Showa Univ J Med Sci 26(2), 149～157, June 2014

Original

Improvement and Evaluation of an Individual Identification System Using High Frequency Electrocardiogram

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Abstract: Biometric identification techniques are widely used as individual identification methods in security systems. We have studied the high frequency component of electrocardiogram (HFECG) as a new biometric modality. In this technique, a HFECG segment containing individual characteristics is extracted and used for identification. Identification performance depends greatly on extraction accuracy, but the current extraction method using the peak point on R waves as fiducial points can result in unsatisfactory performance. In this study, we propose a new fiducial point determination technique utilizing waveforms transformed from ECGs. The algorithm is based on differential calculus and produces sufficient performance despite having less complexity than other signal detection techniques. Comparative evaluation established that identification performance was improved using the new method.

Key words: high frequency electrocardiogram, biometric identification, fiducial point

Introduction

In recent years, biometric individual authentication has gained attention and is particularly being applied in the field of security[1-5)]. This is a new method that uses biological information to detect and identify individuals. In conventional non-biometric individual authentication techniques, the possibility of loss, falsification and theft of information has been present. Biometric authentication uses information obtained from the human body and therefore, the possibility for loss, falsification and theft is low. It is anticipated that this method could solve many security system issues that occur at present.

Recent commercial applications include behavioral information such as voiceprints, handwriting and morphological information of organ and tissue shapes such as fingerprints and vein patterns. We have proposed that electrocardiograms could be used as a source of new biological information for the authentication of identity. The source of the electrocardiogram is the beating heart, which is an organ that is not separated from the living body. Therefore, its use

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is applicable to the field of both security and forensic individual identification. The use of this biosignal has an additional advantage in that it is relatively easy to measure. Several research reports have proposed the use of electrocardiograms for individual identification[6–9] but the issue of an effect of the autonomic state on the clinical use of electrocardiogram waveforms is important.

We have developed a system that focuses on the high frequency component of electrocardiograms in order to solve this issue[10]. The frequency band between 0.05 and 100 Hz is used for clinical electrocardiograms (ECGs), but when ECGs are used in this study as an individual identifying characteristic, the signal component in the high frequency band between 40 and 200 Hz is used (HFECG). We have established a system that selects the characteristic waveforms manifested in HFECG waveform segments before and after R waves. Individual differences are recognized from the results of this analysis of these waveforms using an artificial neural network (ANN)[10]. This system uses the R wave peak on the ECG as the reference point to select out a signal segment. The peak positions are uncertain in some subjects and this decreases the recognition rate. In this study, we propose a new method to calculate a robust reference point from the ECG. The algorithm is based on differential calculus and demonstrates sufficient performance despite less complexity than other signal detection techniques. We performed a fundamental evaluation by comparing the wave segments selected out using the previous method and our proposed method. The recognition accuracies using the two methods were compared in the overall evaluation.

Materials and Methods

Use of HFECG in an individual recognition system

The configuration of the recognition system in this research is shown in Fig. 1. The initial measurement of the user's ECG is performed with attached electrodes and is amplified by the measurement apparatus. Then ECG and HFECG recordings are filtered and the characteristic user information associated with QRS waves in the HFECG segments is selected using the R waves found in the ECGs of all users. The data sampled from the HFECG segment represents the input into the ANN, which in turn produces an output that corresponds to each registered user. Training of the ANN is carried out using some beats of HFECG segments for all the registering users and desirable outputs, prior to any analytical use. When an HFECG segment is submitted to the trained ANN, degrees of similarities between the input segment and registered users are generated at the ANN outputs. The final individual identification is obtained by determining the registered user with the largest similarity to the data.

