Human Identification from Brain EEG signals Using Advanced Machine Learning Method

EEG-based Biometrics

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***Abstract*—EEG-based human recognition is increasingly becoming a popular modality for biometric authentication. Two important features of EEG signals are liveliness and the robustness against falsification. However, a comprehensive study on human authentication using EEG signal is still remains. On the other hand, low-cost wireless EEG recording devices are now growing in the market places. Although these devices have the potential to many applications, researches have yet to be done to find the feasibility of these devices. In this study, we propose a method for human identification using EEG signals obtained from such low-cost devices. EEG signal is first preprocessed to remove noise and artifacts using Bandpass FIR filter. These signals are then divided into disjoint segments. Three feature extraction methods, namely multiscale shape description (MSD), multiscale wavelet packet statistics (WPS) and multiscale wavelet packet energy statistics (WPES) are then applied. These features are finally used to train a supervised error-correcting output code multiclass model (ECOC) using support vector machine (SVM) classifier, which ultimately can recognize humans from test EEG signals. A preliminary experiment with 9 EEG records from 9 subjects shows the true positive rate of 94.44% of the proposed method.**

Keywords—EEG signals, multiscale features, supervised classification, human recognition, low-cost wireless EEG recording devices.

I. INTRODUCTION

There are widely used methods of human identification like passwords, PINs, and RF cards, which are easily forgotten, stolen or lost. Biometrics, which refers to the technique used to identify individuals using unique biological features, are more attractive alternatives. Existing technologies mostly use fingerprints, speech, facial features, iris and signatures as a base for recognition. These traits however, are known to be vulnerable to falsification as it is possible to forge or steal. Brain electroencephalogram (EEG) signal can be used as a viable biometric because of its robustness against falsification. They can be used not only for biometric recognition, but also for remote healthcare services [1].

EEG records the brain's electrical activity by measuring the voltage fluctuations on the scalp surface with simple placement of the electrodes on the skin. These signals represent brain activities, determined by the person's unique pattern of neural pathways and thus are impossible to imitate. These signals can be made unique by controlling mood and mental state of the individual, which makes them very difficult to be recorded under force and threat. Moreover, brain signals are related to the subject's genetic information, which makes them unique for each individual and stable over time [1].

Biometric identification researches can be grouped into three classes according to the type of EEG acquisition protocols: (i) while relaxation with eyes closed, (ii) while exposed to visual stimuli, and (iii) while performing mental tasks. Although several recent studies reported 87.5% to 98.56% identification accuracy, achieved by using various features (channel energy, auto-regressive model, wavelet or Fourier domain features, statistical features etc.), a systematic study involving low-cost, portable devices with minimum number of electrodes still remains. This paper therefore concentrates on the feasibility of using low-cost portable EEG technology towards human recognition.

The rest of the paper is organized as follows: Section II presents the system architecture and algorithmic details of the proposed EEG-based recognition framework. Section III includes the experimental evaluation along with a discussion. Finally, the work is concluded through section IV with some future plans.

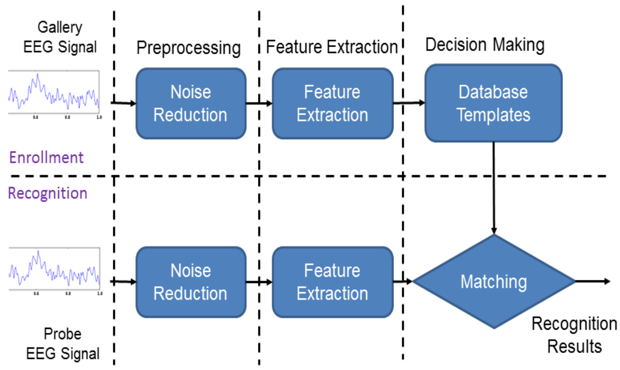

Fig.1 Block diagram of the recognition system.

