Biometrics System Technology Trends Based on Bio-signal

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Abstract

Biometrics is a technology that authenticates, identifies, and recognizes user using individual unique physical or behavioral characteristics. The scope of services is expanding with necessity and utility in a wide range of fields such as finance, security, access control, medical welfare, public service, quarantine, and entertainment. Research using bio-signal inside the body than bio-information outside the body is being actively conducted. In this paper, we analyze research about technologies of biometrics systems using bio-signals such as ECG, heart sound, EMG, EEG, and present the necessary technologies for the development direction. In the future, bio-signal based database construction in complex conditions, deep learning network design through analyzes big data, and biometrics system technologies applied in a real-time environment are expected to be studied.

Keywords: biometrics, bio-signal, ECG, heart sound, EEG, EMG

1 Introduction

Biometrics is a technology that compares and judges bio-information and signal presented by registering and storing in real-time analysis using individual unique bio-information and signal. Information used for biometrics can be divided into bio-information and bio-signal. Bio-information that can be acquired from the outside and the surface of the body can be obtained through lifelong unchanging physical and behavioral characteristics. Bio-information that can be obtained from physical characteristics includes fingerprints, face, iris, retina, veins, etc., and bio-information that can be obtained from behavioral characteristics includes signature, voice, and gait. Bio-signal inside the body are typical behavioral (body functional) characteristics such as electrocardiogram (ECG), heart sound, electromyography (EMG), and electroencephalogram (EEG).

Biometrics using bio-information has always been exposed to threats of counterfeiting and disguise, such as making fake fingerprints, making a disguised face, and making a fake iris. There have been financial forgery accidents by manufacturing fake silicone fingerprints with 3D printers in Korea, electronic passport forgery accidents using fake fingerprints at Japanese international airports, and hacking accidents caused by a German hacker group copying the iris of a Russian president. This has become a social problem along with negative aspects of biometrics. Accordingly, major advanced countries [1, 2] are researching and developing biometric systems using bio-signals. Bio-signals can be used as non-face-to-face authentication technology that does not cause any objection or discomfort by using not only the ECG generated inside the body but also the heart sound, EMG, and EEG signals.

Various studies are being conducted on biometrics technology using bio-signals. Biometrics technology using the ECG includes individual authentication, identification, and disease recognition [3, 4, 5],

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biometrics technology using heart sound is individual authentication and identification [6, 7], and biometrics technology using EEG is individual authentication, situation recognition [8, 9], and biometrics technology using EMG is individual authentication and situation recognition technologies [10, 11].

2 Bio-signal based biometrics system

The technical structure of the biometrics system is shown in Figure 1. Step 1 is the process of acquiring bio-signal data and dividing it into registration and recognition data; Step 2 is a process of analyzing a signal with pre-processing and normalization based on signal processing; Step 3 is the process of analyzing real-time data by extracting features suitable for biosignals and reducing the dimension of feature vectors; Step 4 is the process of personal authentication, identification, and situation recognition through machine learning, a classifier.