The data samples in a wave segment are applied to the ANN input cells, so the temporal accuracy of waveform extraction is important because it directly affects the accuracy of recognition. The temporal positional relationship between ECG waveforms and HFECG waveforms is shown in Fig. 2. In this analytical system, 200 ms of HFECG waveforms were selected from 75 ms before the peaks of the R waves to 125 ms after the peaks. In our previous study, the R peak was as a suitable reference because it is the most characteristic point

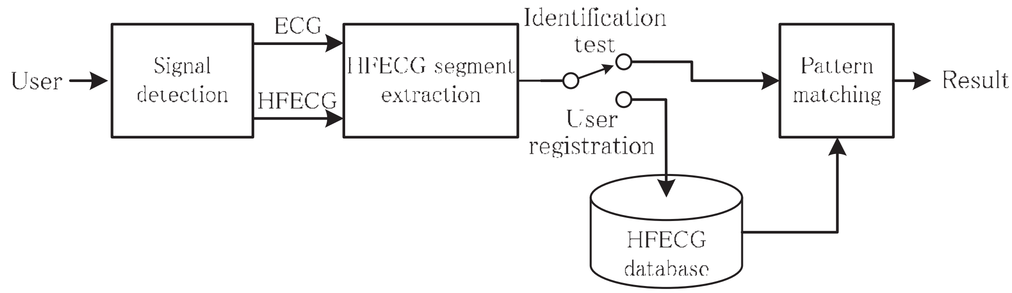

Fig. 1. Functional diagram of HFECG individual identification system

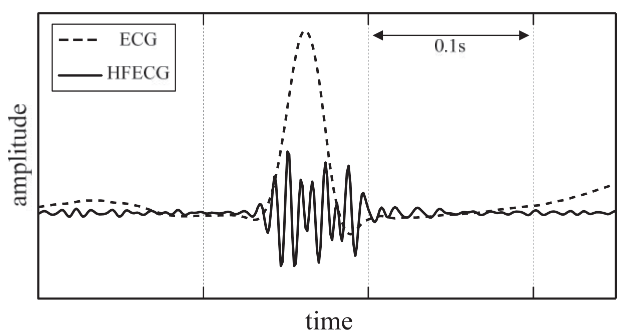

Fig. 2. ECG and HFECG

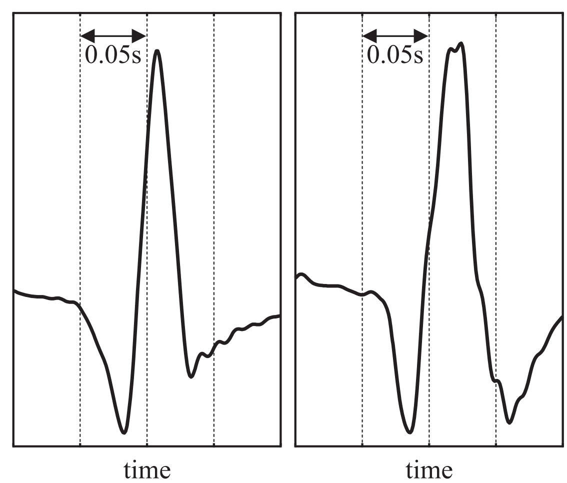

Fig. 3. Examples of R wave shapes on ECG

on ECG waveform.

The R wave peak is used as a fiducial point and generally has a peaked shape (Fig. 3a). A close examination of the waveforms obtained via the 1 kHz sampling frequency used in our system shows some cases in which a peak cannot be determined on an R wave (Fig. 3b). The two R waves in Figs. 3a and 3b are examples of typical measurement results for successful and troublesome cases, respectively. In the case shown in Fig. 3a, the recognition accuracy is high because the waveform extraction is stable. In the case shown in Fig. 3b, the waveform extraction causes a shift of the HFECG segment in the temporal region because of an unstable reference point produced by two peaks on the R wave. This shift can degrade the recognition performance because the ANN may not recognize the shifted waveform as being from the same individual even if the two waveforms are relatively similar.

Improvement and evaluation of wave extraction methods

1. Proposed method for fiducial point detection

The method that we are proposing is based on a fiducial point detection technique. It uses the characteristics of the R wave, which has a convex shape and precipitous inclinations before and after the wave. The peak on a convex-shaped waveform is determined by the point of intersection in the time domain when the differentiated waveform is changing from a positive to a negative value and is equal to zero. The result of the general differential operation for a digital time series does not have sufficient amplitude for detection in HFECGs sampled with a high sampling rate. This occurs because the amplitude difference between neighboring samples is small. In our proposal, a waveform calculated by a modified differential operation is used to detect a peak on a convex waveform that has precipitous inclinations. In this method, the difference between distanced samples is calculated according to equation (1).

$$d_i = x_{i+a} - x_{i-a} \tag{1}$$

Where, x_i is an ECG data series and a is a constant.

