ECG-based Identity Validation during Bathing in Different Water Temperature **

Jianbo Xu, Peng Cui and Wenxi Chen*

Abstract— **This paper proposes a novel identity validation method using ECG signal measured during bathing at 5 different bathtub water temperature ranges, that are 37±0.5 °C, 38±0.5 °C, 39±0.5 °C, 40±0.5 °C and 41±0.5 °C, respectively. The experiment includes 5 male and 5 female subjects, each subject collects 2 ECG recordings at each bathtub water temperature range, one day one recording, 10 ECG recordings are collected from each subject, each ECG recording is 18 minutes long, the sampling rate is 200 Hz. During the data processing stage, we perform spectrum analysis, baseline wandering removal, 50 Hz electromagnetic interference removal, signal smoothing, R peaks detection, and QRS complex segmentation. During the classification stage, we perform identity validation using long short-term memory (LSTM) classification network. 5 classification models are trained based on different bathtub water temperature ranges and the cross-validation method is used. Preliminary validation results show that different bathtub water temperature has an important impact on the identity validation. In order to precisely and quickly perform identity validation at different bathtub water temperature ranges, the final classification model is trained based on the samples from 5 different bathtub water temperature ranges. The highest and average identity validation accuracies are 98.43% and 97.68%, respectively.**

I. INTRODUCTION

Bathing is very popular in Japanese daily life. For many people, bathing in a bathtub at home everyday is necessary, and they think it an effective way to relax, to keep cleaning and healthy. However, the drowning accidents during bathing at home increased about 1.7 times from 2004 to 2015 [1], [2]. One of the main reasons resulting in drowning accidents is that when a person is in a relaxed state during bathing, the brain will temporarily lose consciousness because of the drowsiness, and then the body will slowly sink underwater, which will most likely cause drowning accidents. When the drowning accident is happening during bathing, if we can timely give hazard alarm and automatically send the information of the people to the hospital, then it will be very helpful for the emergency treatment. However, we must know who is in the bathtub before the drowning accidents happening. Therefore, how to quickly and accurately perform identity validation using ECG during bathing is the preliminary task.

The earliest research on bathtub ECG can be traced back to 1986 [3], which mainly focuses on heart disease detection and preventive diagnosis with the bathtub ECG. Subsequently, the bathtub ECG has increasingly been the research focus in the field of health care monitoring [4]–[9]. In 1996, M. Ogawa et al. firstly explored the feasibility of personal identification using bathtub ECG [7]. The experiment included 2 groups of subjects, one group included 5 members from a family, another group included 8 healthy male volunteers. However, the ECG data were collected only at 40 °C and 41 °C bathtub water temperature, and the best classification rate was only 91.6% based on the family members group, which could not meet the practical application. In 2001, since L. Biel et al. proposed the ECG signal as an emerging biometric technology [10], then more and more papers explore the ECG in the identity validation application in recent years, but only a few papers related to the bathtub ECG.

In our previous research, we further proved the feasibility of bathtub ECG in identity validation and the accuracy is 97.2% [2]. Then, we explored the impact of bathtub water temperature on identity validation with ECG signal during bathing and we found that the bathtub water temperature had an important impact on the amplitude and R-R interval (RRI), which indirectly affected the validation accuracy [11]. In order to improve the identity validation accuracy using ECG signal at different bathtub water temperature, we transformed the one-dimensional (1-D) QRS complex to 2-D QRS grayscale image by calculating the grayscale of the 1-D QRS complex, the identity validation accuracies are 87.07% and 87.32% at two different bathtub water temperature ranges, respectively [12]. However, this accuracy is only based on the low bathtub water temperature of 37±0.5 °C and high bathtub water temperature of 41±0.5 °C, which don't include other common bathtub water temperature ranges. Therefore, further improvements are still needed during the different bathing environment.

II. METHODOLOGY

A. Data Collection System

The traditional ECG collection method attaches the electrodes on the skin surface, which results in great uncomfortable to the subjects. In order to let the subject be unaware of monitoring the ECG data during bathing, we use the non-contact electrodes to automatically collect the ECG data. When the people are in the bathtub, the electricity arrives in the electrodes by water. There is obvious baseline wandering if the 4 limbs of the people are intensely moving back and forth. Therefore, it is a big challenge to collect high-quality ECG data for the research work.

