

Study on a Biometric Authentication Model based on ECG using a Fuzzy Neural Network

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Abstract. Traditional authentication methods use numbers or graphic passwords and thus involve the risk of loss or theft. Various studies are underway regarding biometric authentication because it uses the unique biometric data of a human being. Biometric authentication technology using ECG from biometric data involves signals that record electrical stimuli from the heart. It is difficult to manipulate and is advantageous in that it enables unrestrained measurements from sensors that are attached to the skin. This study is on biometric authentication methods using the neural network with weighted fuzzy membership functions (NEWFM). In the biometric authentication process, normalization and the ensemble average is applied during preprocessing, characteristics are extracted using Haar-wavelets, and a registration process called “training” is performed in the fuzzy neural network. In the experiment, biometric authentication was performed on 73 subjects in the Physionet Database. 10-40 ECG waveforms were tested for use in the registration process, and 15 ECG waveforms were deemed the appropriate number for registering ECG waveforms. 1 ECG waveforms were used during the authentication stage to conduct the biometric authentication test. Upon testing the proposed biometric authentication method based on 73 subjects from the Physionet Database, the TAR was 98.32% and FAR was 5.84%.

1. Introduction

Due to rapid advancements in IT technology, issues regarding privacy violation prevention and data protection have become increasingly important and the demand for biometric authentication is on the rise. Existing authentication technology is reliant on passwords or objects, which involves the risk of exposure, forgetting, loss, or theft. However, the more advanced biometric authentication technology uses an individual's unique data to verify identify. Unique data is generally categorized into action-based features and physical features. Action-based features include voice, signature, or walk, while physical characteristics include fingerprints, iris, face, and ECG. Of these, fingerprints, voice, iris, and face are used as the main mobile biometric authentication features [1-3]. Fingerprint authentication has been used for over 100 years in various application fields. A fingerprint is formed when the sweat glands form grooved into the palm of the hand. They appear around 13-19 weeks while in the womb and their shape never changes. However, fingerprints may become damaged and there is still the risk that an attacker may steal finger the fingerprint. Voice authentication recognizes the user through an individual's unique speech patterns. These speech types are behavioural and are formed as a result of physiological factors. Voice authentication is the most natural authentication method since the system's equipment does not require contact with the user's body. However, the disadvantage of the voice authentication system is that there is no reliability. There are dangers of manipulation where someone may imitate the voice of someone who is already authenticated in the voice authentication system database. Moreover, a person's voice is inconsistent according to their present health conditions



there may be overlapping noise, hence its authentication rate suffers compared to other biometric authentication methods. Therefore, its drawback is that it is not suitable for quiet indoor environments compared to public areas. The iris is known to be different even among identical twins and never changes throughout a person's lifetime as long as there is no major external trauma or illness. The patterns of the iris are formed within 6 months after birth and are determined at around 2-3 years old. The shape of the iris on the left and right differs for every individual. The advantage of iris authentication is that the target can be detected with a camera even at a distance of about 1m. However, there is the issue of privacy violations because the camera films an individual's face. Face authentication is a method of authenticating the shape of an individual's face, and is most commonly used when a person is verifying another person's identity. Face authentication involves assessing whether or not a person is who they say they are by comparing the present image with a face image in the database. To authenticate a face, it is important for the device that will process extracted features to have quick operation processing speeds. Moreover, data will change significantly depending on disguises, aging, hair length, direction of light, or expression, thus there is the disadvantage of decreased reliability in fields that required higher security. While there are many advantages and disadvantages to commonly used authentication methods, ECG biometric authentication involves unique biometric features from the electrical physiological factors of the heart, location and size of the heart, physical conditions, etc. ECG biometric authentication is advantageous in that it does not require any particular actions or positions and enables unrestrained measurements in the mobile environment, and is difficult to duplicate or forge since it involves biometric signals that are recorded from a person's beating heart [4, 5].