A detailed procedure of the detection method is shown below:

1) Detection of the R wave peak on the ECG.
2) Calculation of the waveform for detection using equation (1).
3) Search for a point where the waveform from step 2) changes from positive to negative (crosses over 0) in proximity to the peak detected in 1).
4) The point identified at step 3) is set as the fiducial point.

2. Data used for evaluation

The data used in the evaluation were obtained from simultaneous ECG and HFECG data recorded from 15 healthy subjects aged between 20 and 29 years old. Since a different series of ECG and HFECG should be used for the recognition and registration processes, we measured two sets of 120 s of data for each subject and extracted 100 beats of HFECG wave segments from each data set. The measurements were carried out with the subject in the supine position, with silver/silver chloride electrodes attached to the body according to limb lead I. Signals from the electrodes were amplified, filtered, and stored into a personal computer (PC) using a multi-channel A/D converter. Settings for the amplifiers, the filters and the A/D converter are shown in Table 1.

All the measurements were performed at the Department of Biomedical Engineering, Faculty of Engineering of Tokyo City University. Measurement procedures were carried out in compliance with the Tokyo City University's code of ethics for medical research. Due attention was given to the handling of personal information and human rights. This study was also approved by the Ethics Committee of Showa University School of Medicine.

3. Evaluation method

In the first step, an evaluation was performed to determine parameter a within equation (1), which changed and the waveforms that were obtained from the calculated results were evaluated. A large amplitude and precipitous change in the proximity of the point when the waveform crosses the zero value are required to determine an accurate fiducial point. The optimum value of a was set in the system and subsequent evaluations were performed according to the value of a that had been determined.

Table 1. Measurement conditions

Apparatus	Item	Value
Amplifier for ECG	Notch filter	50 Hz
	High-pass filter	5 Hz
	Low-pass filter	80 Hz
	Amplification	48 dB
Amplifier for HFECG	Notch filter	50 Hz
	High-pass filter	40 Hz
	Low-pass filter	150 Hz
	Amplification	74 dB
A/D Converter	Sampling frequency	1 kHz
	Resolution	16 bit
	Input voltage range	± 5 V

Waveforms selected by using the previous extraction method and by using the proposed method were compared to evaluate the accuracy of extraction for high frequency electrocardiogram waveforms. In the previous method, R waves are detected first as the data segments where the ECG amplitude exceeds a previously set threshold. R peaks selected as the fiducial point were detected as the largest value on R waves. In the proposed method, the fiducial point is calculated using the technique shown in the previous section with an a value fixed in the preliminary evaluation.

The final evaluation was a comparison of the recognition performance of the proposed system with the previous system, using an ANN with a three-layer configuration. The number of cells in the middle layer was fixed to 20 and the number of cells in the input layer was 200 that were applied with 200 ms of electrocardiogram data. The final decision obtained from the system was evaluated and the correct decision rate for each subject was calculated with 100 beats of the HFECG.

Results

The waveforms calculated using equation (1) with four different a values are shown in Fig. 4. The ECG used in Fig. 4 had a biphasic R wave and therefore the previous extraction method could not detect an accurate fiducial point. Waveforms for an additional three subjects also showed similar shapes and dependency on a.

As a result of initial examinations a value of $a = 10$ was set for all the system evaluations. The next evaluation of the detection of the fiducial point is shown in Fig. 5 and Fig. 6, which indicate the waveforms of the HFECG segments for two subjects. These data sets were selected out with fiducial points detected by the previous method as well as the proposed method. A

