Biometrics Authentication using Another Feature of Heartbeat Waveform

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Abstract: In this paper, we propose a personal authentication method using heartbeat waveforms to enhance the security in wireless communication. The heartbeat waveform of a human being has discriminative characteristic features, and the mimicking is very difficult. Therefore, their application to personal authentication has been studied. Existing methods for heartbeat based personal authentication are focused only on the amplitude of the heartbeat. In order to increase the amount of heartbeat features, we propose an authentication method using the area of heartbeat in addition to the amplitude. To validate that our personal authentication method is applicable, we perform some experiments to show that our method provides better authentication than existing ones.

1 INTRODUCTION

Over the past decade, the integration degree of LSIs is quickly and drastically improved toprovide us with smaller and more intelligent sensor devices working with lower power and higher frequency. Such sensor devices are applicable for life computing that is contrasted with existing scientific computing. Indeed, they can be used for supporting various activity of human being. ICT based healthcare is a hot research area of the life computing. We are developing a smart healthcare navigation system that consists of sensor devices for user's vital data, a smartphone and a knowledge base server. A part of the smart healthcare system is reported in (M. Uchimura, et al., 2012). The sensor devices of the smart healthcare navigation system sends user's vital data such as heartbeat to the smartphone in wireless communication.

Bluetooth is used for communication between the smartphone and the sensor devices. Although Bluetooth provides encryption and authentication as security measures, they often become the attack target. To include personal information, the communication data must not be subjected to interception or tampering. Enhanced security mechanisms for Bluetooth are required. Bluetooth employs a PIN (Personal Identification Number) (C.S.R. Prabhuand, A. Prathap Reddi, 2004) system as personal authentication by entering a verification code over four digits during pairing. However, spoofing is possible in this authentication method, so the security level is not strong.

On the other hand, biometrics (Anil K. et al., 1999; P. Sasikala and R.S.D. Wahidabanu, 2010) has been actively studied as stronger personal authentication against spoofing. Biometrics is an individual authentication method that extracts specific features from particular patterns of user's behaviour or body forms of the user to identify whether it is the same person or not. Biometric authentication methods using a part of user's body have much less possibility of losing and difficult lending to others. Thus, false acceptance and rejection are less likely to occur.

As a biometric authentication method, studies (P. Sasikala and R.S.D. Wahidabanu, 2010; Y. Wang et al., 2008; S.A. Israel et al., 2005) for personal authentication using electrocardiographic waveforms are reported. In the studies, authentication using the features of the height and the distance of the three peak waveforms (P wave, QRS wave and R wave) observed ECG (Electrocardiogram) is proposed. Although the authentication method uses different parameters, more effective parameters are required in order to improve the authentication rate. In this paper, we propose a new biometrics authentication method using heartbeat waveform where the area information of the three peak waveforms is adopted in addition to the amplitude.

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The rest of the paper organized as follows. In section 2, existing research for personal authentication using electrocardiogram is described. In section 3, we explain the proposed method of personal authentication using heartbeat waveforms. In section4, the experiments are reported to validate the proposed method.

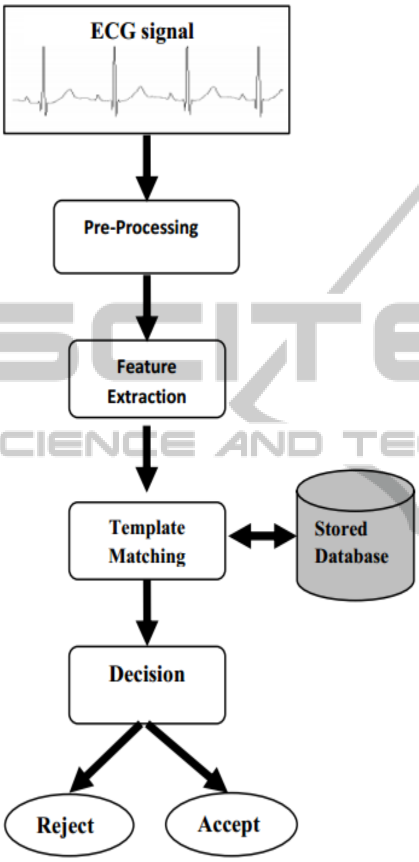

Figure 1: Procedure of existing authentication methods.