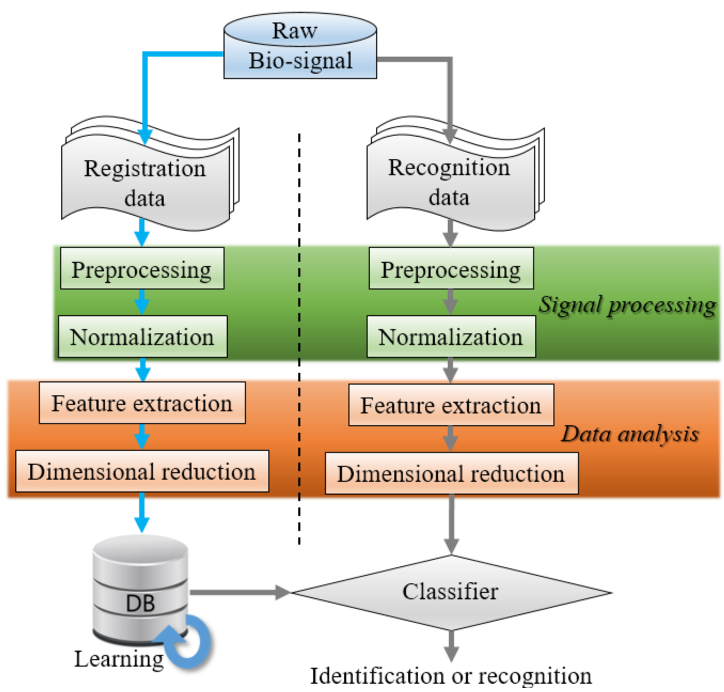

Figure 1: Biometrics system structure

2.1 ECG-based biometrics technology

Biometrics using an ECG is being actively studied for personal authentication, identification, and disease recognition system. Table 1 shows trends in ECG-based biometrics technology, classified according to signal processing, data analysis, machine learning, and performance. Table 1 is classified according to the subjective judgment of the author, and the classified contents are as follows. Research on personal authentication and identification is mainly conducted, and expanded research on personal authentication, identification and disease recognition is studied in international. The lead-I acquired by the standard 12-lead method is used for an ECG data. The MIT-BH database is mainly used in the official database physionet [12]. It was developed directly in South Korea and used by acquiring an ECG signals, but medical equipment is widely used in international. Frequency based filters are applied, but frequency filters, wavelet transforms, and target heart rate definitions are used in abroad for ECG signal processing.

The morphological features of the time domain are mainly used, but the features are extracted and used in the time domain, frequency domain, and phase space in abroad for data analysis. The morphological features in the time domain of ECG are shown in Figure 3. ECG lead-I consists of P wave, Q wave, R wave, S wave, T wave as shown in Figure 3. The average and differential values are extracted as features after setting a section using morphological features [13].

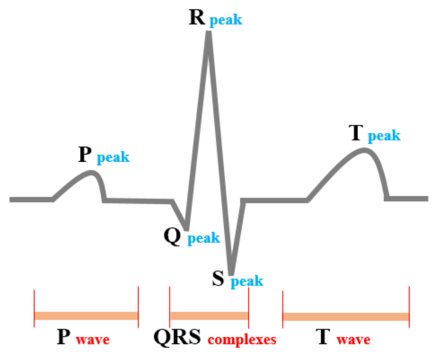

Figure 2: ECG lead-I signal structure

Table 1: Biometrics technology trends based on ECG

Ref.	Bio-signal	Processing	Data analysis	Performance
[14]	ECG	Butterworth filter	Morphological features	SVM, authentication rate 98.59%
[15]	ECG	Butterworth filter	Morphological features	SVM, identification rate 93.89%
[5]	ECG	-	LE	ANFIS, recognition rate 95%
[16]	ECG	Wavelet transform	EEMD,PCA	k-NN, identification rate 95.56%
[17]	ECG	Butterworth filter	AC, DCT, MFCC, LDA	k-NN, identification rate 97.31%
[3]	ECG	Wavelet transform	DWT, PCA	SVM, authentication rate 98.7%
[18]	ECG	FIR filter	CWT, LDA	ED, identification rate 97%
[19]	ECG	Butterworth filter	DWT, CWT, PCA	RMSE, authentication
[4]	ECG	-	Sparse coefficientss	k-NN, identification rate 99.48%
[20]	ECG	Target heart rate	LE, CD, RMS	SVM, identification rate 81.73%

Arbitrarily set sections [21], morphological features [22], autocorrelation (AC) [23], and heart rate variability feature values [24] are used. The features in the frequency domain are extracted using discrete wavelet transform (DWT) [25] and wavelet transform [3, 18], Mel frequency cepstrum coefficients (MFCC) [17], ensemble empirical mode decomposition (EEMD) [26]. Features in the phase space domain have not been studied in Korea and are extracted using Lyapunov exponent (LE), the correlation dimension (CD), root mean square (RMS) by Lorentz attraction [20] in abroad. Principal component analysis (PCA) and linear discriminant analysis (LDA) are the most used discriminant analysis for data analysis. Machine learning mainly used for personal authentication, identification and verification of recognition performance are support vector machine (SVM), k-nearest neighbor (k-NN), Euclidean distance (ED), and fuzzy theory. The excellent performance of personal authentication using an ECG signal was analyzed as 98.7% for 18 subjects using wavelet transform signal processing, DWT feature extraction, PCA dimensionality reduction, and SVM. The excellent performance of individual identification is analyzed as 99.48% for 100 subjects using sparse coefficient feature extraction, k-NN. The excellent performance of disease recognition is 95% for the four heart diseases using Rafnov's exponential feature extraction, adaptive network-based fuzzy inference system (ANFIS).

2.2 Heart sound based biometrics technology

Heart sounds are the sounds produced by the beating heart and the resulting blood flow. The locations where heart sounds can be measured according to the position of the auscultation method are shown in Figure 3. Heart sounds are acquired from the aorta, pulmonary artery, tricuspid valve, and mitral valve. The signal can be analyzed as the S1 and S2 heart sounds as shown in Figure 4.