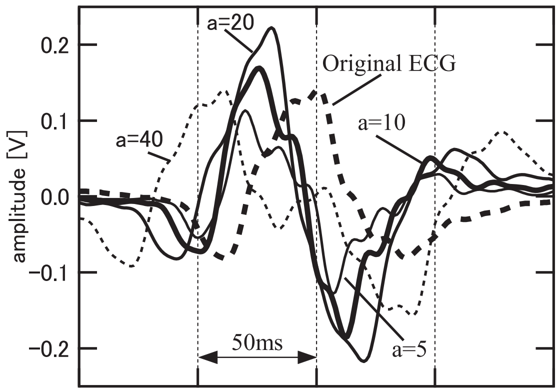

Fig. 4. Relationship between parameters and waveforms

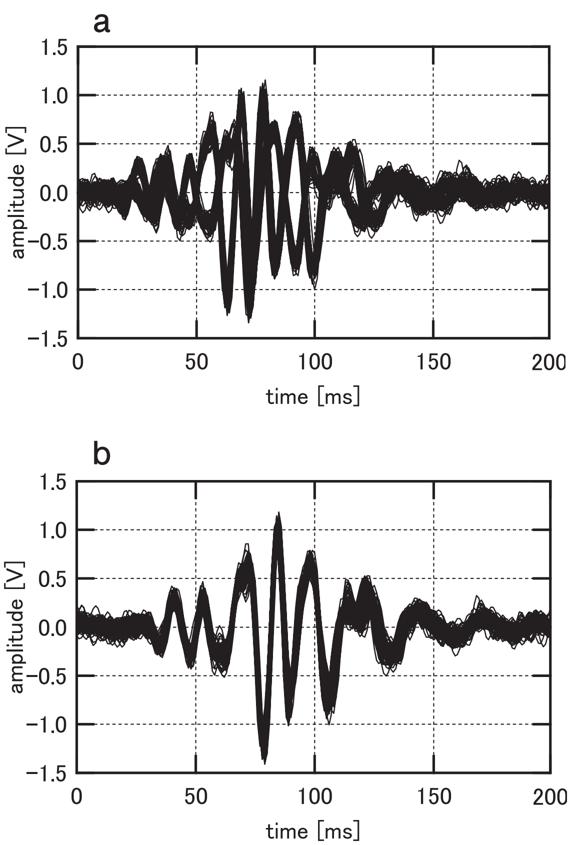

Fig. 5. Extracted waveforms (example 1)
a) Waveforms by the previous method
b) Waveforms by the proposed method

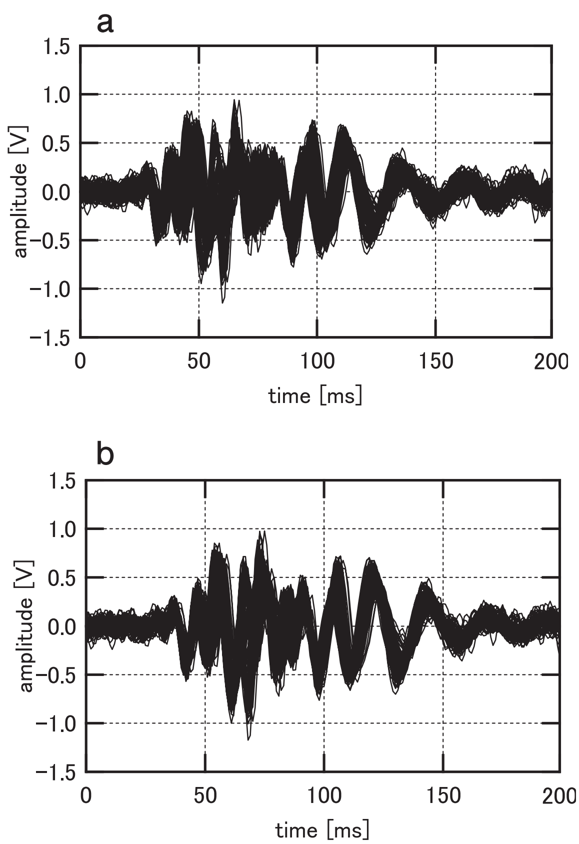

Fig. 6. Extracted waveforms (example 2)
a) Waveforms by the previous method
b) Waveforms by the proposed method

total of 100 HFECG segments are superimposed on each graph. Fig. 5 was calculated using the ECG with a biphasic R wave from the same subject as used for Fig. 3b and Fig. 4.

