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Individual Identification with High Frequency ECG : Preprocessing and Classification by Neural Network

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Abstract— In this research, we proposed that high frequency component of HFECG was applicable biometric feature for new identification system. We developed identification method by using neural network (NN), and aimed at the improvement of the classification rate. Preprocessing prior to NN is performed by justification on time axis and normalization on amplitude. As a result, an average of 99% classification rate was obtained from 9 subjects. We also made an attempt to identify in shorter time by shifting of the HFECG by a few samples to NN.

I. INTRODUCTION

Recently, "Biometric personal authentication" attracted attention that uses individual biological information for the key as a new security system. A lot of non-biometric methods like card key, password, signature, etc. have been used for authentication. However, the counterfeit and the theft were easily possible and the security levels were not so high as the key that should defend important information or property. On the other hand, the biometric personal authentication provides not only a lower risk of theft and forgery but also few human errors such as losses and forgetting. In recent ten or twenty years, biometric authentification technique has been attracted attention to improve these problems, and many biometric features have been tested. [1,2] Especially, fingerprint and vein pattern have been getting popular because of low device cost and high security level. There are many biometric features which may be used for authentification, however, most of features, such as electromyogram, DNA is not suitable for commercial application because of instability, higher cost, inconvenience, etc. Electrocardiogram (ECG) is one of the feature which is usable for the purpose.[3 - 6] It provides not only higher security against theft but no losses or forgetting. Moreover, the electrocardiogram can be easily measured than other biological signals and that has a high perpetuity and universality. Usually, in the electrocardiogram used on the clinical setting, the frequency band is 0.05-100Hz. However, waveform change in a subject created by physiological change of the subject may affect the performance. We proposed that higher frequency component in ECG (HFECG) can be used as stable feature for individual classification. Fig.1 shows the waveform difference between ECG and HFECG. In this paper, we made a system with neural network (NN) and preprocessing method for HFECG to improve system performance. Performance was evaluated finally with 9 subjects.

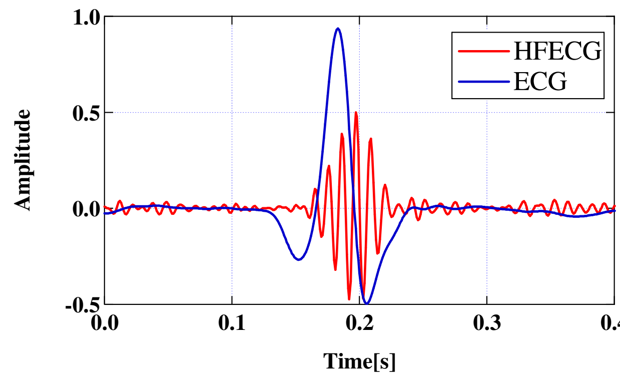

Fig.1 ECG and HFECG
(not in the same scale on amplitude)

II. METHODS AND MATERIALS

A. *Signal acquisition and preparation*

Fig.2 shows the outline for recording the ECG and HFECG. Standard limb lead 1 was used for lead system. HFECG and ECG were obtained using band-pass filters with different frequency bands. Amplitude at the filter output for HFECG is far smaller than ECG because spectrum power density of ECG is tend to concentrate under 40Hz. Gain for Amp. 3 is set to 26dB higher than Amp. 2. Finally, ECG and HFECG are sampled at 1000Hz, 16bits, and stored to personal computer (PC).

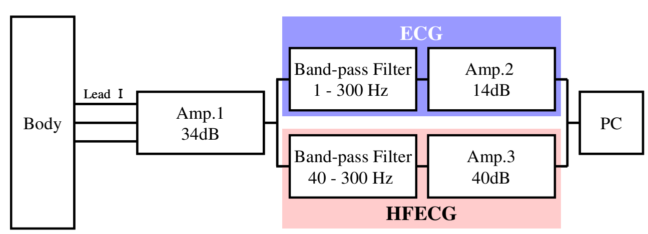

Fig.2 Measurement system

Sampled ECG and HFECG are preprocessed for NN as shown in fig.3. First of all, HFECG segments were extracted from measured waveforms beat by beat. A segment was extracted where the peak point of R wave was fixed on the center of the segment. Then, the segment length was 0.2s because HFECG appears to the QRS wave.100 HFECG segments was stored for each subject.

