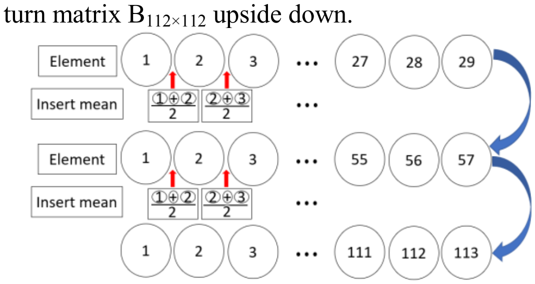

Figure 5. Flowchart of the inserted mean.

Each data set is a 112×112 binary matrix, the flowchart of the inserted mean and output of each process is shown in Figures 5 and 6.

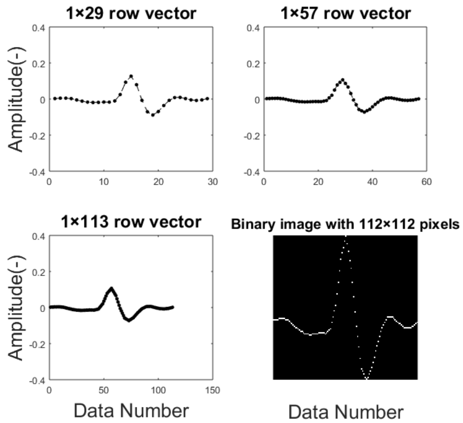

Figure 6. The output of every process.

At last, we get 360 binary images in total for every individual, using the first 300 to train and the last 60 to test. Then we put every individual's training data and test data together, the ultimate training data set is a 112×112×3000 3D matrix and the test data set is a 112×112×600 3D matrix.

The designed CNN model includes 5 layers, they are input layer, Convolution layer, Pooling layer, Hidden layer and Output layer. The parameter and activation function in every layer are shown in Table 1.

TABLE I: PARAMETERS OF THE CNN MODEL

Layer	Remark	Activation Function
Input	112×112 nodes	-
Convolution	20 convolution filters (9×9)	ReLU
Pooling	1 mean pooling (2×2)	-
Hidden	100 nodes	ReLU
Output	10 nodes	Softmax

C. System Architecture for Personal Identification

The whole architecture of biometric system for personal identification includes 2 important parts: the Data processing Stage and Personal Identification Stage. The details are shown in Figure 7.

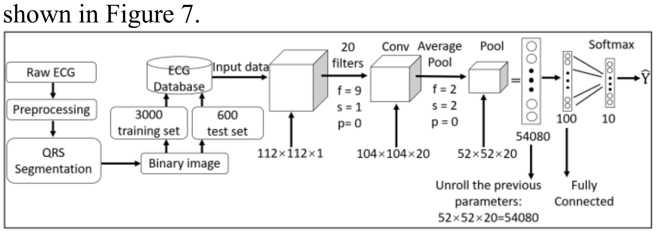

Figure 7. Architecture of the biometric system for personal identification.

III. EXPERIMENT RESULTS

We implement personal identification by the biometric system shown in Figure 7. The Softmax Activation Function is used to calculate the output probability of every individual in the out layer. Its output is represented using a 10×1 matrix, every element is equivalent to everyone's probability, and the sum of all elements is 1. When the label of the input data is the same with the row of the largest element in the 10×1 matrix, we add 1 to the accuracy. Using the final accuracy divided by 600, we can get the personal identification rate.

In our preliminary experiment, the final personal identification rate is very low. The training matrix shows that each individual's data is strictly concentrated on. After we randomly rearrange their order, the identification rate is 82.67% when all the training data and test data are collected at low water temperature. If we use the data set at high temperature to test the CNN model directly, the identification rate is only 13.33%. Conversely, when we use the data set at high temperature to train and test the designed CNN model, the identification rate is 85.50%, but if we use the data set at low temperature to test the CNN model directly, the identification rate is only 12.17%. The details are shown in Table 2 and Table 3.

TABLE II: COMPARISON OF IDENTIFICATION RATE IN 4 DIFFERENT EXPERIMENTS

Experiment	Training Data Set	Test Data Set	Identification Rate (%)
1	L	L	82.67
2	L	H	13.33
3	H	H	85.50
4	H	L	12.17

L means the data are recorded at low temperature, H means the data are recorded at high temperature.