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The data collection system is shown in Fig. 1, there are four rectangular stainless steel electrodes attached on the bathtub wall, which are close to the right arm, left arm, right foot and left foot, respectively. The electrodes and the ECG monitor (OpenBCI Ganglion Biosensing Board) are connected by a metal shielded wire, the ECG monitor and the laptop (MacBook Pro) are connected by Wi-Fi.

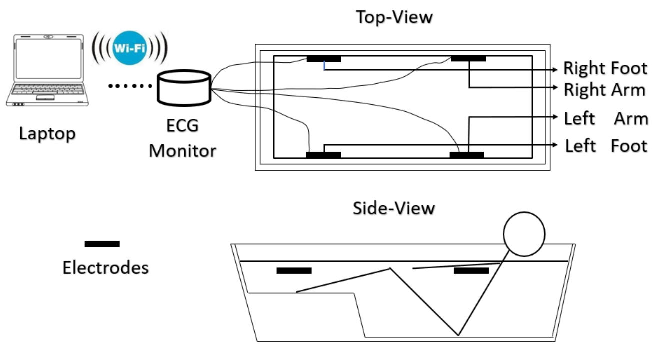

Fig. 1. Data collection system

Three channel's ECG data are collected, which are lead I, lead II, and lead III. The ECG data of lead I is the potential difference between the left arm (positive) and right arm (negative); lead II is the potential difference between the left foot (positive) and right arm (negative); lead III is the potential difference between the left foot (positive) and left arm (negative). When the subject lies in the bathtub, the electricity on the four limbs arrives in the electrodes by water, there is a shielded wire welded on each electrode. The ECG signal are finally stored on the laptop after passing through the shielded wire, the ECG monitor, and the Wi-Fi channel.

B. Subjects and ECG Recordings

The experimental procedures involving human subjects described in this paper were approved by the Public University Corporation, the University of Aizu Research Ethics Committee. Written informed consent was obtained from each participant before the experiments.

This preliminary experiment include 5 male and 5 female subjects with healthy conditions, aged between 20 to 30 years old. During the data collection process, most of the subjects feel comfortable when the bathtub water temperature ranges are 38$\pm$0.5 °C and 39$\pm$0.5 °C, and 2 subjects can not bear the 41$\pm$0.5 °C hot water temperature and 3 subjects feel uncomfortable. When we check the raw ECG data at each bathtub water temperature range and compare them together, we find that the raw ECG data at 40$\pm$0.5 °C and 41$\pm$0.5 °C bathtub water temperature ranges include more noise and there are also more false R peaks detection and QRS segmentations.

C. Data Processing

The data processing and identity validation are implemented using the MATLAB (R2019a). In this paper, we only use the ECG data from lead I, the flowchart of data processing and identity validation is shown in Fig. 2.

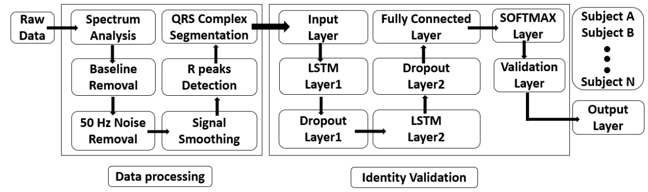

Fig. 2. Flowchart of data processing and identity validation

Before the noise removed, spectrum analysis is implemented based on the raw ECG data. The spectrum analysis result shows that there is an obvious 50 Hz hum noise in the raw ECG data components, which mainly comes from the electromagnetic interference that is generated by the power supply network and its equipment.

First, the baseline wandering is removed, which mainly caused by the movement and respiration of the subject. We use the 1-D wavelet decomposition at level 10 with 'Daubechies Wavelet' to decompose the raw ECG data. Then, we reconstruct the baseline wandering approximation coefficient based on the decomposed 1-D wavelet coefficients at level 8 and subtract it from the raw ECG data.

