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User Authentication System Based on Baseline-corrected ECG for Biometrics

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ABSTRACT
Recently, ECG-based user authentication technology, which is strong against forgery and falsification, has been actively studied compared to fingerprint and face authentication. It is impossible to measure the open ECG DB measured with expensive medical equipment in daily living, and the ECG measured with the developed device for easy ECG measurement has much noise. In this paper, we developed a device that easily measures the ECG for user authentication in everyday life, measured the ECG through the development equipment, adjusted the baseline correction of the measured ECG, extracted it from the adjusted ECG do. The proposed system includes the steps of obtaining ECGs, pre-processing ECG signals, segmenting the signals and extracting features thereof to evaluate user authentication performance. The ECG lead-Ⅰ was obtained from 100 subjects for 120 seconds while they were comfortably positioned. Although the maximum user authentication performance of the existing algorithm was EER of 1.82%, it was observed the maximum performance of the proposed user authentication system was 0.71% higher than the existing algorithm.

KEY WORDS: ECG; User authentication; Baseline correction; EER

1 INTRODUCTION

RECENTLY, the biometrics technology converging IT with BT has been studied. The biometrics technology for verifying personal identity has been used for online banking, information and communication, medical services, social welfare service, administration, entry control, departure and entry examination while crossing national borders, and the entertainment sector all over the world. Therefore, biometrics featuring security and convenience is a technology for using, analyzing, enrolling and saving unique bio information and signals of a person in real time to compare them with proposed bio information and signals for verifying the person's identity as illustrated in Xiao (2007). biometrics using bio information including fingerprints, faces and irises has always been exposed to forgery and disguise threats, for example, forged fingerprints, disguise, and forged irises, and it is not easy to keep a constant pose as illustrated in Dahiya, et al. (2012), Kim, et al. (2017). Therefore, as illustrated in Reference below (Gutta, et al., 2016; Louis, et al., 2016; LDas, et al., 2016; Kim, et al, 2017), not only major advanced countries including the US, Canada and European countries but also Asia countries are studying and developing a biometrics system which uses biosignals, is strong against forgery and falsification and it is easy to use for user authentication.

An exemplary biosignal, that is, ECGs, has unique features of a person depending on electrophysiological factors and the location of the person's heart, and physical conditions of the person. Therefore, because it is hard to forge an ECG, biometrics studies by using ECGs as illustrated in Tan, et al. (2016). The ECG signals for user authentication and identification are used in biometrics by using a common DB(Database) measured in a medical instrument, a DB measured with the developed instrument, and a DB measured with a device. The common DB is an ECG measured by an expensive medical instrument, and the authentication performance thereof by using ECGs of many subjects was higher than that of using ECGs of the smaller number of subjects measured in a device as illustrated in Arteaga-Falconi, et al. (2016).

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Therefore, user authentication reliability is low for reproducibility verification. The DB measured by a developed instrument was used to analyze user authentication performance for the smaller number of subjects to obtain high performance as illustrated in Kang, et al. (2016). The DB measured with a wearable device cannot measure exact ECGs, heartbeats, or it is not user-friendly as illustrated in Chun, et al. (2016) and Choi, et al. (2016). In addition, the measured ECG DB is composed of massive DB, and massive data processing technology can be applied to cloud computing for real-time data processing as illustrated in Peng, et al. (2017), Nalinipriya, et al. (2017).

This paper aims to develop an instrument used first to measure an ECG and a user authentication system using the ECG measured in a wearable device, and propose user authentication system for measuring an ECG with the developed instrument, correcting the baseline of the measured ECG signal and using extracted features. The proposed system includes the steps of obtaining ECG lead-I, removing noise, correcting the baseline thereof based on the primary regression analysis, segmenting one ECG cycle, extracting features in each domain in one cycle and analyzing user authentication performance. The ECG lead-I obtained from 100 subjects were measured while they were positioned comfortably. It was observed that user authentication performance by using the proposed method lowered maximum 1.49% and minimum 0.58% lower than the existing method in terms of Equal Error Rate (EER), implying a good performance. The EER performance when using tested data of 13s in the time and frequency domains where the best performance was observed was 0.98%, implying a good performance.

This paper is composed of the following Chapters. Chapter 2 describes a biometrics system using ECGs; Chapter 3 describes the proposed algorithm in detail; Chapter 4 describes the method of experiment, result, and future studies; and Chapter 5 draws a conclusion.

2 BIOMETRICS SYSTEM USING ECG

THE existing algorithm for user authentication using ECG consist of pre-processing and segmenting an ECG, features extracting and classifying as illustrated in Louis, et al. (2016). Therefore, Fig.1 shows the architecture of biometrics technology using ECGs. Step 1 is for obtaining, enrolling biosignal data and segmenting them into recognized data; step 2 is for processing data signals by removing noise, setting up and segmenting into a reference point and non-reference points; step 3 is for extracting features matching the biosignals, reducing the feature vector dimension to analyze the data in real time; and step 4 is for applying machine learning which is a final classifier to evaluate user authentication performance.

The first task carried out in biometrics is to build an ECG DB. Therefore, MIT-BIH and PTB is usually used in PhysioNet which is an official database, or the ECG DB is built by measuring ECGs by means of the developed instrument, medical instruments, wearable devices and mobile devices as illustrated in Dar, et al. (2015) and Amiruddin, et al. (2015).