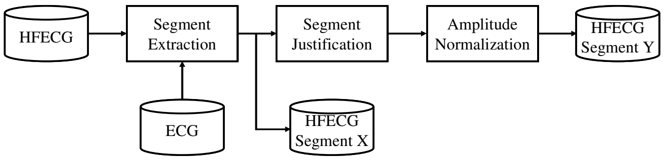

Fig.3 Preparation flow for NN

Segment justification block and amplitude normalization block shown in Fig.3 are additional blocks to improve system performance. Even in the same subject, HFECG has beat by beat fluctuation on time axis and amplitude. Segment justification block corrects segmentation error on time axis and amplitude normalization block is for amplitude correction. Effectiveness of these blocks is evaluated with HFECG segment X and Y in fig.3.

Segment justification is performed with cross correlation function. As a reference, average is calculated with all 100 beats of segments for a subject. For the next step, cross correlation is calculated between each segment and the average. Justification is performed by shifting start point of a segment where cross correlation is maximized. All 100 beats of the segments for each subject are corrected by the method.

Amplitude difference between subjects is important information for classification, however, amplitude fluctuation within the same subject degrade classification performance. Reference for amplitude normalization is maximum amplitude in all the extracted segments from all subjects.

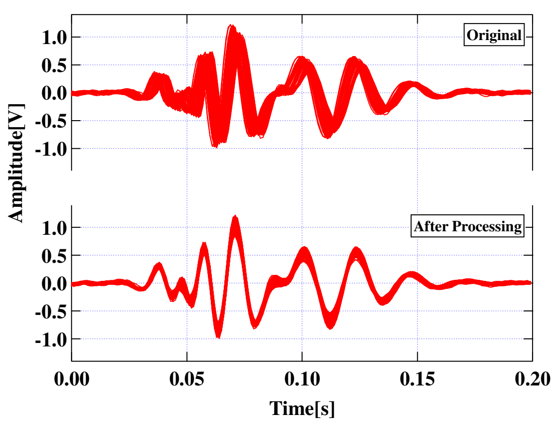

Fig.4 Justification on time axis

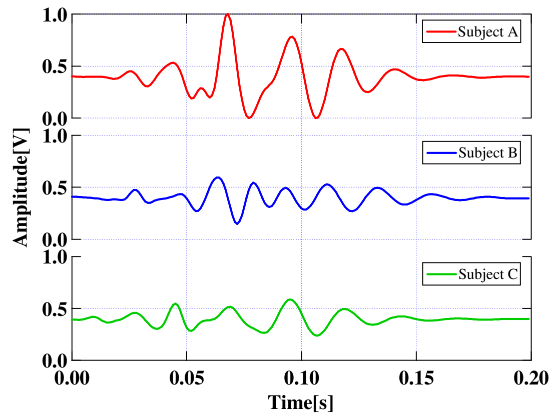

Fig.5 Normalization on amplitude

A. *Learning and Classification with NN*

In this paper, we used a NN with three layers. Number of input cell equals to the number of data samples in a segment. Output cell corresponds to each subject. Fitness indexes are obtained at the output which means how much degree the segment matched with each subject. A subject corresponding to the maximum fitness index is chose as a classification result.

For preliminary evaluation the best amount of learning and segment length were decided by using classification rate. Tested numbers of segments are 1, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100s and segment lengths are 0.1s and 0.2s.

Classification performance was tested with HFECG segment X and Y shown in Fig.3 to evaluate effectiveness of two preprocessing method. Classification rate is the rate of correctly classified segments in all the tested segments.

All the evaluations were done with nine healthy adult male subjects. Subject lies on one's back on the bed. 120s of ECG and HFECG were measured.

B. *A faster method to get classification results*

The preprocessing method depicted in the section A can only be done after acquiring 100 heart beats from the subjects. It takes a lot of time to obtain a classification result. We have tested a faster classification method for shorter processing time. As signal source, a segment from HFECG segment X shown in fig.3 is used for a classification result. A set of the segments which is calculated by shifting an original segment sample by sample. A final decision is made with multiple classification results by NN with these segments. In this paper, a fitness index at a cell is evaluated in order to clarify the behavior of NN with shifted segments.