The first study on ECG biometric authentication was proposed by Lena Biel [6] in 2001. Henceforth, biometric authentication algorithms using ECG have been introduced by T. W. Shen [7], Steven A. Israel [8], Konstantinos N. Plataniotis [9], and Gerd Wubbbeler [10]. The characteristics of ECG biometric authentication usage thus far have mainly developed through the reference point analysis method and structural analysis method. Although the reference point analysis method was widely researched in the beginning, the trend of research is moving toward the structural analysis method because since the former method was found to directly reflect detection authentication errors as is [4]. The structural analysis method extracts features by categorizing signals into single cardiac impulse units from all ECG signals. Individual authentication algorithm studies are being conducted using various categorization methods such as the neural network, SVM, KNN, etc. as classifiers [11-14]. There are also research based on the number of ECG data channels and ECG measurement status. Although individual authentication using multichannel ECG signals achieves a near 100% accuracy, this accuracy decreases when the number of the channel is reduced [15, 16]. Biometric authentication technology using ECG is highly likely to become commercialized like the now ubiquitous fingerprint authentication technology. With the recent rise mobile device dependency, there is need for biometric authentication technology with increased convenience while maintaining a certain level of accuracy and reliability regarding personal information protection and authentication.

This paper used the structural analysis method, which extracts features using the structure of ECG waveforms, for effective biometric authentication using the low computing power of the mobile environment. Further, a biometric authentication test was conducted using the ECG of 73 subjects in the Physionet Database, which is a 1-lead signal that minimizes the number of electrodes for simple measurements in the mobile environment [23]. Haar-wavelet transformation was used as the structural analysis method for extracting ECG signal features, and the features were extracted using the wavelet coefficients a_4 , d_3 , and d_4 . A study that authenticates an individual's waveforms by training in the neural network with weighted fuzzy membership functions (NEWFM) based on the extracted features was proposed [17, 18].

Section 2 is regarding the structure and training of the neural network with weighted fuzzy membership functions, which is a related study, and Section 3 includes a detailed explanation of the proposed ECG biometric authentication method. Next, Section 4 is regarding the experiment and results for a fair performance evaluation, and Section 5 is the conclusion.

2. Proposed ECG Biometric Authentication Model

Figure 1 is a diagram of the biometric authentication model proposed in this study. The proposed biometric authentication model is divided into preprocessing, biometric feature extraction, and biometric authentication. During the preprocessing stage, the sampling rate and amplitude are normalized, and signals are extracted in ECG waveform units, then the ensemble average is applied to obtain a stable feature value even from a changing heart rate [24]. Noise removal and ECG waveform division can be performed simultaneously by extracting features using wavelet transformation during the biometric feature extraction process, and a strong resolution is achieved for the factors of each feature in the ECG signal. Biometric features are extracted through Haar-wavelet transformation coefficients a_4 , d_3 , and d_4 , and the extracted features are entered into the neural network with weighted fuzzy membership functions for use in order to categorize ECG waveforms in the proposed biometric authentication model.

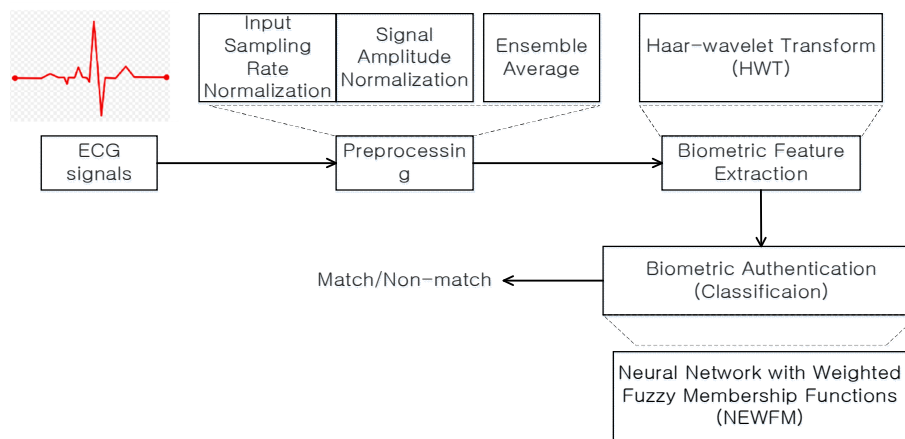


Figure 1. Structure of the proposed ECG biometric authentication model.