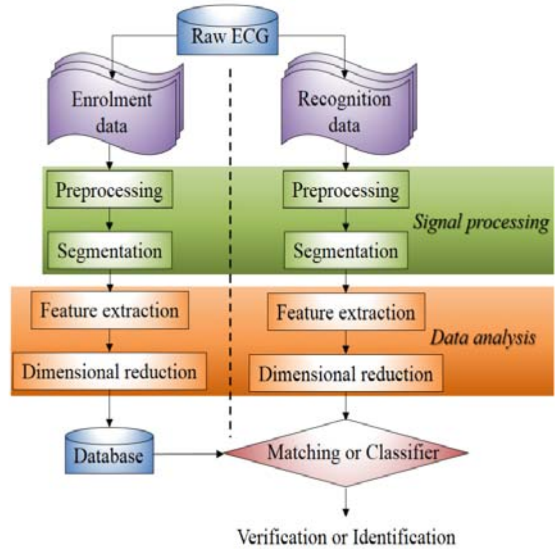

Figure 1. Biometrics system blocks using ECG.

The ECGs obtained from the common database and measured have noise because they are measured by instruments, and signal processing is thus essential. ECG have a modulated wave at 60Hz and broadband white noise in power lines of a measuring instrument (power line interference), motion noise caused by a moving subject or peripheral devices, and baseline change noise caused by subject's breathing as illustrated in Shen, et al. (2002) and Fattah, et al. (2012). To remove the aforementioned noises, it is essential to conduct filtering and normalization. Filtering is conducted to remove noise with a frequency filter and through wavelet decomposition. Exemplary frequency filters include high-pass filter, low-pass filter, and band-pass filter-based Butterworth, Chebyshev and Notch filters as illustrated in Lugovaya (2005). Wavelet decomposition is subdivided into the steps to remove noise components after transform by means of the function for wavelet transform, and the noise components are removed by excluding the noise component coefficient in the subdivided steps as illustrated in Belgacem, et al. (2012). Normalization is conducted through up-sampling, down-sampling and over-sampling based on re-sampling by using thresholds proposed in this paper as illustrated in Zhao, et al. (2013). As a result, raw ECGs are used to output constant clean signals. Segmentation by using ECGs pre-processed for extracting time and features in biometrics establishes sections through the method for setting up a fiducial point and non-fiducial points as illustrated in Coutinho, et al. (2013), Wang, et al.

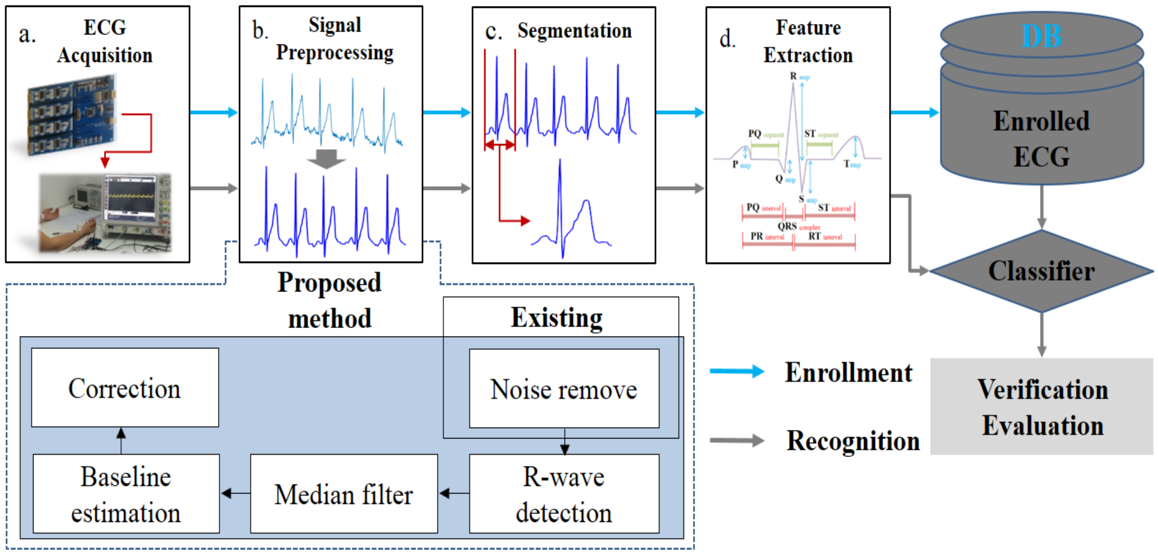

Figure 2. Proposed user authentication system using ECG.

(2013). The fiducial point is enrolled and segmented to match the recognition time by setting up its initial point and end point by using P, QRS and T waves in the whole ECG. The non-reference points are enrolled without consideration of their end point and end point and segmented just in consideration of the recognition time in the whole ECG.

Data analysis by using the segmented ECG is composed of feature extraction and dimensional reduction by discriminant analysis. Features are selectively extracted by means of the proposed algorithm from the time, frequency and phase domains as illustrated in Arteaga-Falconi, et al. (2016), Zhao, et al. (2013), and Lin, et al. (2014). Discriminant analysis is conducted to reduce dimensions by using extracted features. Exemplary discriminant analysis includes principal component analysis and linear discriminant analysis. The primary component analysis is to find an axis for reducing a dimension the most efficiently, and reducing the dimension with the axis to extract features as illustrated in Boumbarov, et al. (2008). The linear discriminant analysis is to collect internal distributed data while protecting dimensional data and reduce external distributed data by finding the axis going farther away as illustrated in Pathoumvanh, et al. (2013). Deep learning for extracting features and reducing feature dimensions in parallel is now applied after using a neural network to apply it.