II. Proposed Method

An overview of the proposed system is shown in Fig.1. The raw EEG signal is first filtered using Bandpass FIR filter to remove body motion effects and power line frequency noise. Noise-reduced EEG signals are then arbitrarily divided into five segments. Two multiscale methods, namely multiscale wavelet packet decomposition and multiscale shape description, are then applied to each segment for EEG feature extraction. In the first method, EEG segments are decomposed into four levels using wavelet packet decomposition [6-7]. The sub-bands corresponding to delta, theta, alpha, beta, and gamma frequency bands of brain signals are used for statistical feature extraction. In the second method, multiple binary patterns are extracted at each sample point of the EEG signal [2]. Due to limited data (one record per subject with a total of nine subject), Three segments from each EEG signal are used to train ECOC-SVM classifier, while the rest two segments are used to test the learned model.

A. Signal Acquisition

The raw EEG signals were collected from 9 adult participants (all females, age range 18-25) using "EMOTIV INSIGHT", a five channel mobile EEG device (San Francisco, USA). The data was sampled at 128 Hz. Approximately, 1 minutes of raw EEG signals were recorded, which made about 7680 samples for each channel. Five channels were placed on the scalp at positions AF3, AF4, T7, T8, and Pz to record the EEG signals. The sensors were placed according to the standard of international system. Figure 2 shows the EMOTIV mobile headset and the workbench for EEG processing.

(a) (b)

Fig.2 EEG recording device (a) INSIGHT EEG headset, (b) Insight workbench for EEG recording.

Data were collected from 9 subjects, in several recording sessions over a course of 6 weeks. All subjects were female students from the department of Information Science, Ochanomizu University, whose age ranged from 22 to 24 years. Subjects were requested to sit on a reclining chair and remain calm and relaxed throughout the whole recording procedure. Each session consisted of 1 trial per subject, where each trial consisted of 2 tasks "eye-close" and "eye-open". Only the results of the first task (i.e., eyes close) are presented here. They were also instructed to minimize any movements to minimize motion artifacts to the EEG signal. During signal acquisition, subjects were asked to clear their minds of any thoughts and to be relaxed.

B. Preprocessing

EEG signal is usually noisy. It is necessary to reduce various noises and artifacts before feature extraction [4]. We applied a Bandpass FIR filter to remove noises due to body motion and power line frequency at 60 Hz. Filter has following specifications: (i) lower cutoff frequency of 0.5 Hz; (ii) upper cutoff frequency of 59 Hz, and (iii) filter order=8. Figure 3 and 4 show the data before and after bandpass filtering, respectively. From the plots, we can see the filtered signals preserve essential frequency components in the original data

C. Feature Extraction

Multiscale Shape Descriptor (MSD): This feature extracts local morphology of the EEG signal at multiple scales. All polarity information compared to the central sample in a window is computed as a binary pattern, which is then multiplied by the binary weights to come up with the feature value. Above computation is continued at all sample positions and finally pattern histogram is computed. If the noise reduced N-sample EEG signal is represented by $x(i)$, the multiscale local shape descriptors (*MSD*) at i^{th} sample point can be defined by computing histogram of local shape patterns, $LSP_p(i)$ using

$$MSD(i) = \{H(LSP_{P_{\min}}(i)), \ldots, H(LSP_{P_{\max}}(i))\} \quad (1)$$

where

$$LSP_P(i) = \sum_{k=-P/2}^{P/2} s(x(i+k) - x(i))\, w\left(\frac{P}{2} - k\right),$$

$$P/2 \le i \le N - P/2$$

In the above equation, N is the signal length, P is an odd number indicating the size of a neighborhood at each sample point, s *(.)* and w *(.)* are the binary and weight functions, respectively. $P_{\min}$ and $P_{\max}$ are the minimum and maximum window sizes, empirically selected to 3 and 15 in our current study. Please refer to [2-3] for detail description.