2.1. Preprocessing

The individual ECG signals that are entered are expressed through E in Formula (1). r in Formula (1) is the number of samples in individual ECG signals that were entered, and a ECG signal length of 2,000 seconds is used for input.

$$E = (e_1, e_2, e_3, e_4, \dots, e_n) \quad (1)$$

ECG signals have varying sample rates depending on the measurement instrument. To experiment on signals that were obtained from different instruments, there must first be a process of converting the signals of various input sampling rates into an average sampling rate signal. Further, the intensity of heartbeats among subjects of ECG measurement will differ according to whether or not they exercise, take medication, etc. Therefore, there must also be a process of normalizing the ECG signal amplitude. preprocessing is performed by calculating an individual's average ECG waveform and applying the ensemble average of all ECG waveforms to calculate the average space of average ECG waveform samples and align ECG waveforms [24].

2.1.1. Input Frequency Sampling Rate Normalization. Since the ECG sampling rate varies according to the ECG measurement instrument, there must first be a normalization process into an ECG signal of a standard sampling rate with a unified sampling rate of diverse ECGs. The sampling rate normalization process can be divided into up-sampling normalization and down-sampling normalization. Up-sampling normalization converts signals with low sampling rates into signals with

high sampling rates while down-sampling normalization converts signals with high sampling rates into signals with low sampling rates process 1 shows the up-sampling normalization process through pseudocodes and process 2 shows the down-sampling normalization process. The initial sampling rate is received as a variable in the input_sample_rate and the standard sampling rate that is desired for output is received as a variable in standard_sample_rate. The two variables are divided to calculate the rate, then ECG samples are added or deleted to match this rate and the sampling rate is normalized and stored in the sig.

```

Input: E
Input: Input_sample_rate
Input: Standard_sample_rate
[1]: rate=
      Input_sample_rate/Standard_sample_rate
[2]: for i=0 to n
[3]:   index=i+1
[4]:   num_1=round(index*rate+0.5, 1)
[5]:   num_2=num_1+1
[6]:   sig[i]=(e[num_1]*rate* ndex)/num_2
[7]: end for

```

```

Input: E
Input: Input_sample_rate
Input: Standard_sample_rate
[1]: rate=
      Input_sample_rate/Standard_sample_rate
[2]: len=floor(length(E)/rate, 1)
[3]: sig[len]=0
[4]:for i to len
[5]:   index=floor(i*rate, 1)
[6]:   num_1=integerthrow(i*rate)
[7]:   sig[i]=e[index]
[8]:   if num_1==0
[9]:     i=i+1
[10]:   sig[i]=e[i]
[11]:   end if
[12]: end for

```

Process 1. Up Sampling Normalization.

Process 2. Down Sampling Normalization.

2.1.2. ECG signal amplitude normalization. To normalize the intensity of the ECG signal that is entered, the maximum value of the input ECG signal is showed through E_{max} in Formula (2) and the minimum value of the input ECG signal is shown through E_{min} in Formula (3). r in Formula (2) and (3) is the length of the input ECG signal.

$$E_{max} = (e_1, e_2, e_3, e_4, \dots, e_n) \quad (2)$$

$$E_{min} = (e_1, e_2, e_3, e_4, \dots, e_n) \quad (3)$$

The variable that will be stored after normalizing the amplitude is defined through E_{NA} in Formula (4). Formula (5) shows the process of normalization between 0 and 1 by using the maximum and minimum value of ECG signals.

$$E_{NA} = (a_1, a_2, a_3, a_4, \dots, a_n) \quad (4)$$

$$a_i = \frac{e_i - E_{min}}{E_{max} - E_{min}}, \text{ where } i = 1, 2, 3, 4, \dots, r \quad (5)$$

Process 3 shows the process of normalization between 0 and 1 as a (pseudocode). This process receives the ECG signal that will undergo amplitude normalization at E_{NA} , then the value that is obtained by normalizing amplitude using the maximum and minimum values of each ECG signal is stored in E_{NA} .