Machine learning is a classifier for evaluating user authentication and identification performance by using dimension-reduced data, and classified into supervised learning and unsupervised learning. Supervised learning is a method for using a correct answer set (class) established in advance and learning for prediction. Unsupervised learning does not have a correct answer set (class), and clusters sets with similar patterns. Unsupervised learning is composed of the parametric method and the non-parametric method.

The classifier using the extracted feature data used SVM, K-NN, Euclidean distance, and deep learning as illustrated in Homaeinezhad, et al. (2012), Chun (2016), and Phaudphut, et al. (2016). The SVM (support vector machine) is an exemplary type of supervised learning and a classification modeling method for determining which category a new data belongs to and presenting it as a boundary in a mapped space. Other exemplary methods include the decision tree learning method, K-Nearest Neighbors (KNN) algorithm and Random Forests. Gaussian Mixture Model (GMM) is a parametric method for modeling data distribution to know the probability that an identified data is selected for a given Gaussian. The k-average algorithm is a non-parametric method and a clustering algorithm for using k average vectors.

3 PROPOSED USER AUTHENTICATION SYSTEM

FIGURE 2 shows user authentication system proposed in this paper for using ECGs. The proposed architecture is composed of the steps of obtaining ECGs, pre-processing ECG signals, segmenting the signals, extracting features, and evaluating user authentication performance. The ECGs were measured by means of Cypress cortex-M3 which is a development device, and obtained by means of the oscilloscope MSO9104A available from Keysight. Features extracted by using the ECG segmented into one cycle were extracted from time and frequency domains and DNN. The SVM is a classifier finally used to evaluate user authentication performance.

3.1 Developed instrument and measurement for ECG acquisition

The ECG DB for user authentication is composed of an open DB and a DB for measuring and obtaining ECGs. The common DB is composed of exemplary MIT-BIH and PTB which MIT and Harvard University provide as an open source. This DB was used to classify ECGs collected from hundreds of patients by diseases and body conditions to evaluate performance of many studies for diagnosing diseases and developing user authentication technology. However, most of them are data measured just once, and it is thus hard to verify reproducibility for user authentication. Therefore, the ECG DB directly obtained is measured by wearable devices or mobile devices. which can configure ECG data through measurement repeated over a long time or by instruments developed for wearable devices.

In this paper, the instrument initially developed for obtaining ECGs was used as a wearable device. The ECG measured with the developed instrument has more noise than the common DB obtained with the medical instrument of high precision. Equation (1) was used to compute the mean squared error of the 16273 recording samples of Normal Sinus Rhythm in MIT-BIH which is a common DB and the ECG sample measured with the developed instrument in order to compare and analyze noise levels.

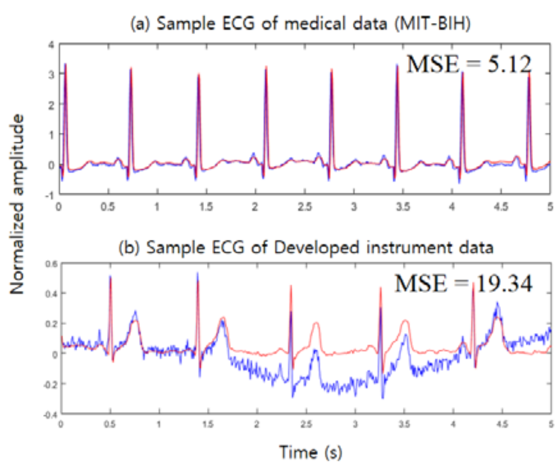

Figure 3. Comparison of (a) medical data(MIT-BIH) and (b) development equipment data. Signal of blue line are raw signal of each data, where as those of red line are denoised signal.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2 \quad (1)$$

In equation (1), n represents the number of data of the ECG sample; Yˆ represents a pre-processed ECG; and Y represents a non-pre-processed ECG. The same pre-processing technology was applied to each ECG sample. The computation showed the Mean Squared Error (MSE) of the 16273 recording samples was 5.12 but the MSE of the ECG sample measured with the developed instrument was 19.34 which implies more noise. Fig. 3 shows the MSE difference between the ECG data measured with a medical instrument and the ECG data measured with the developed instrument. The MSE of greater values has more noise than original signals. Because the ECG measured with the developed instrument has much noise, it is essential to remove as much noise as possible.

3.2 ECG signal preprocessing

Because the ECG measured with the developed instrument has much noise, it is removed in the pre-processing process. The pre-processing process is composed of the steps of removing noise and correcting the ECG. The noise in the measured ECG is removed through frequency filtering, R-wave detection and median process except QRS. The Signal to Noise Ratio (SNR) was computed to examine the level of noise removal. Because signals with greater SNRs have less noise, they are good signals. Fig. 4 shows comparison of SNRs by frequency filtering and the median filter in pre-processing ECGs. The SNR of ECG passing through the median filter by using the R-wave peak was 0.12dB higher than the SNR of 1.33dB of ECG passing through the band-pass filter.