By analyzing the characteristics of the raw ECG data we find that decomposition at level 10 and reconstruction at level 8 can not only effectively separate the baseline wandering component from raw ECG data, but also could keep the useful information of the ECG data as much as possible.

Next, we use the second-order infinite impulse response (IIR) digital notch filter and 1-D digital filter to remove the 50 Hz electromagnetic interference noise. First, we calculate the numerator coefficient and denominator coefficient of the digital notch filter with the notch located at ω and the bandwidth at 0.0071 at the –3 dB level, the ω must meet the condition 0.0 $<\omega<$1.0, and the difference equation of the 1-D digital filter is shown in equation (1).

$$y[n] = \sum_{i=0}^{N} b_i x[n-i] - \sum_{i=1}^{M} a_i y[n-i], \qquad n \geq 0 \tag{1}$$

where $x[n]$ is input to the filter, $y[n]$ is output to the filter, a_i and b_i are the numerator coefficient and the denominator coefficient of the digital notch filter.

At last, we use the 5-point moving average method to smooth the data, the mathematical formula of the moving average is shown in equation (2):

$$y[n] = \frac{1}{M} \sum_{j=0}^{M-1} x[n-j] \tag{2}$$

where $x[n]$ is input signal, $y[n]$ is output signal, M is 5.

The detailed results in each progress are shown in Fig. 3. At last, we perform R peaks detection and QRS complex segmentation, the result is a 1$\times$30 array (select 14 points before R peak and 15 points after R peak), this array is taken as the input data.

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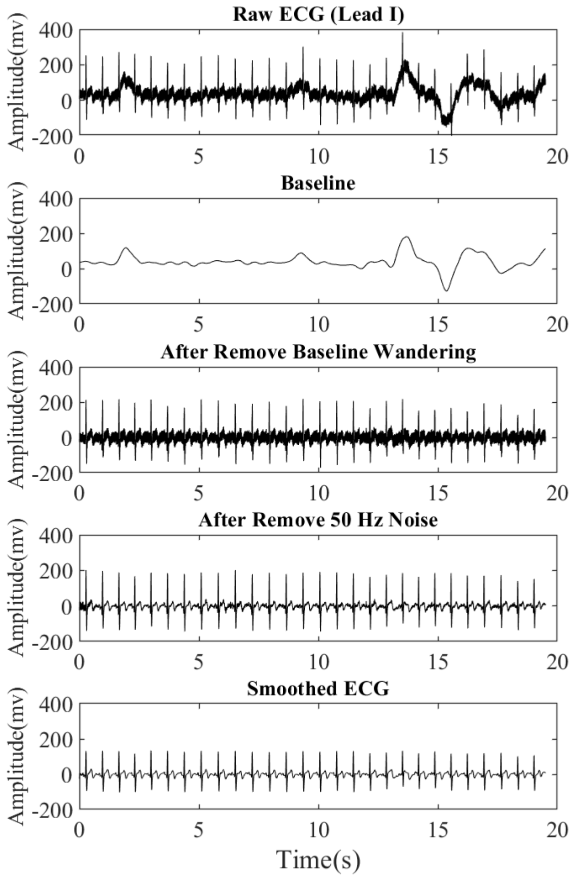

Fig. 3. Noise removal and signal smoothing process

D. Identity validation

Because of the good performance on processing a large amount of data and automatically extracting features, deep neural network (DNN) has been attractive in various applications of both academia and industry [13]–[15]. However, DNN cannot effectively model the changes in time series. Due to the ECG is a signal that appears strictly in chronological order, therefore, we choose the long short-term memory (LSTM) networks to perform identity validation. The LSTM is a type of artificial recurrent neural network (RNN), it has been used in the deep learning field since it was proposed in 1997 [16], which is suitable for processing and predicting important events with relatively long intervals and delays in time series. The detailed parameters of the LSTM networks which are used in this paper are shown in Table I.

TABLE I
DETAILED PARAMETERS OF LSTM NETWORKS

	Layers	Parameters
1	Input	Sequence input with 1 dimensions
2	LSTM	125 hidden units
3	Dropout	20%
4	LSTM	100 hidden units
5	Dropout	20%
6	FullyConnected	10 fully connected layer
7	ActivationFunction	Softmax
8	LossFunction	CrossEntropy

During the training progress, the epoch is 10, the min batch size is 10, the learning rate schedule is constant, the learning rate is 0.001, and the hardware resource is single GPU.