TABLE III: MISIDENTIFICATION INFORMATION OF EACH SUBJECT IN TEST STAGE

Subject	N1	Error Rate(%)	N2	Error Rate(%)	N3	Error Rate(%)	N4	Error Rate(%)
1	3	0.50	57	9.50	5	0.83	55	9.17
2	30	5.00	60	10.00	9	1.50	54	9.00
3	6	1.00	50	8.33	8	1.33	47	7.83
4	5	0.83	56	9.33	4	0.67	49	8.17
5	4	0.67	48	8.00	5	0.83	51	8.50
6	8	1.33	25	4.17	19	3.17	47	7.83
7	28	4.67	60	10.00	20	3.33	59	9.83
8	3	0.50	54	9.00	4	0.67	47	7.83
9	11	1.83	57	9.50	11	1.83	59	9.83
10	6	1.00	53	8.83	2	0.33	59	9.83
Total	104	17.33	520	86.67	87	14.50	527	87.83

N1, N2, N3 and N4 represent the number of misidentification in every experiment.

IV. DISCUSSION

In this paper, we explore the impact of bathtub water temperature on personal identification with ECG signal using convolutional neural network, aiming at discovering an effective way to reduce or avoid the drowning accidents during daily bathing at home. The average family member are usually less than 10, so, the preliminary experiment only includes 10 volunteers. Every volunteer has 2 ECG records, one record is about 5±1 minutes which are collected at low bathtub water temperature (38±0.2 ℃ in average), the other record is about 4±1 minutes which are collected at high bathtub water temperature (42±0.5 ℃ in average). In the data preprocessing stage, we normalize the raw data and remove the baseline drift and noise. Then, template matching method is applied to perform R peaks detection. Finally, we segment the QRS complex on a beat-by-beat basis and convert it into binary image, the pixels are 112×112.

For every individual, we select the first 300 binary images as the training data and the last 60 binary images as the test data. Next, put all the training data and test data together, respectively. Eventually, the final training data is a 112×112×3000 3D matrix, the final test data is a 112×112×600 3D matrix.

In experiment 1, we use the data which is collected at low water temperature to train and test the designed CNN model, the preliminary identification rate is only 10.00%, all the elements of the Softmax output are 0.10. We find that in the training data and test data matrix, every subject's data set are strictly concentrated on. Then we randomly rearrange their order, this time, the final identification rate is not more than 66.50%. When all the data set are normalized once again based on the QRS segmentation matrix, the best and robust identification rate is 82.67%.

In experiment 2, we use the test data which is collected at high bathtub water temperature to test the trained CNN model in experiment 1, the identification rate is only 13.33%.

In experiment 3, we use the training data and test data which are collected at high bathtub water temperature to train and test the CNN model, the identification rate is 85.50%.

In experiment 4, when we use the test data which is collected at low bathtub water temperature to test the trained CNN model in experiment 3, however, the final identification rate is only 12.17%.

From the 4 experimental results, we can see that different bathtub water temperature have an important impact on the ECG signal during bathing. The same subject's ECG varies greatly at different bathtub water temperature. One possible reason is that some subjects are very sensitive to the changes of different bathtub water temperature due to personal physique, which not only increase the range of the baseline drift, but also enhance or weaken the amplitude and frequency of ECG signal.

In the training data matrix, the order of each subject's data should be random, otherwise, it will mislead the CNN model to an extreme when it learns the QRS complex features.

We normalize the data twice in our whole experiment. In order to save storage space and computational cost, we normalize the raw ECG signal. While implement personal identification, we normalize the data once again, which aims at improving the convergence speed of the Softmax function.

In the future work, we will focus on collecting more ECG records with more subjects at different bathtub water temperatures during bathing and try to use different CNN models to perform deep learning.

V. CONCLUSION

This paper explores the impact of bathtub water temperature on personal identification with ECG signal based on convolutional neural network. Four different experiment results show that different bathtub water temperature has an important impact on the ECG signals, especially on the baseline drift and the amplitude and frequency of the ECG signal.

In the data training stage, if each individual's data set is concentrated on, it will mislead the CNN model to an extreme while it is performing the deep learning. In data preprocessing stage, normalization based on the raw ECG can reduce the computational cost and storage space. It can accelerate the convergence speed of the Softmax function if we normalize the training data and test data while performing deep learning.

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