A total of 100 beats of HFECG were used to obtain recognition data for each subject. The recognition performance for 15 subjects is shown in Table 2. The data from subject N in Table 2 was also used for Fig. 3b, Fig. 4, and Fig. 5 and the data on subject O corresponds to Fig. 6.

Table 2. Recognition results for 15 subjects

Subject	Recognition rate using current method (%)	Recognition rate using proposed method (%)
A	100	100
B	99	100
C	100	100
D	100	100
E	86	100
F	94	95
G	100	95
H	100	100
I	100	100
J	100	100
K	100	100
L	84	94
M	93	100
N	96	100
O	100	100
Minimum recognition rate	84	94
Mean recognition rate	96.8	98.9

Discussion

The optimization of the parameter a in the proposed method is of major importance. The data presented in Fig. 4 shows that the larger parameter yields the larger amplitude. This confirms our proposal that it is effective to calculate the difference between distant samples rather than using conventional differential calculus. Furthermore, samples with a value of a exceeding 20 decreases amplitude collapses the waveform as is evident for a waveform with $a = 40$ in Fig. 4. This is consistent with the observation that R waves are approximately 70 ms to 90 ms in width. In principle, when the distance between two samples controlled by a in equation (1) exceeds one-half of the R wave width, equation (1) does not accurately reflect the characteristic component of the R wave to the converted waveform. Therefore, $a = 20$ is the maximum value that can be accurately used in the system with 1 kHz sampling frequency.

Finally, we fixed the value of $a = 10$ in the waveform examination with four subjects.

The quality of the wave segment selected out is shown in Fig. 5. The 100 waveforms in Fig. 5b overlap well and two examples of temporally shifted waveforms are seen in Fig. 5a. This clearly shows that the fiducial point detection algorithm with the proposed technique identified a unique point for all the 100 beats of ECG. The zero crossover point for the waveform shown in Fig. 4 does not correspond to the R peak itself but detects the R wave that has a characteristic wave shape. Therefore, the steadily detected fiducial point produces the overlap of all the waveforms in Fig. 5. These observations show that detection of a stable fiducial point can be carried out even for R waves with vague peaks. The previous algorithm detected two points on the biphasic R waves in uncertain manner as shown in Fig. 3b. Our analyses demonstrated that the temporal jitter of extraction was not improved using the proposed method (Fig. 6). This jitter is caused by noise interference at the time of measurement as well as beat-by-beat waveform variation. As a result, it is highly unlikely that the jitter caused by these factors can be avoided.

A comprehensive evaluation of the system is shown in Fig. 2. The data in Table 2 shows that a high recognition rate can be achieved with the previous technique but with some subjects, such as E and L, showing a low recognition rate. The data in Table 2 demonstrates that the proposed technique improves the identification performance for all of the subjects. This is apparent for subject L whose HFECG wave segment extracted by the previous method has temporal jitter (Fig. 5a). The detection of the fiducial point for subject L was reflected clearly in the recognition results. On the other hand, some subjects, who had wave segments with a certain extent of temporal jitter, still obtained good rates of recognition. For example, subject O had a wave segment with a remarkable temporal jitter (Fig. 6) and showed a 100% recognition rate with the proposed method. It is likely that this is a result of the learning and recognition processes being carried out by the ANN. The system is optimized during the learning process to obtain the best result with the wave segments in which temporal jitter already exists. Therefore, the system can reach the correct answer for the wave segment with an acceptable range of jitter.

In conclusion, this study proposes a novel fiducial point detection algorithm that requires less calculating power than other techniques such as wavelet analysis. A comparative evaluation between the previous technique and the proposed method showed that the temporal jitter in extracted wave segments was largely improved. We also showed that the proposed method could improve the performance of the individual identification system for normal HFECG during rest.

In future studies, we plan to survey the performance of the proposed method under various conditions. The behavior of the system will be examined for abnormal ECGs and ECGs under conditions of different autonomic nervous system activities. We believe that higher accuracy of recognition, usability and robustness will be attained by the improvements based on these evaluation results.

Acknowledgement

A part of this work was supported by the scientic research fund (No 23659266) from the Japan Society for the Promotion of Science.

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[Received April 1, 2014 : Accepted May 8, 2014]