2 PERSONAL AUTHENTICATION USING ELECTROCARDIOGRAM

Electrocardiogram is time variant biological information. Personal authentication using electrocardiogram is reported in (P. Sasikalaand, R.S.D. Wahidabanu, 2010). Figure 1 shows the procedure: preprocessing, feature extraction (S. Banerjee, R. Gupta, M. Mitra, 2012; S. Pal, M. Mitra, 2010), comparison with the template stored in the database, and decision.

2.1 Pre-processing

First, noise removal is applied to the measured electrocardiograms as pre-processing. the wavelet transformation (S.Pal and M. Mitra, 2010; Foo-Tim Chau et al., 2004) and the median filter are used.

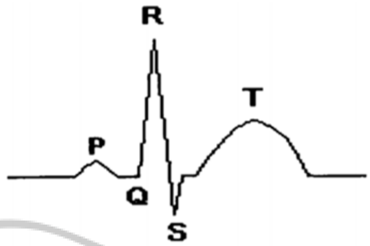

Figure 2: Each point of P, Q, R, S, T.

The median filter is to sort the values within a window on array data and select the middle value among the sorted ones as the new center value for the window. Thus, it is possible to reduce baseline drift along the measured data stream. The definition of the discrete wavelet transform is given below.

$$(\mathrm{W\varphi f})(\mathrm{b,a}) = \frac{1}{\sqrt{a}} \int_R f(t)\, \overline{\varphi\left(\frac{t-b}{a}\right)}\, dt \tag{1}$$

It can be used for knowing "characteristic of temporal change" and "mixed rate of the component frequencies", and it is possible to extract information about time and frequency simultaneously. In the noise removal using the wavelet transformation, wavelet expansion coefficients are obtained first. The expansion coefficients with smaller absolute values are modified to 0, and the reconstruction is performed based on the expansion coefficients. Thus, the data stream becomes smooth.

2.2 Feature Extraction

The wavelet transformation is used for the detection of a P wave peak, each feature point in QRS complex waves, and a T wave peak. The P wave is a waveform showing the excitement of atria, and let P be the P wave peak. The QRS complex waves reflect the electrical excitation of ventricles. Let Q, R, and S be the peak of the first negative wave, the peak of the first positive wave, and the peak of the negative wave following the positive wave of the QRS complex waves, respectively. The T wave is a waveform showing the repolarization of ventricular muscle. Let T be the T wave peak. Figure 2 shows each point of P, Q, R, S, and T. QRS complex waves correspond to the maximum values of the wavelet expansion coefficients. Figure 3 shows the original data stream and the corresponding maximum values of the wavelet expansion coefficients. A P wave is observed from 200 milliseconds before a QRS complex wave to the QRS complex wave. Therefore, P is the maximum value in the range of 200 milliseconds. T corresponds to modulus maxima larger than a threshold ε. The threshold is calculated by the Root Mean Square (RMS) of the data stream between two Rs.

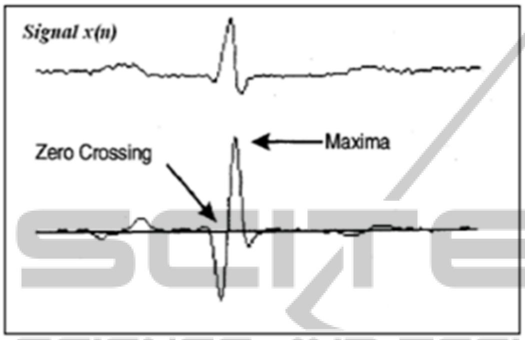

Figure 3: Original data stream and wavelet expansion coefficients.