III. RESULTS

The details of the training dataset and test dataset are shown in Table II.

First, 5 classification models (model 1-5) are trained based on each bathtub water temperature range and the cross-validation method is used. Then we use the ECG data which are collected at 5 different bathtub water temperature ranges to train another classification model and use the ECG data at each bathtub water temperature to test it, respectively. Each accuracy is shown in Table II.

TABLE II
DATASET AND VALIDATION ACCURACY

Model	Training Dataset Source	No. of Training Dataset	Test Dataset Source	Accuracy (%)
1	37±0.5	15219	37±0.5	**97.79**
			38±0.5	87.03
			39±0.5	77.28
			40±0.5	80.47
			41±0.5	80.69
2	38±0.5	16047	37±0.5	80.98
			38±0.5	**97.97**
			39±0.5	85.99
			40±0.5	91.32
			41±0.5	85.16
3	39±0.5	17323	37±0.5	84.61
			38±0.5	79.41
			39±0.5	**96.26**
			40±0.5	77.42
			41±0.5	79.66
4	40±0.5	17329	37±0.5	82.29
			38±0.5	94.07
			39±0.5	83.07
			40±0.5	**96.16**
			41±0.5	85.39
5	41±0.5	18095	37±0.5	92.54
			38±0.5	93.92
			39±0.5	87.77
			40±0.5	89.93
			41±0.5	**94.85**
Final	[36.5, 41.5]	84013	37±0.5	98.14
			38±0.5	98.43
			39±0.5	98.16
			40±0.5	97.34
			41±0.5	96.31

IV. DISCUSSION

In this paper, a novel identity validation method using the 1-D ECG signal during bathing based on different bathtub water temperature ranges has been proposed. For each subject, both of the training ECG recording and test ECG recording are 18 mins, one recording is used to train and another recording is used to test, and each dataset represents a QRS complex. Under normal circumstances, a person's ECG is stable in the short term. However, the ECG will also change due to internal reasons such as disease outbreaks or external reasons such as external stimuli. During the data collection stage, the body below the neck of the subject is

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in the water, the stimulation from the water pressure and hot water temperature will cause some changes to the ECG.

Table II shows the details of the training dataset, test dataset, and accuracy. When the bathtub water temperature increases, the number of total heartbeats is also increasing, the RRI and amplitude of the ECG also change at different bathtub water temperature. For classification model 1, the 10 training ECG recordings are collected at 37±0.5 °C water temperature range, total training heartbeats are 15219, the test ECG recordings are collected at 5 different bathtub water temperature ranges, respectively. Table II shows that only the test dataset is collected at the same bathtub water temperature range with the training dataset, the classification accuracy is highest, which directly proves that the ECG changes greatly at different bathtub water temperature.

For the final classification model, the average accuracy is 97.68%, the highest accuracy is 98.43%, which is based on the 38±0.5 °C water temperature range. Our questionnaires show that most of the subjects feel more comfortable when the bathtub water temperature ranges are 38±0.5 °C and 39±0.5 °C, and they feel a little cold when the bathtub water temperature is 37±0.5 °C, but they feel too hot when the bathtub water temperature ranges are 40±0.5 °C and 41±0.5 °C. Therefore, we can conclude that the ECG is more stable when the subject feels comfortable and the classification accuracy is also higher at a comfortable state.

In the future work, we will find more subjects, which should include the child and the older, the healthy and unhealthy, as well as the people from different skin colors and races. We will also explore how to collect the ECG during bathing and how to perform identity validation using ECG if there are two or more people in the bathtub at the same time.

V. CONCLUSIONS

This paper explores identity validation using the ECG signal based on different bathtub water temperature ranges using the long short-term memory classification network. Heart rate analysis result shows that the average heart rate accelerates when the bathtub water temperature increases. Cross-validation results show that the ECG changes greatly at different bathtub water temperature and the bathtub water temperature has an important impact on the identity validation. For most of the subjects, the ECG is more stable when they are in the most comfortable bathtub water temperature circumstances during bathing, and correspondingly the identity validation accuracy is higher. The final classification model can accurately perform identity validation at the most commonly used bathtub water temperature ranges in daily life and the validation accuracy could meet the practical applications.