2.1.3. Ensemble average. Although the P-wave and T-wave of ECG signals show significant changes on the time axis, the QRS complex is an unchanging feature on the time axis. In order to obtain a

stable feature value in a state where heart rate changes, this study used an alignment method that emphasizes the QRS complex. The Pan-Tompkins QRS complex detection algorithm was used to detect the location of R-peaks in the ECG signal [21]. R in Formula (6) stores the location value of R-peaks that are detected through the QRS complex detection algorithm, and m is the number of pulse beats that are found in individual ECG signals. One pulse beat can be defined as one ECG waveform. Formula (7) is shown as a 2-dimensional vector by applying the ensemble average of one ECG waveform [24]. k of Formula (7) is the ensemble average of one ECG waveform, and m is the number of ECG waveforms that are found in the ECG signal.

$$R = (r_1, r_2, r_3, r_4, \dots, r_m) \quad (6)$$

$$E_{AL} = \begin{pmatrix} l_{11} & l_{12} & \dots & l_{1k} \\ l_{21} & l_{22} & \dots & l_{2k} \\ \vdots & \vdots & \dots & \vdots \\ l_{m1} & l_{m2} & \dots & l_{mk} \end{pmatrix} \quad (7)$$

The P-wave of all ECG waveforms is an atrial depolarization that occurs when an electrical stimulation from the sinus node contracts the atrium, and the time required is between 0.05 to 0.12 seconds. The T-wave is the ventricular repolarization that shows period of recovery after the atrium was contracted. The time required is between 0.1 to 0.25 seconds. Therefore, 40 samples and 80 samples were extracted from the left and right of the R-peak respectively. These 120 samples were configured as one ECG biometric feature. Figure 2 shows the ECG signal before applying the ensemble average as a dotted line and the ECG signal after applying the ensemble average as a solid line.

Process 4 is the process of applying the ensemble average. The ECG signal that has undergone the normalization process in the previous stage in E_{AL} is received as input. The location value of the R-peak that was detected through the Pan-Tompkins QRS complex detection algorithm is stored in $peak[r]$. This process involves applying the ensemble average that calculates the average space of an ECG signal's waveform and re-aligning it based on the R-peak to store it into E_{AL} once again.

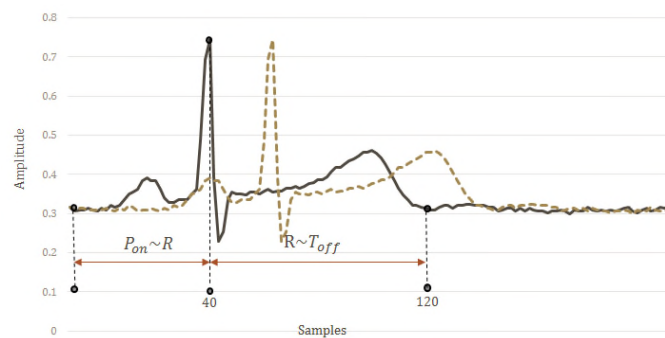


Figure 2. ECG waveform before applying ensemble average (dotted line) and ECG waveform after applying ensemble average (solid line)

Input: E_{NA}

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[1]:  $E_{max} = \max(E_{NA})$ 
[2]:  $E_{min} = \min(E_{NA})$ 
[3]: for  $i = 0$  to  $r$ 
[4]:  $E_{NA}[i] = (E_{NA}[i] - E_{min}) / (E_{max} - E_{min})$ 
[5]: end for
```

Input: E_{AL}