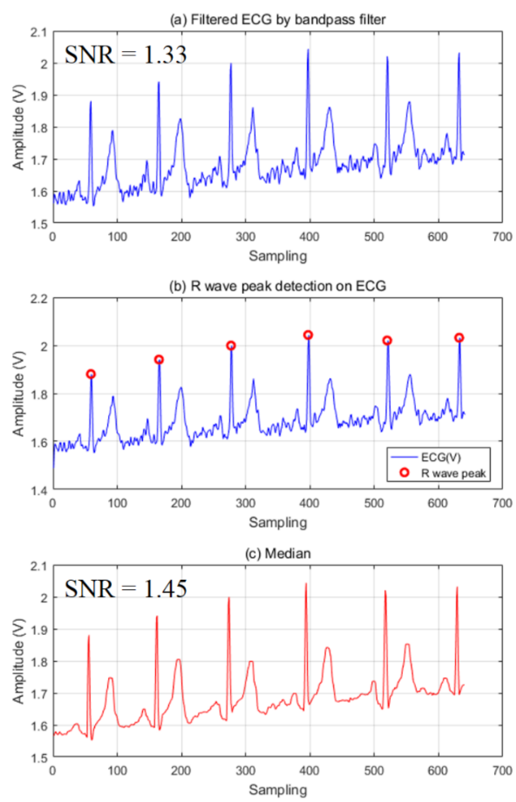

Figure 4. Denoising process: (a) Filtered ECG by bandpass (b) R wave peak detection (c) Filtered ECG by median.

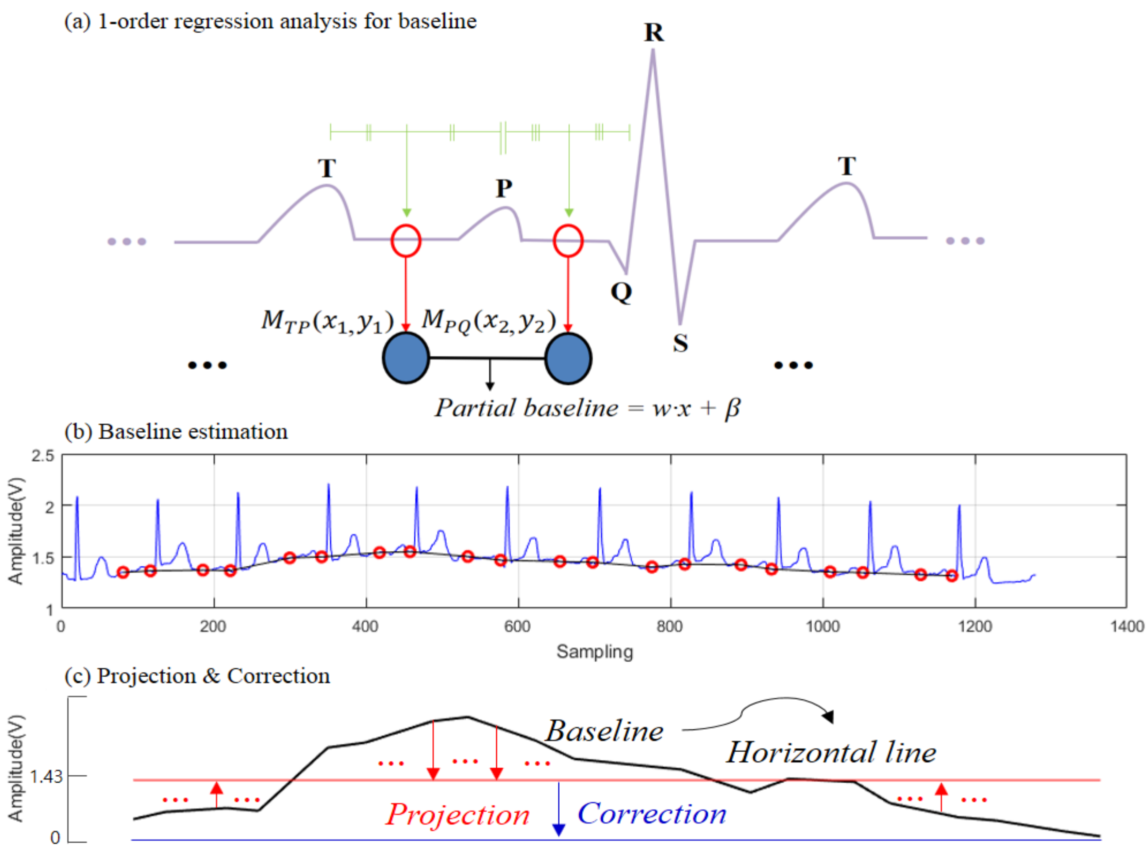

Figure 5. **Baseline correction process is (a) 1-order regression analysis for baselin (b) baseline estimation (c) projection and correction.**

For frequency filtering, a band-pass filter was applied to remove 60 Hz of power line interference, motion artifact (> 40 Hz) caused by motion, and contact noise (< 0.5 Hz) of an electrode for measurement as illustrated in Lugovaya (2005). The R-wave peak of ECG passing through the band-pass filter was detected by means of the threshold value of the algorithm by Pan and Tompkins (1985). The detected R-wave peak is used to set up the QRS complex section to use the median filter. The QRS complex section has unique physical feature information of a person. Therefore, the other section than the QRS complex section passes through the median filter as shown in Fig. 4(c). Although the frequency filter and the median filter using the R-wave peak are used, the baseline change noise by subject's breathing is not removed. In the correction process using continued primary regression analysis to remove baseline change noise, the baseline change in an ECG caused by subject's breathing was estimated. The method proposed to estimate baseline change is for estimating a partial baseline. The partial baseline is computed by means of equations (2), (3) and (4) for primary regression analysis by using the median value of M_{TP} ($x1$, $y1$) between waves T and P of an ECG and the median value of M_{PQ} ($x2$, $y2$) between waves P and Q. Fig. 5(a) shows the process of aforementioned estimation.

$$Partial\ baseline = w \cdot x + \beta \tag{2}$$

$$w = \frac{y_2 - y_1}{x_2 - x_1} \tag{3}$$

$$\beta = y_1 - \frac{y_2 - y_1}{x_2 - x_1} \cdot x_1 \tag{4}$$

To estimate the whole baseline, the partial baseline is estimated repeatedly by using the last M_{PQ} ($x2$, $y2$) value of the ECG as shown in Fig. 5(b). The estimated whole baseline is subject to projection and correction as shown in Fig. 5(c). The projection process is conducted for the horizontal line created by using a median value of the whole baseline. The whole baseline is gathered by means of the following algorithm with values for projection on the horizontal line.