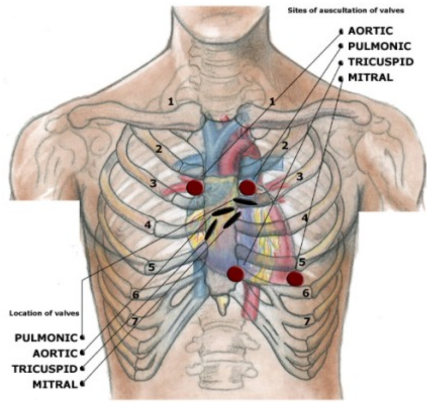

Figure 3: Auscultation points structuree

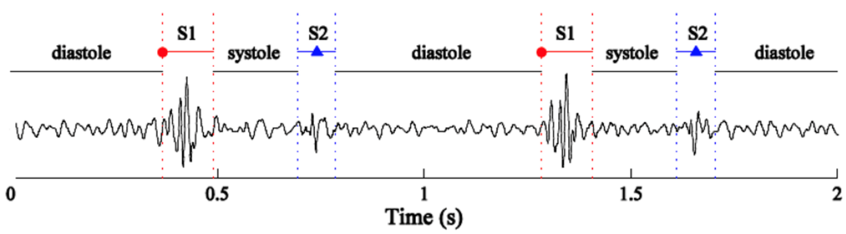

Figure 4: Waveform of S1 heart sound and S2 heart sound

Biometrics using heart sound is being studied such as personal authentication and identification in Table 2. The heart sound signal used for biometrics is acquired using medical equipment without using public DB. The signal processing of the heart sound for noise removal uses a wavelet transform and a Butterworth filter. Features are extracted using the ratio of the S1 heart sound to the S2 heart sound in the time domain for data analysis. Algorithms applied to extract features in the frequency domain are MFCC, linear frequency cepstrum coefficients (LFCC), linear frequency band cepstrum (LBFC), the first to second ratio (FSR), and continuous wavelet transform (CWT). The accuracy of personal authentication and identification was analyzed using machine learning such as ED, SVM, and Gaussian mixture model (GMM). The excellent accuracy of personal authentication using heart sound signals acquired by medical equipment is the equal error rate (EER) of 7.8% for 52 subjects by MFCC, linear frequency cepstral coefficients (LFCC) feature extraction, and SVM. The excellent accuracy of personal identification was 96.01% of 7 subjects by LBFC feature extraction and GMM.

2.3 EEG based biometrics technology

Biometrics using EEG is being studied for situationa recognition and personal authentication as shown in Table 2. Word recognition identifies specific words using EEG signals according to imagination. Photo recognition is identified using EEG signals that according to a given photo. Situation recognition

Table 2: Biometrics technology based on Heart sound, EEG, EMG

Ref.	Bio-signal	Processing	Data analysis	Performance
[6]	Heart sound	Wavelet transform	CWT	ED, authentication rate 71.06%
[26]	Heart sound	Butterworth filter	MFCC, FSR	ED, authentication EER 8.7%
[27]	Heart sound	-	MFCC, LFCC	SVM, authentication EER 7.8%
[7]	Heart sound	-	LBFC	GMM, identification rate 96.01%
[9]	EEG	Butterworth filter	AR coefficients, LDA	SVM, recognition rate 98.96%
[28]	EEG	Laplacian filter	γ-band, LDA	SVM, recognition rate 94.08%
[29]	EEG	FIR filter	AR	MMSE, recognition rate 100%
[8]	EEG	Butterworth filter	CC, LDA	SVM, authentication 86.1%
[30]	EMG	RMS, Median	-	PCA, recognition rate 100%
[10]	EMG	-	Non-uniform filter bank	GMM, identification rate 81.73%
[11]	EMG	Wavelet transform	MAV	SVM, recognition rate 99%
[31]	EMG	Notch filger	FFT	PCA, recognition rate 85%

is identified using EEG signals when instructed to close and open eyes. The EEG signals that occur depending on the situation are generated as γ, β, α, θ, and δ waves by electric potential fluctuations induced in the cerebrum as shown in Figure 5.