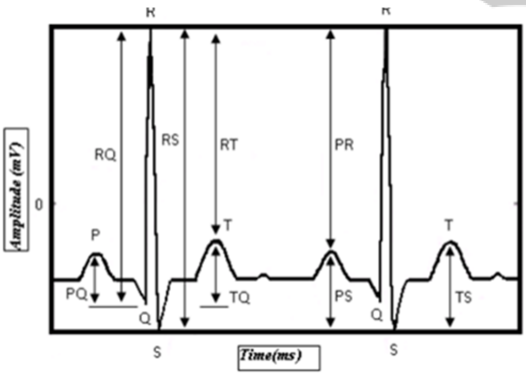

Figure 4: Amplitudes of PR, RQ, RS, RT, PS, TS, PQ and TQ.

Amplitudes of PR, RQ, RS, RT, PS, TS, PQ, and TQ are calculated from QRS complex waves, a P wave, and a T wave. Figure 4 shows these amplitudes.

2.3 Authentication Process

Authentication process is to compare measured data stream with the amplitudes (PR, RQ, RS, RT, PS, TS, PQ, TQ) in templates that are recorded in the database in advance. When a measured data stream set and the average value of a template are close enough, it can be estimated that they are from the same person. The human heart rate is not always constant. To complement this fluctuation, we define a criterion to allow the error as the range of ±10%. Authentication is performed by the number of data stream sets that are within the criterion (±10%) among eight amplitudes. The larger the number is, the more likely the same person they are.

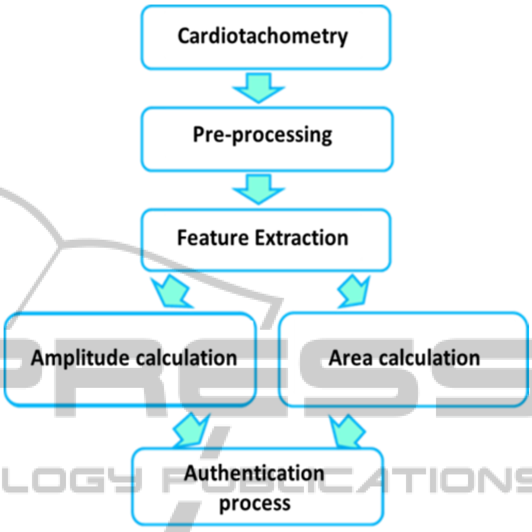

Figure 5: Procedure of the proposed method.

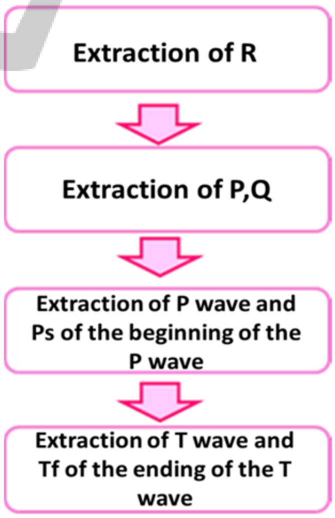

Figure 6: Procedure of feature extraction.

3 PROPOSED METHOD

Since existing heartbeat based authentication methods just employ amplitudes as features, it may occur that different persons are regarded as the same person if their ECG waveforms are similar each other. We propose a new method for heartbeat based authentication with more features to reduce such misjudgement. We include the area size of each wave as the extra feature. In this section, we describe the proposed method for personal authentication using heartbeat waveform. Figure 5 shows the procedure of the proposed method

3.1 Outline of the proposed Method

Given measured ECGs, the method performs pre-processing on the data stream to remove noise and normalize them using the cepstrum (D. G. Childers et al., 1977), and applies the wavelet transformation to extract features. In the feature extraction, it extracts P, Q, R, S, T, P_s and T_f, where P_s and T_f represent the beginning point of P waves and the ending point of T waves, respectively. After the calculation of the area sizes of P waves, QRS complex waves, and T-wavesas well as amplitudes of PR, RQ, RS, RT, PS, TS, PQ, and TQ, it performs the authentication processing by comparing the template.