Step 1: Total baseline values set, where $i = 1, \ldots, M$

$$\mathbb{B} = \{B_i | i = 1, \ldots, M\}$$

Horizontal line parameter $\rho_{horizontal\ line}$

$$\rho_{horizontal\ line} = \frac{\mathrm{sum}(\mathbb{B})}{M}$$

Step 2: procedure projection values set, $\mathbb{X}_{\rho}^{(i)}$

If $Bi > \rho_{horizontal\ line}$

$\chi_i = -(B_i - \rho_{horizontal\ line})$

Else If $Bi < \rho_{horizontal\ line}$

$\chi_i = \rho_{horizontal\ line} - Bi$

Else If $Bi = \rho_{horizontal\ line}$

$\chi_i = Bi$

End

$\mathbb{X}_{\rho}^{(i)} = \{\chi_i | i=1, \ldots, M\}$

The projection values aligned on the horizontal line is corrected as point 0 by using total baseline values. The ECG corrected as point 0 did not affect unique feature values of a person concerned, and the baseline change noise was removed.

3.3 Segmentation

ECG lead-□ is an electric signal periodically creating P, QRS complex and T waves through atrial depolarization, ventricular repolarization and ventricular depolarization. Segmentation is conducted for user authentication by using periodical ECGs. The segmentation process by using pre-processed ECGs determines the time for user authentication, As the time of ECG used for user authentication is longer, better performance is implemented, but the time for authentication becomes longer. Researchers have studied how to enhance performance over ECG time used for authentication and identification. ECG segmentation for user authentication is a technology for establishing a reference point and non-reference points. Most technologies for ECG segmentation are used for segmenting reference points than non-reference points because of periodical signal characteristics of ECGs.

In this paper, one cycle was segmented, which consisted of P, QRS and T waves for segmenting reference points by using ECGs pre-processed in the proposed method. For the segmentation, the pan-tomkins algorithm was used to extract the R-wave peak. The R-wave peak was used to segment one cycle from P to T wave domains.

3.4 Feature extraction

One cycle of the segmented ECG was used to extract features. The features were extracted from time and frequency domains, and additionally by deep learning. Fig.6 shows the features extracted from the time domain. Features extracted from one segmented cycle include the amplitude of P, Q, R, S and T waves, the slope of PQ section which is a static section and the ST domain, and the time in the PQ domain which is a complex section of each wave, the QRS complex domain, ST domain, PR domain, RT domain, PS domain, QT domain and PT domain.

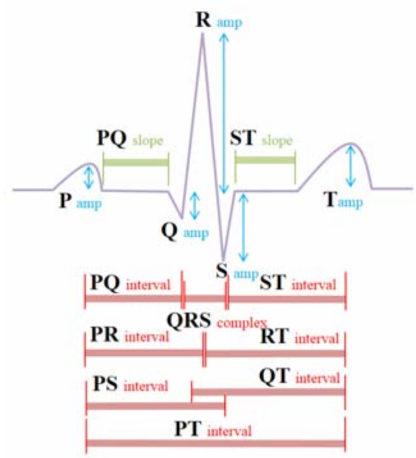

Figure 6. Features extracted from one segmented cycle: amplitude of P, Q, R, S and T waves, slope of PQ and ST domains, and time of PQ, QRS complex, ST, PR, RT, PS, QT and PT domains.

Ensemble Empirical Mode Decomposition (EEMD) is a method for adding artificial noise to the data in the time domain, and removing the artificial noise through the ensemble average in the end. The process of EEMD is as follows. The first step is to add white noise w(t) following normal distribution to the data r(t) in the time domain as in equation (5).

$$x(t) = r(t) + w(t) \quad (5)$$

The second step is to find local maximum/minimum values of data x(t) in the time domain to which white noise was added, and use cubic spline interpolation to connect the local maximum/minimum values, respectively, and thus create the upper/lower envelop. The third step is to compute the average m(t) of the created upper and the lower envelops to find the difference between the average and the data x(t) in the time domain to which white noise was added. The result is Intrinsic Mode Function (IMF) h1(t) illustrated in equation (6).