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REFERENCES

[1] Data resource: Japanese society of legal medicine. `http://www.jslm.jp/problem/yokusou.pdf`. 2014-3.

[2] Jianbo Xu, Tianhui Li, Ying Chen, and Wenxi Chen. Personal identification by convolutional neural network with ecg signal. In *2018 International Conference on Information and Communication Technology Convergence (ICTC)*, pages 559–563. IEEE, 2018.

[3] Subhash C Kwatra and Vijay K Jain. A new technique for monitoring heart signals-part i: instrumentation design. *IEEE transactions on biomedical engineering*, (1):35–41, 1986.

[4] H Mizukami, T Togawa, T Toyoshima, and M Ishijima. Management of pacemaker patients by bathtub ecg. *Iyo Kizai Kenkyujo hokoku. Reports of the Institute for Medical and Dental Engineering, Tokyo Medical and Dental University*, 23:113–119, 1989.

[5] Tatsuo Togawa, Toshiyo Tamura, Jianxin Zhou, Hiroshi Mizukami, and Masayuki Ishijima. Physiological monitoring systems attached to the bed and sanitary equipments. In *Images of the Twenty-First Century. Proceedings of the Annual International Engineering in Medicine and Biology Society,*, pages 1461–1463. IEEE, 1989.

[6] T Togawa, H Mizukami, and T Tamura. Physiological monitoring techniques for home health care. *Biomedical sciences instrumentation*, 28:105–110, 1992.

[7] Mitsuhiro Ogawa, Yuichi Kimura, Toshiyo Tamura, and Tatsuo Togawa. Fully automated ecg data acquisition in a bathtub. In *Proceedings of 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, volume 1, pages 55–56. IEEE, 1996.

[8] Toshiyo Tamura, Takumi Yoshimura, Kazuki Nakajima, Hidetoshi Miike, and Tatsuo Togawa. Unconstrained heart-rate monitoring during bathing. *Biomedical instrumentation & technology*, 31(4):391–396, 1997.

[9] Atsushi Kawarada, Masayulu Nambu, Toshiyo Tamura, Masaydu Ishijima, Ken-ichi Yamakoshi, and T Togawa. Fully automated monitoring system of health status in daily life. In *Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (Cat. No. 00CH37143)*, volume 1, pages 531–533. IEEE, 2000.

[10] Lena Biel, Ola Pettersson, Lennart Philipson, and Peter Wide. Ecg analysis: a new approach in human identification. *IEEE Transactions on Instrumentation and Measurement*, 50(3):808–812, 2001.

[11] Jianbo Xu, Tianhui Li, Ying Chen, and Wenxi Chen. The impact of bathtub water temperature on personal identification with ecg signal based on convolutional neural network. In *2018 IEEE 4th International Conference on Computer and Communications (ICCC)*, pages 1341–1345. IEEE, 2018.

[12] Jianbo Xu, Tianhui Li, Peng Cui, and Wenxi Chen. Improvement of ecg based personal identification performance in different bathtub water temperature by cnn. In *2019 IEEE 10th International Conference on Awareness Science and Technology (iCAST)*, pages 1–5. IEEE, 2019.

[13] Huakun Huang, Lingjun Zhao, Huawei Huang, and Song Guo. Machine fault detection for intelligent self-driving networks. *IEEE Communications Magazine*, 58(1):40–46, 2020.

[14] Fazle Karim, Somshubra Majumdar, Houshang Darabi, and Samuel Harford. Multivariate lstm-fcns for time series classification. *Neural Networks*, 116:237–245, 2019.

[15] Huakun Huang, Shuxue Ding, Lingjun Zhao, Huawei Huang, Liang Chen, Honghao Gao, and Syed Hassan Ahmed. Real-time fault-detection for iiot facilities using gbrbm-based dnn. *IEEE Internet of Things Journal*, 2019.

[16] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

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