3.2 Pre-processing

Pre-processing is applied to the measured data stream. In the pre-processing, noise reduction and normalization using the cepstrum are performed for the subsequent process of the wavelet transformation. The existing method uses the median filter (Ioannis Pitas and Anastasios N. Venetsanopoulos, 1990), but the proposed method uses the cepstrum. The median filter can eliminate singularities such as pulse noises. However, it is not possible to remove larger envelopes. On the other hand, the cepstrum is a method that calculates the envelope of the measured data stream. Because it is a noise during measuring, the envelope shape is correctable by setting them to 0. Thereafter, it removes noises using the wavelet transform as described in the section 2 in order to smooth the waveform.

When measuring positions stir even a little during the measurement of the heartbeat waveforms, the sizes of the waveforms also change a little. Therefore, it should be normalized by aligning with 1 the height of the R wave peaks and applying the correction to the entire waveforms.

3.3 Feature Extraction

Figure 6 shows the procedure of feature extraction.

R wave peaks are extracted using the wavelet transformation as well as section 2. Figure 7 shows a heartbeat waveform and the corresponding wavelet expansion coefficients.

Next, it detects S and Q based on the calculated R wave peaks. Q is found where derivative is reversed for the first time before the R wave peak. S is also found where derivative is reversed for the first time after the R wave peaks.

P and Ps that is the beginning of the P wave are found as follows. A search window starts at 200 ms before the onset of a QRS complex wave and ends at the onset of the QRS complex wave. Therefore, the maximum value in the window is the P wave peak.

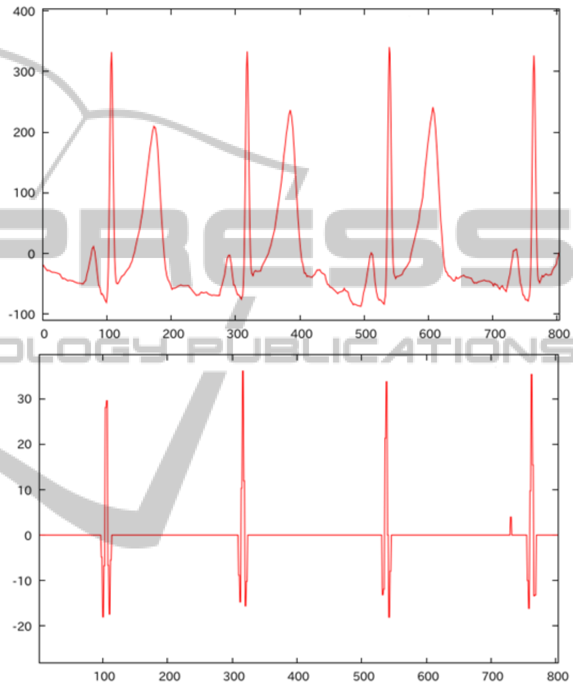

Figure 7: Heartbeat and wavelet expansion coefficient.

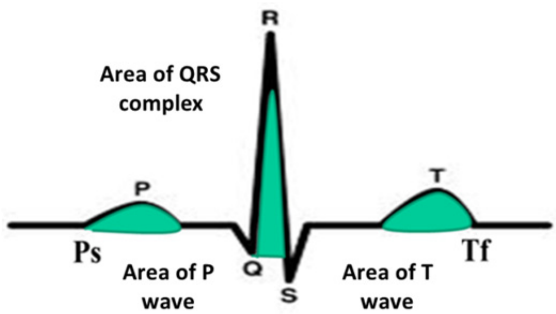

Figure 8: Area of QRS complex wave, P wave and T wave.

Ps is found where derivative is reversed for the first time before the P wave peak.

T and T_f that is the ending of the T wave are found as follows. A search window starts at the QRS complex wave peak and ends at the onset of the next P wave. The maximum value in the window is the T wave peak. T_f is found where derivative is reversed for the first time after the T wave peak.

3.4 Calculation of Area Sizes and Amplitudes

As with the method described in section 2, magnitudes (amplitudes) of PR, RQ, RS, RT, PS, TS, PQ, and TQ are obtained. Furthermore, the proposed method calculates the area sizes of QRS complex waves, P waves, and T waves. The area sizes are calculated using the quadrature by parts. The area size of a QRS complex wave is calculated from the height of Q to the height of R. The area size of a P wave is calculated from the height of P_s to the height of P. The area size of a T wave is calculated from the height of T_f to the height of T. Figure 8 shows areas of a QRS wave, a P wave, and a T wave.