$$h_1(t) = x(t) + m(t) \quad (6)$$

The fourth step is to repeat the second and the third steps k times until the computed IMF h1(t) is close to the average 0 of the upper and the lower envelops. The result is to make the first IMF c1(t) illustrated in equation (7)

$$h_{1k}(t) = h_{1(k-1)}(t) - m_k(t)$$

$$c_1(t) = h_{1k}(t) \quad (7)$$

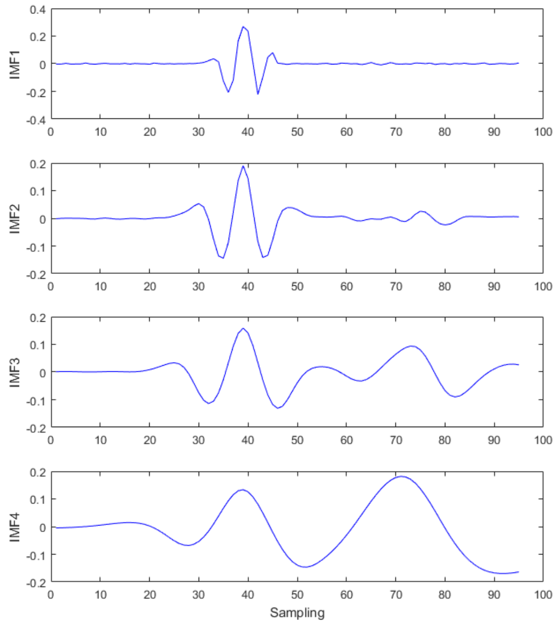

Figure 7. **One cycle of ECG converted with IMF1~4 of EEMD.**

The fifth step is to calculate the difference between data x(t) in the time domain to which white noise was added and the created IMF c1(t) to find the remainder r1(t) obtained by removing the first IMF illustrated in equation (8).

$$r_1(t) = x(t) - c_1(t) \tag{8}$$

The sixth step is to replace x(t) in the second step with r1(t)and make, it subject to the second to fifth steps to compute the second IMF c2(t). As the aforementioned steps repeat, n IMFs are calculated, and equation (9) finally calculates trend $r_n(t)$.

$$r_2(t) = r_1(t) - c_2(t)$$

$$\dots$$

$$r_n(t) = r_{(n-1)}(t) - c_n(t) \tag{9}$$

The seventh step is to set up different white noise added in the first step and repeat the first to sixth steps m times. Through the aforementioned process, n IMFs of which the cycle is different each other and the same m trends are created, respectively. In this paper, 12 IMFs and one trend were created, and features were extracted by using high-frequency components of first to fourth IMFs.

Frequency features using one segmented cycle were extracted by using Autocorrelation (AC) / Discrete Cosine Transform (DCT) and Mel Frequency Cepstrum Coefficients (MFCCs). Features using AC/DCT, MFCCs and Power spectrum were clustered and extracted, respectively.

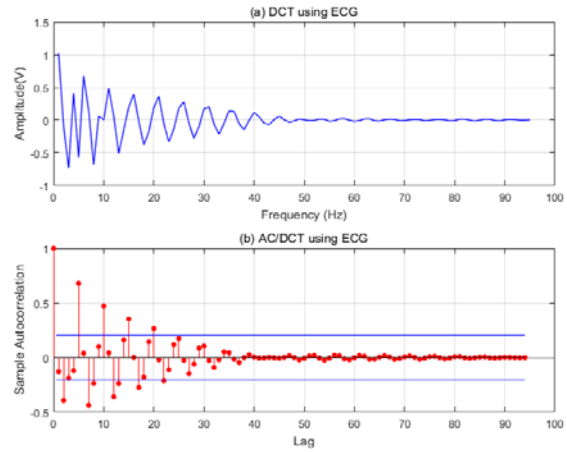

Figure 8. **(a) DCT signal converted by using one cycle of ECG (b) AC to notify the coefficient and position of cycle component using DCT.**

DCT is a method for using one segmented cycle, FFT for the time axis and FFT for the voltage axis again, and Fig. 8(a) shows the output signal in this method. DCT in one cycle is composed of DC components and cos components. The time domain f(x, y) is transformed into the frequency domain to become F(u, v). u and v are the position values of the coordinate in the frequency domain. AC for finding cycle components by using u and v, the output of DCT, is a coefficient to examine the possibility that successive error terms are related each other. The limit line for extracting coefficient values is composed of a lower limit line and an upper limit line. The upper limit line is a positive limit line, and the lower limit line is a negative limit line. The limit lines are used to predict whether the voltage values of an ECG on the frequency axis are random or not, present values and future values. In this paper, as shown in Fig. 9 (b), the feature coefficients were extracted by the coefficients above the upper limit and those below the lower limit.

MFC is a method for representing power spectra of short-time signals in the time domain and obtained through cosine transform of the log-scale power spectrum in the frequency domain of non-linear Mel-scale. Although the frequency bands of a normal cepstrum are uniformly divided, those of MFCC are uniformly divided in Mel-scale. Fig. 9 shows a block diagram computed with MFC by using segmented one cycle of ECG. One cycle which is an input signal is divided into frames by synthesizing the W (window) function and transformed into the frequency domain by means of FFT. Mel Filterbank is obtained from each bank by using frequency bands to divide them into multiple filter banks. The filter sequence shows a linear center frequency and bandwidth in the low frequency (1000 Hz or lower) and increases in a log scale as the frequency becomes higher (1000 Hz or higher).

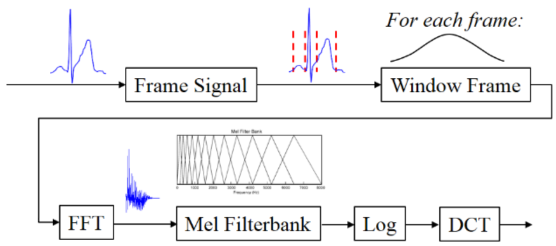

Figure 9. **MFC block diagram using one cycle of ECG.**

Mel in Mel Filterbank is computed by means of log as in equation (10).

$$M(f) = 1125\,ln\left(1 + \frac{f}{700}\right) \tag{10}$$

M(f) computed with equation (10) obtains the cepstrum in the secondary frequency domain in the DCT process. The bandwidth of each filter is determined by the critical bandwidth. Therefore, Mel energy is transformed into M-squared order about Mel scale energy through DCT. In this paper, the order of M-th power is used to collect the coefficients of MFC by DCT to extract MFCCs as features as shown in Fig. 10.