```
Input:  $peak[r]$ 
[1]:  $sig\_num = [], sig = []$ 
[2]: for  $i = 0$  to  $n$ 
[3]:  $before\_loc = peak[i] - 40$ 
[4]:  $after\_loc = peak[i] + 80$ 
[5]  $sig\_num =$ 
 $\quad \text{transpose}(E_{AL}[before\_loc:after\_loc])$ 
[6]:  $E_{NA}.append(sig\_num)$ 
[7]: end for
```

Process 3. Amplitude Normalization**Process 4. Ensemble Average****2.2. Feature extraction using haar-wavelet transform**

Wavelet transformation is a multi-resolution system that converts input sampling frequencies into other sampling frequencies to process signals in different frequency bands. Wavelet transformation is categorized into the scale coefficient (a) and transition element (d) from the wavelet generating function (ψ), and can be shown through Formula (8).

$$\psi(a, d)(x) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi\left(\frac{t-d}{a}\right) dt \quad (8)$$

The scaling coefficient (a) and transition element (d) in Formula (8) are converted for the wavelet transformation of ECG signals. This can be categorized into high frequency signal $d_2^j[x(n)]$ and low frequency signal $a_2^j[x(n)]$, and ECG signal is shown through $d_2^j[x(n)] + a_2^j[x(n)]$ [20].

Formula (9) and (10) show that the number of samples becomes divided in two according to a decrease in Level j . Formula (9) is a high frequency detail signal. The input signal's high frequency component is divided through Level j according to the transition element (d) of the wavelet function. Formula (10) is the frequency component's approximation signal and divides the frequency component through scale factor (a) of the input signal by Level j .

$$d_{2j}[x(n)] = \sum_{k=1} d_{2j}(k) \psi_{2j}(n - 2^j k) \quad (9)$$

$$a_{2j}[x(n)] = \sum_{k=1} a_{2j}(k) \psi_{2j}(n - 2^j k) \quad (10)$$

In this paper, wavelet features were extracting using the Haar-wavelet transform (HWT), which is the most simple and easy to use. Figure 3 shows the multi-resolution analysis process of dividing input signals into high frequency portions and low frequency portions, then dividing the low frequency portion again using the same method. The wavelet coefficients in Level (1-2) are influenced by frequency interference, and the wavelet coefficients in Level (3-4) are influenced by base line conversions. $x[n]$ in figure 3 shows the input ECG signals. $g[n]$ refers to the detail signal and $h[n]$ refers to approximation. $\downarrow 2$ means that the number of the transformation coefficient during the down-sampling process gets reduces in half. The wavelet coefficients that are extracted as features of biometric authentication included 7 samples from a_4 , 15 samples from d_3 , and 7 samples from d_4 , hence a total of 29 wavelet coefficients were converted into on ECG biometric feature. Figure 4 is a diagram of the wave coefficients a_4 , d_3 , and d_4 of MIT-BIH Normal Sinus Rhythm Record No. 16265.

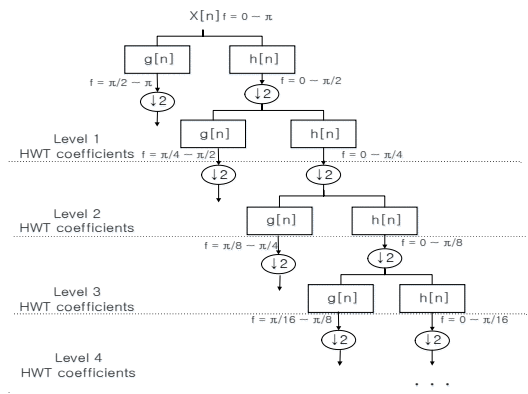


Figure 3. Division of scale Level 4 ECG signals through Haar-wavelets.

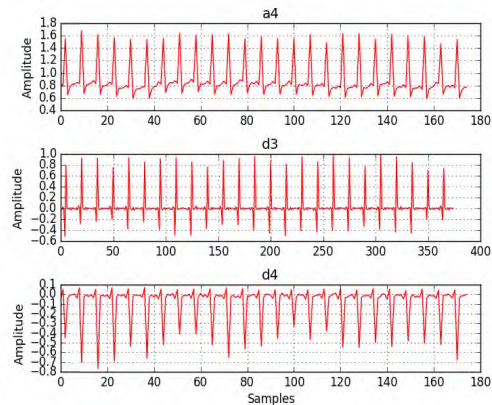


Figure 4. a_4 , d_3 , and d_4 signals of MIT-BIH Normal Sinus Rhythm Record No. 16265.

2.3. Training in the neural network with weighted fuzzy membership functions