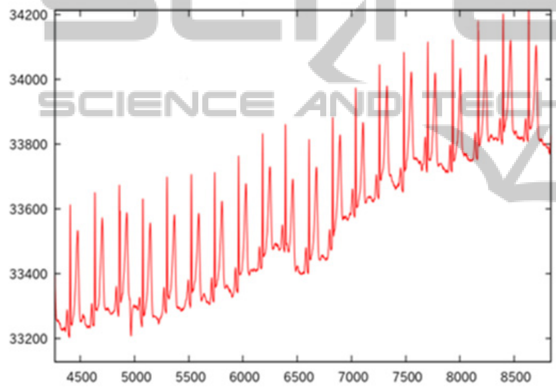

Figure 9: The original data stream measured by Enobio.

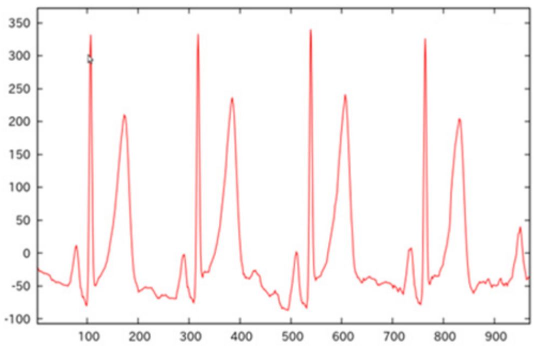

Figure 10: Waveform after noise removal.

3.5 Authentication Process

This subsection explains authentication process. The averages of the amplitudes of PR, RQ, RS, RT, PS, TS, PQ, and TQ and the area sizes of the QRS complex waves, P waves, and T waves are recorded in the database in advance as templates. Comparing the measured data stream with the templates about amplitudes and area sizes, we count the number of measured data stream sets that are between ±10% of the templates, and the number is used for the authentication process.

Table 1: Template own and Template other.

	Amplitude	Area	Amplitude and area
Template own	6	2	9
Template other	7	2	8

Table 2: Differences between the maximum number of matches with others and with the same person about a template.

Difference	Amplitude	Area	Amplitude and area
-1	0	0	0
0	2	7	0
1	11	11	2
2	6	2	3
3	0	0	7
4	0		3
5	0		2
6	1		0
7	0		0
8	0		1

Table 3: Differences between the maximum number of matches with others and with the same person about an individual.

Difference	Amplitude	Area	Amplitude and area
-1	1	0	0
0	1	7	0
1	12	12	2
2	2	1	5
3	3	0	9
4	0		1
5	0		2
6	0		0
7	1		1
8	0		0

4 EXPERIMENTS

4.1 Environments

The ECG Measurement is performed with Enobio (Starlab Living Science, 2013), which is a non-invasive electrophysiology information storage system developed by Starlab. Enobio measures the three types of signals: EEG (Electro-encephalogram), EOG (Electro-oculogram) and ECG. In the case of measuring ECGs, an electrode of Enobio is put on a wrist of an examinee that is in the resting state for 5 minutes. The measured data are clipped out by 1,024 samples (about 4 seconds) of stable heartbeat waveforms. The averages of the area and amplitude for the three waveforms are obtained. As templates for comparison, the averages of areas (QRS waves, P waves, and T waves) and amplitudes (PR, RQ, RS, RT, PS, TS, PQ, and TQ) are recorded in advance. The examinees are twenty women who are between 21 and 24 years old.

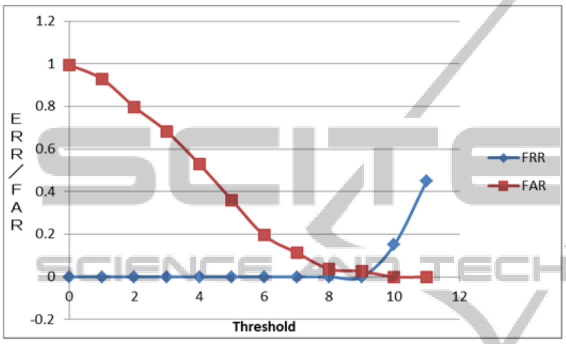

Figure 11: Threshold and ERR/FAR.