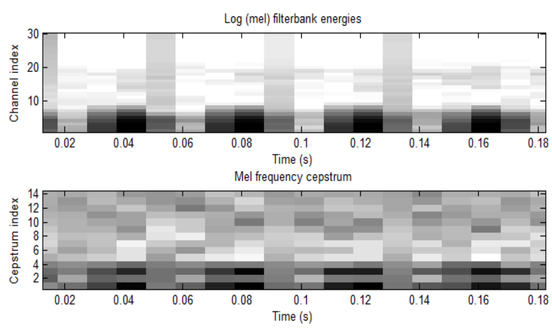

Figure 10. **MFCCs using ECG by Mel-scale filter bank.**

Deep learning is a branch of machine learning. It is composed of input layers, hidden layers and output layers. The artificial neural network composed of multiple hidden layers is a deep neural network. The deep neural network models complex nonlinear relations and is computed every layer composed of multiple nodes. A node receives multiple inputs, and controls the coefficients as many as the number of inputs to give a different weight to respective inputs. In the end, all multiplied values are added and enter the cell body as inputs into the activation function as shown in Fig. 11. Features are automatically extracted from the data output of the activation function, and adjusted depending on the increase in hidden layers and the number of repetitions. Automatic feature extraction is computed when learning unlabeled data, and the output thereof becomes the input thereof when passing through the neural network.

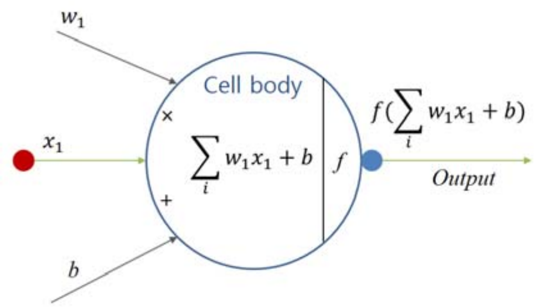

Figure 11. **One node computed in hidden layer of DNN.**

The neural network in which the input is the same as the output conducts the reconfiguration task of efficiently encoding and decoding inputs. Error backpropagation for minimizing output data errors depending on the number of repeated reconfigurations repeats to update values of each coefficient in the learning process through the Gradient Decent Method. The data output with minimized errors is classified through the last layer, and it is possible to obtain the probability of a specific label through Logistic or Softmax.

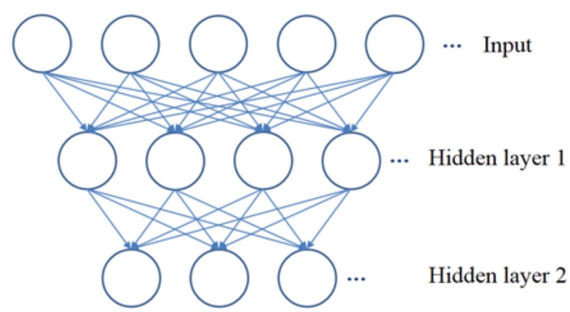

Figure 12. **Architecture for extracting features in DNN.**

In this paper, the hidden layer is composed of layers 1 and 2. Features were extracted from the final output layer except Softmax for error backpropagation and classification through labelling as shown in Fig. 12.

4 EXPERIMENTAL RESULT

USER authentication performance was verified by using Intel Core i5 processor PC Matlab R2016a. For user authentication, 100 subjects for obtaining ECGs consisted of 89 males and 11 females whose age ranged from 23 to 34 years old, and ECGs were measured for 2 minutes per person. For configuring a fair ECG DB, the ECG was measured for 10 seconds and again after resting for 10 seconds. The ECG was measured while all 100 subjects were comfortably positioned. Randomly, the time for learning data used for user authentication was 50s and the time for recognition data was 10s. The EER for analyzing user authentication performance was computed with a threshold which is a point where the False Rejection