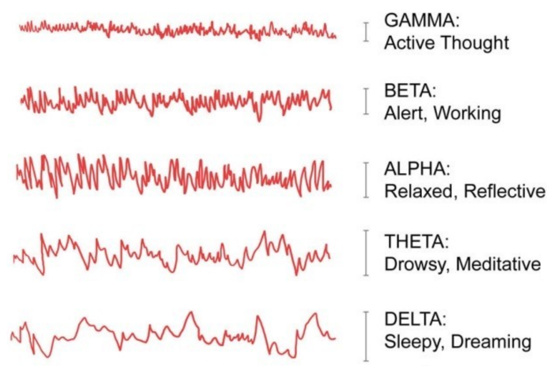

Figure 5: Waveform structure of EEG

The γ wave is generated in the band above 30 Hz during extreme arousal and excitation. β waves are generated in the 14∼30Hz and 5 10uV bands during mental activity or tension in the awake state. The α wave is generated in the 8∼13Hz, 50uV band when the eyes are closed and resting. The θ wave is generated from a child as a waveform with irregular amplitude at 4 to 7 Hz. The δ wave is generated in the 0.3∼3Hz and 20∼200uV bands during sleep. The EEG signal is acquired according to the condition in the medical device and used as data. The noise present in the EEG signal is removed by Butterworth, Laplacian and FIR. Features for data analysis are extracted by autoregressive (AR) and cross-correlation (CC) coefficients in the time domain. LDA is mostly used for discriminant analysis for data analysis of the extracted features. LDA is mostly used for discriminant analysis for additional data analysis of the extracted features. The system is verified by SVM, minimum mean square error (MMSE) to obtain the best estimate for the variable. The excellent accuracy of situation recognition is 100% using FIR filter signal processing, autoregressive coefficient feature extraction, and MMSE. The excellent accuracy of personal authentication is 86.1% of 10 subjects by Butterworth filter signal processing, point-association coefficient feature extraction, and SVM.

2.4 EMG based biometrics technology

Biometrics technology using EMG is as shown in Table 2. The operation for acquiring the EMG signal is defined according to the proposed state. The EMG signal is acquired by the surface extraction method by medical equipment and development equipment. The EMG signal is generated with a voltage value of mV in a wide frequency band of 5 to 10,000 Hz. Noise is removed by RMS, median, notch filter and wavelet transform in signal processing technology using the acquired EMG. The feature extraction algorithm for data analysis is mean absolute value (MAV), fast fourier transform (FFT) in the frequency domain, and non-uniform filter band after setting the interval in the time domain. PCA is mostly used for discriminant analysis for data analysis of the extracted features. The machine learning used for system verification is SVM and GMM. The excellent accuracy of situation recognition using EMG is 99% of four motions by RMS filter, wavelet transform, MAV, and SVM. The excellent accuracy of individual identification is 81.73% of 49 subjects by non-uniform filter band, GMM.

3 Development direction of bio-signal based biometrics technology

Research for enhanced biometrics systems such as high performance algorithms to satisfy user needs is required [32]. The technology required for a more enhanced bio-signal based biometrics system is a high performance algorithm that analyzes bio-signal based big data in a complex state.

3.1 Big data based on bio-signal

Currently, bio-signal based biometrics is being studied using the physionet of bio-signal public DB, medical equipment, and development equipment, but it remains a limitation in considering only fragmentary situations. In the future, various bio-signals in the complex state of individuals will be databased and, a multifunctional biometrics system will satisfy users needs. It is necessary to build a database because big data analysis of the individual's complex state biosignals is required.

3.2 Big data analytics and machine learning

Biometrics system technology is required using bio-signals acquired in the complex state of individuals. High performance algorithm is required to analyze big data of bio-signals in a complex state. There are limitations in big data analysis, processing and delays in time using machine learning technology. Deep learning is an artificial neural network based machine learning technology that can learn on its own [33, 34]. Big data can be analyzed and recognized, inferred, and judged by the deep learning technology applied to biometrics. The structure of a 5-layer neural network with a hidden layer structure is shown in Figure 6. Biometrics using deep learning based bio-signals is expected to process big data of bio-signals and use them extensively [35].

4 Conclusions

Biometrics technology is continuously being researched and developed, and it is evolving into a biometrics system suitable for a real-time environment. In this paper, we analyzed the key technologies of the biometric system such as signal processing, data analysis, and performance. In order to develop the biorecognition system, the construction of big data of biosignals acquired in a complex state and the application direction of the deep learning algorithm to analyze big data are presented. The biometrics system is related to various industries including finance, security, access control, medical welfare, public

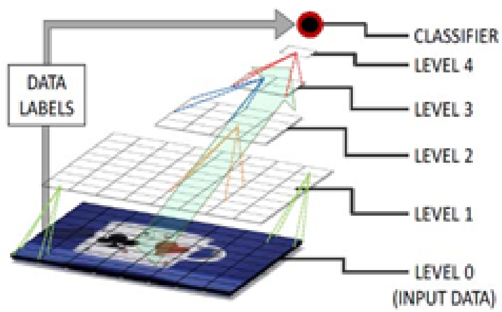

Figure 6: Deep learning based on 5 layer neural network structure

service, and marketing that can be applied, and is considered to be a research field with high growth potential.

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