4.2 Experimental Results

Figure 9 shows the original data stream measured with Enobio. Small noises and large envelopes are observed in the original data stream. Figure 10 shows the data stream clipped with 1,024 samples from the original data stream with the pre-processing of noise removal using the wavelet transformation and cepstrum. Noises and envelopes are well removed, and it becomes a smooth waveform.

Table 1 shows the minimum numbers of matches (between ±10%) of areas, amplitudes, areas-amplitudes for the same person, and the maximum values among the numbers of matches with others. “Template own” in the table is the minimum number of matches with the person of the templates while “Template other” is the maximum number of matches with others in the templates. In the case of amplitude with the same person, six or more data sets are within ±10%. With others, seven or less data sets are within ±10%. In the case of area with the same person, two or more data sets are within ±10%. With others, two or less data sets are within ±10%. In the case of area and amplitude with the same person, nine or more data sets are within ±10%. With others, eight or less data are within ±10%.

Table 2 shows the differences between the maximum number of matching data sets with others and the number of matching data sets with the same person regarding to a template. In the case of amplitude, the differences exist from 0 to 6 while the major differences are from 0 to 2. On the other hand, in the case of area and amplitude, the differences exit from 1 to 8 while the major differences are from 1 to 5. The differences are larger than amplitude.

Table 3 shows the differences between the maximum number of matching data sets with others and the number of matching data sets with the same person regarding to an individual. In the case of amplitude, the differences exist from -1 to 7 while the major differences are from 1 to 3. On the other hand, in the case of area and amplitude, the differences exit from 1 to 7 while the major differences are from 1 to 5. The differences are larger than the amplitude.

Figure 11 shows the result of FRR (False Rejection Rate) and FAR (False Acceptance Rate). The threshold where FRR is almost the same as the FAR is 9. EER (Equal Error Rate) is about 0.26%.

4.3 Discussions

Table 1 shows the results of minimum number of matches with the same person and the maximum number of matches with others. In other words, when the number of matches with the same person is large and the number of matches with others is small, the accuracy of authentication is high. However, in the case of amplitude, authentication is difficult because the number of matches with others is larger than the number of matches with the same person. On the other hand, in the case of amplitude and area, the minimum number of matches with the same person is larger than the maximum number with others. Therefore, the authentication is possible.

Tables 2 and 3 show the results of the minimum differences between the numbers of matches with others and each individual. In other words, it shows the accuracy of the proposed method. The larger the differences are, the higher the accuracy of authentication is. In the case of just amplitude, the number of differences is 0 in Tab. 2 and the number of differences is -1 and 0 in Tab. 3. Thus, the authentication is very poor.

On the other hand, the proposed method is provides better authentication because the differences are one or more. In addition, the differences in the proposed method are larger than just amplitude as described in Tab. 2 and Tab. 3.

Thus, existing methods provide poor authentication while the proposed method gives better personal authentication. Furthermore, it is concluded that the number of required matches for right authentication is 9.

5 CONCLUSIONS

In this paper, we have proposed a biometric authentication method using area and amplitude information obtained from heartbeat waveforms. In this method, noise reduction is performed using the wavelet transformation and the cepstrum to execute normalization based on R wave peaks. Then, the wavelet expansion coefficients are calculated with the wavelet transformation to extract feature points P, P_s, Q, R, S, T, and T_f. Amplitudes and area sizes are calculated with the feature points to be compared with the data sets in the templates, and authentication is performed.

The experiment results show that we define the standards to judge if it is the same person or not. In addition, it is contemplated that combinatorial use of amplitude and area leads to higher accuracy.

For our future work, we have more experiments with larger numbers of examinees. In addition, we would like to devise new parameters other than area and amplitude.

It is known that heartbeat waveforms change with age (Sara Bachman et al., 1981). Several weeks, or even several months later, it should be checked whether authentication is still possible or not. If changes are observed by individual, it would be possible that we use this change rate as a new parameter.

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