The neural network weighted fuzzy membership functions (NEWFM) is a supervised fuzzy neural network that categorizes classes using the boundary sum of weighted fuzzy membership functions that were trained from input. [Figure 5] is a diagram of the structure of the neural network with weighted fuzzy membership functions. The neural network with weighted fuzzy membership functions consists of the input layer, hyperbox layer, and output layer. The input layer has N nodes and each node is connected to one input feature. The number of nodes in the hyperbox layer is the number obtained by multiplying the number of nodes in the input layer and the number of nodes in the output layer. The nodes in the hyperbox layer are bundled as the hyperbox group, and the number of hyperboxes is identical to the number of nodes in the output layer. Each node is connected to one hyperbox. The weighted fuzzy membership functions have three linguistic variables that are large, medium, or small, and the data that is entered through the results of the weighted fuzzy membership function is assessed through the boundary sum of this variable [17, 18].

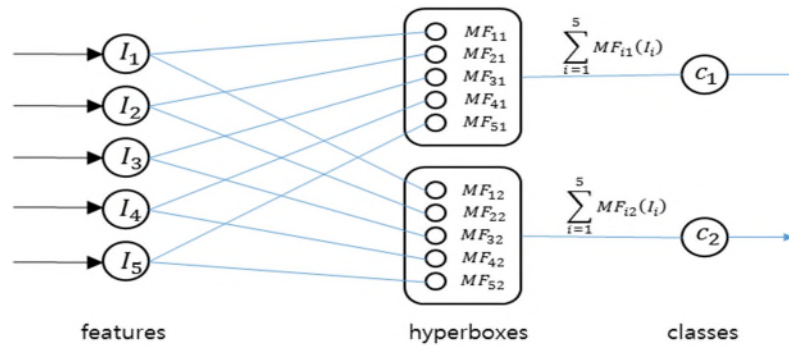


Figure 5. Structure of the neural network with weighted fuzzy membership functions (NEWFM)

To apply biometric authentication using ECG to the NEWFM, each ECG biometric feature that was extracted through Haar-wavelets was matched to one input node to compose authenticated class nodes and unauthenticated class nodes of the output layer. The process of training ECG waveforms from the user and those that are not from the user are registered in the NEWFM, and authentication is when an individual's waveforms are categorized through the results of the trained weighted fuzzy membership functions.

3. Experiment and results

In order to make multicategory classifications through a secondary categorization algorithm that differentiates Class 1 and Class 2, the neural network with weighted fuzzy membership functions uses the One Against One[19] evaluation strategy to select the classifier with a high Sugeno value.

The TAR (true acceptance rate) and FAR (false acceptance rate) indices from Formula (11) and (12) were used to evaluate the experimental results of ECG biometric authentication.

$$TAR = \frac{TN}{FN+TN} \times 100 \quad (11)$$

$$FAR = \frac{FP}{TP+FP} \times 100 \quad (12)$$

Here, TP (true positive) shows the number of times a person in the database was authentication, TN (true negative) shows the number of times the information of a person who is not in the database was denied, FN (false negative) shows the number of times a person who is in the database was denied, and FP (false positive) shows the number of times the database of another person who is not in the database was authenticated [22]. The false acceptance rate (FAR), in which the actual values differs

from expected values), serves as an important factor of evaluation in the biometric authentication algorithm. FAR is when another user's ECG waveforms are authenticated as the user's ECG waveforms. Table 1 shows the results of the ECG biometric authentication using the above performance index.

This study used ECG data from the Physionet Database [29], which can be compared with other similar studies such as [25-28]. The Physionet Database consists of the European ST-T Database, MIT-BIH Normal Sinus Rhythm Database, MIT-BIH Arrhythmia Database, and QT Database. Of these databases, 73 records were used to verify the biometric authentications. The length of ECG records in the Physionet Database varied from 30 minutes up to 24 hours. These signals were analyzed by doctors and are used in various research projects in medical and electronic fields.