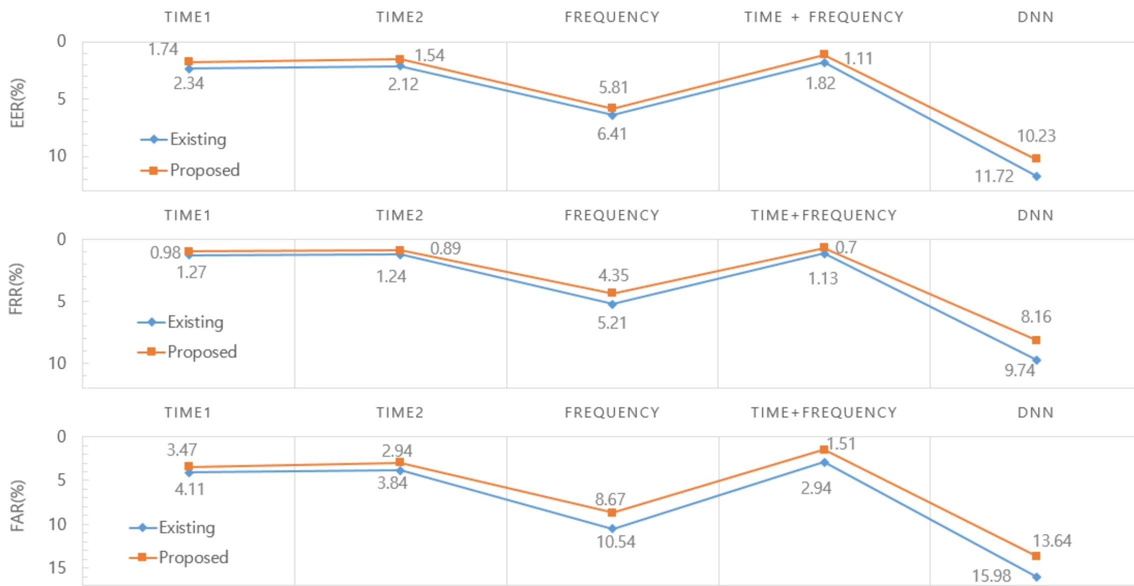

Figure 13. User authentication performance analysis.

Rate equally matches the False Acceptance Rate. The best threshold value for finding the EER was found by using the user's distance data value computed through matching and other data values than the users. The EER of 100 subjects found by using the best threshold value was computed by averaging the EER of each subject. The computed EER was used to compare the performance by using the proposed method and the performance by using the existing method. The sequence of performance analysis was feature extraction from one cycle of ECG which is time domain 1, EEMD which is time domain 2, AC/DCT and MFCC which is the frequency domain, EEMD which converges time with frequency, power spectrum and DNN. SVM was used as machine learning for comparison and analysis.

Fig. 13 shows performance analysis for user authentication. The EER performance of the proposed method using time domain 1 was 1.74% lower than previous 2.34%; the FRR performance was 0.98% lower than previous 1.27%; and the FAR performance was 3.47% lower than previous 4.11%. The EER performance of the proposed method using time domain 2 was 1.54% lower than previous 2.12%; the FRR performance was 0.89% lower than previous 1.24%; and the FAR performance was 2.94% lower than previous 3.84%. The EER performance of the proposed method using the frequency domain was 5.81% lower than previous 6.41%; the FRR performance was 4.35% lower than previous 5.21%; and the FAR performance was 8.67% lower than previous 10.54%. The EER performance of the proposed method using time and frequency domains was 1.11% lower than previous 1.82%; the FRR performance was 0.7% lower than previous 1.13%; and the FAR performance was 1.51% lower than previous 2.94%. The EER performance of the proposed method using DNN was 10.23% lower than previous 11.72%; the FRR performance was 8.16% lower than previous 9.74%; and the FAR performance was 13.64% lower than previous 15.98%. The proposed method lowered EER by maximum 1.49% and minimum 0.58%; FRR by maximum 1.58% and minimum 0.29%; and FAR by maximum 2.34% and minimum 0.64%.

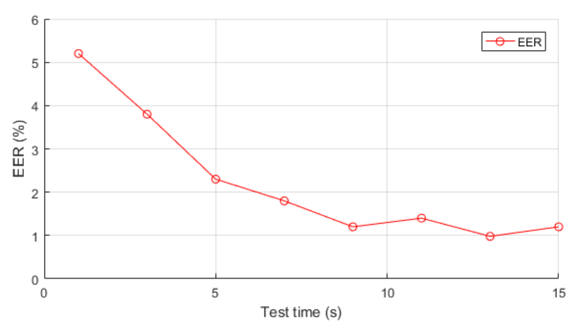

Figure 14. EER performance change depending on test data time.

In this paper, user authentication performance was analyzed depending on the time shown in the maximum performance and the time of recognition data in the time and frequency domains. The recognition data time was from 1s to 15s as shown in Fig. 14. When the test data time was 1s, the EER performance was 5.2%, and the EER performance gradually became lower and showed better performance as the test data time increased. The maximum performance was 0.98%, implying good performance when the time for test data was 13s.

5 CONCLUSION

THIS paper proposes a system for user authentication by correcting the baseline of an ECG obtained with the instrument initially developed for verifying reproducibility of a wearable device through primary regression analysis and using extracted features. The proposed system is composed of the steps of obtaining ECG lead-□ with the developed instrument, removing noise and correcting the baseline based on primary regression analysis, segmenting one cycle of ECG, extracting features from each domain in one cycle, and analyzing user authentication performance.

User authentication performance based on the proposed method lowered EER by maximum 1.49% and minimum 0.58% compared with the existing method, implying a good performance. The EER performance was 0.98% which is a good performance when using the test data time of 13s in the time and frequency domains in which the maximum performance was observed. Therefore, better user authentication performance was obtained about noise in ECGs through the frequency filter and wavelet compression used in the existing method, keeping the QRS complex section, applying the median filter, and correcting the baseline without distorting unique ECG values of a person concerned. It is necessary to further study how to build a DB for ECGs measured under various conditions and from more subjects with the developed instrument sensor data for wearable devices as illustrated in Faye, et al. (2016), Uchida, et al. (2017), and use the DB to analyze user authentication system and performance through deep learning.

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8 DISCLOSURE STATEMENT

THE authors declare that they have no conflict of interest.

9 NOTES ON CONTRIBUTORS

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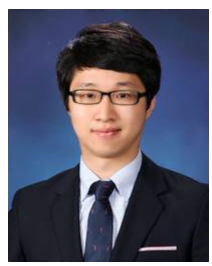

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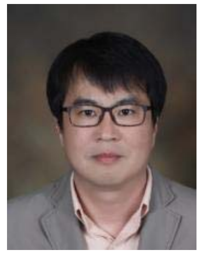

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