III. RESULTS AND DISCUSSTION

A. *Preprocessing*

The results on justification are shown in Fig.4. It is shown that the data segments extracted only with R peak in ECG shown as "Original" were aligned on time axis (shown as "After Processing"). Fig.5, the result of amplitude normalization, shows that amplitude difference between subjects was retained as a feature for classification. Classification performances with or without the preprocessing are discussed in the sections.

B. *Number of segments and segment length for NN*

Evaluation on number of segments shows that 10 segments are the best for learning. Smaller number was not enough to update weights in NN to available level, and larger number gave confusion to NN. In the evaluation on segments length, 0.2s segment gives better result than 0.1s because signal power of HFECG was spread within 0.2s such as shown in fig.4 and 5.

C. *Classification performance*

The improvement in classification rate with preprocessing is shown in Table.1. (a) is the rate for each subject without preprocessing and (b) is obtained with the improved method. As a result, higher average classification rate obtained by the method. (b) also shows that no classification error is occurred except for subject F. Detailed inspection of intermediate result on subject F shows that segment justification was failed for some beats of HFECGs. Higher performance will be expected by improving justification algorithm.

Table.1 Classification performance
(a) with segment X (b) with segment Y

(a)

		Classification Rate[%]
Subjects	A	95
	B	100
	C	100
	D	95
	E	100
	F	86
	G	76
	H	100
	I	100
Average		94.7

(b)

		Classification Rate[%]
Subjects	A	100
	B	100
	C	100
	D	100
	E	100
	F	89
	G	100
	H	100
	I	100
Average		98.8

D. *Faster classification method*

Characteristics on fitness index at the output cell corresponding to subject A with four subjects are shown in Fig.6. It shows that high fitness indexes are obtained with segments shifted within 2 samples from subject A, that is, corresponding subject. For the other subjects, that are B to D, indexes are extremely lower than corresponding. This indicates that the faster method is available for classification. Classification rate analysis should be required for further evaluation.

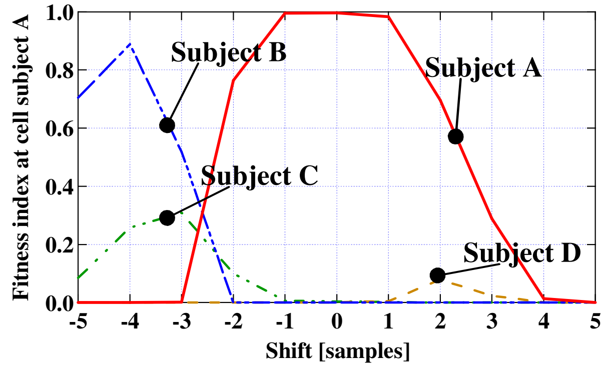

Fig.6 Cell outputs of subject A calculated with 4 subjects

IV. CONCLUSION

In this paper, we proposed an individual classification technique with HFECG. As shown in the results, it will be applicable as new individual identification method. However, we have to work on false acceptance rate and false rejection rate. As a future work, we are planning that ECG with simpler ECG measurement device will be used and evaluated to show reality of the system.

REFERENCE

[1] A.K. Jain, A. Ross, S. Prabhakar, An Introduction to Biometric Recognition, IEEE Trans. Circuits and Systems for Video Technology, Vol.14, No.1, pp.4-20, 2004.

[2] B. Miller, Vital Signs of Identity, IEEE Spectrum, Vol.31, No.2, pp.22-30, 1994.

[3] L. Biel, O. Pettersson, L. Philipson, P. Wide, ECG Analysis: A New Approach in Human Identification, IEEE Trans. Instrum. Meas. Vol.50, No.3, pp808-812, 2001.

[4] Masaki Kyoso, A Study on ECG Identification Technique, Proc. WC2003, TU.TR19, 224, 2003.

[5] Masaki Kyoso, A Technique for Avoiding False Acceptance in ECG Identification, Proc. IEEE EMBS Asian-Pacific Conf. Biomed. Eng. 2003, 4.9.2, 2003.

[6] S.A. Israel, J.M. Irivine, A. Cheng, M.D. Wiederhold, B.K. Wiederhold, ECG to Identity Individuals, Pattern Recognition, Vol.38, pp.133-142, 2005.