2,000 seconds of continuous ECG signals from a random start point in each ECG record was extracted as one ECG section. When the sampling rate and amplitude are normalized for each ECG section and the ensemble average is applied in ECG waveform units, an ECG waveform sample composed of 120 samples and a 2-dimensional vector with m ECG waveforms are generated in one ECG waveform. The Haar-wavelet transform (HWT) is performed on the ECG waveform sample to extract wavelet coefficients a_4 , d_3 , and d_4 as features, and the wavelet coefficient composed of 29 samples is extracted as the ECT biometric feature. The wavelet coefficient that is extracted as the final feature is entered into the NEWFM biometric authentication model to perform ECG biometric authentication.

The proposed biometric authentication model extracted 10, 15, 20, 25, 30, 35, and 40 random ECG biometric features from each record for use in training. The remaining unused ECG biometric features were used to test authentication. One ECG biometric feature is the feature from one ECG waveform, and refers to the length of one heartbeat. One heartbeat refers to the length between ECG signal point P_{on} to T_{off} . Figure 6 shows the results of experimental training using 10 to 40 ECG biometric features from 73 subjects from the Physionet Database.

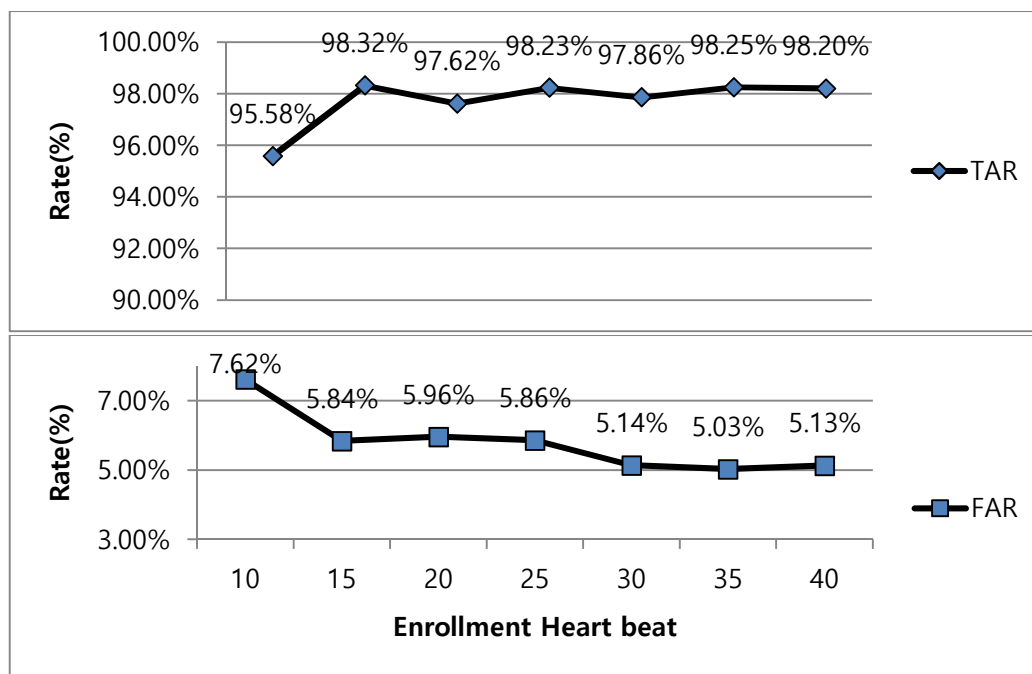


Figure 6. TAR and FAR according to changes in registration time from 10 to 40 seconds.

Upon testing the biometric authentication algorithm in the neural network with weighted fuzzy membership functions according to changes in the number of ECG biometric features that are used for authentication, the TAR was 98.32% and FAR was 5.84% for 15 seconds. The registration time was short while having a stable authentication rate among all the test results. Therefore, 15 ECG biometric features, meaning 15 ECG waveforms, were registered in the NEWFM, and an individual's waveform

was authenticated using one ECG waveform. Table 1 compares the results from other ECG biometric authentication.

Table 1. Results of ECG biometric authentication.

Algorithm	Subjects	TAR	FAR	Authent. lenght	Enroll lenght
Singh et al.[26]	73	82.00%	7.00%	1/2 of record	1/2 of record
Wubbeler et al.[8]	74	97.00%	3.00%	10 s.	10 s.
singh et al. [30]	73	95.55%	3.00%	10 heart beat	10 heart beat
Juan et al.[28]	73	84.93%	1.29%	4 s.	30 .s
Proposed Algorithm	73	98.32%	5.84%	1 heart beat	15 heart beat

4. Conclusion

This study tested the ECG of 73 subjects from the Physionet Database [23]. After the normalization of the sampling rate and amplitude from continuous ECG signals and categorizing each ECG waveform based on R-peaks, Haar-wavelet transform (HWT), which can extract features without detecting a reference point, was used to extract ECG biometric features. The Haar-wavelet transform coefficients a_4 , d_3 , and d_4 were selected as one ECG biometric feature. Biometric authentication was performed on the selected ECG biometric features using the classifiers of the neural network with weighted fuzzy membership functions (NEWFM) [17, 18]. 15 ECG waveforms were used for training NEWFM classifiers. TAR was 98.32% and FAR was 5.84% upon testing with one ECG waveform. This shows that registering just 15 ECG waveforms is sufficient, and more diverse authentication waveform quantities should be tested for authentication in the future. The results of this study were compared against four existing algorithm results. The proposed algorithm had a shorter training time and testing time, and was just as reliable as other algorithms. Various other features will be added in future studies, and feature selection will be used to remove unnecessary features to improve the TAR and FAR and achieve an even shorter registration time.

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