Multiscale Wavelet Packet Statistics (WPS): The second method we used is the wavelet packet decomposition [6-7]. It is a popular feature extraction scheme in the time-frequency domain. It divides the signal into its low frequency and high frequency components and the frequency is down-sampled at every level resulting in a complete wavelet packet tree for a comprehensive signal analysis. EEG signals have five major frequency bands: delta (0-4 Hz), theta (4-8 Hz), alpha (8-15 Hz), beta (15-30 Hz), and gamma (30-60 Hz) bands. For different individuals, the energy distributions of the frequency components are quite different and make it possible to adopt those frequency components as the features to represent the EEG signals. We used four-level wavelet packet decomposition of EEG signal and the coefficients corresponding to nodes (1, 1), (2, 1), (3, 1), (4, 0), and (4, 1) were selected. Note that the first number in each pair indicates the decomposition level, while the second number indicates the subband in the decomposed tree. These coefficients, representing the whole EEG frequency bands (0.5 - 59 Hz), were extracted for further processing. The mean (μ_x) standard deviation (σ_x) and entropy

(ϵ_x) values of each coefficient vector (x_i) were then calculated according to the Eqs. 2-4. However, we observe that the below features, extracted from the EEG bands at the terminal level of the decomposition tree are not very effective. We therefore computed the statistics of Eqs. 2-6 at each level of the wavelet packet tree and concatenated them into a feature vector.

$$\mu_x = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (2)$$

$$\sigma_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)^2} \qquad (3)$$

$$\varepsilon_x = -\sum_i x_i^2 \log\left(x_i^2\right) \qquad (4)$$

Multiscale Wavelet Packet Energy Statistics (WPES): In many studies, it is observed that wavelet coefficient energy, i.e., the absolute values of wavelet coefficients is also a strong feature for classification. Based on this observation, a variation of the WPS feature, called wavelet packet energy statistics (WPES) is also attempted. Since wavelet coefficients appear as positive and negative numerical values, we can define statistics by using rectified coefficient using following equations.

$$\mu_x = \frac{1}{n}\sum_{i=1}^{n}|x_i| \qquad (5)$$

$$\sigma_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|x_i| - \mu_x)^2} \qquad (6)$$

$$\varepsilon_x = -\sum_i |x_i|^2 \log\left(|x_i|^2\right) \qquad (7)$$

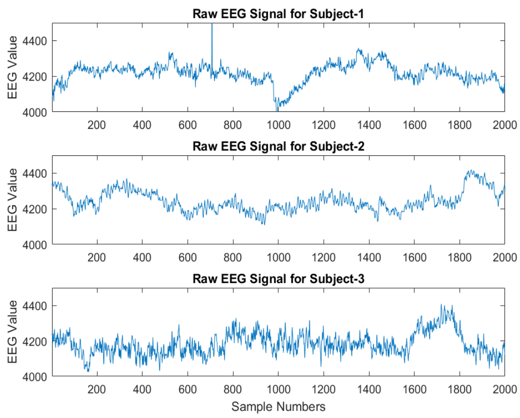

Fig.3 Raw EEG Signals for three persons

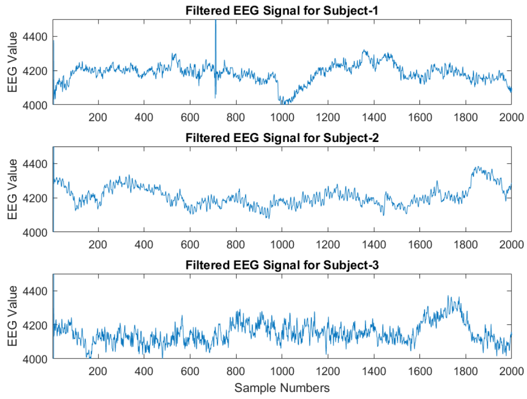

Fig.4 Preprocessing results of raw EEG signals in Fig. 3. Bandpass FIR filter is used with parameters: Order=8, lower cutoff frequency=0.5 Hz, upper cutoff frequency=45 Hz, sampling frequency=128 Hz. Data is offset by about 4100 uV.

Alpha-Beta Statistics (ABS): Multiscale wavelet packet decomposition was also used for brain wave extraction [6]. In this case, the frequently used features are the wavelet coefficients corresponding to the alpha (8 – 15 Hz) and beta (15 – 30 Hz) waves of EEG signal. Since the maximum frequency in our EEG data is 64 Hz, EEG segments are first decomposed into four levels. Then, the coefficients from nodes (4 2), (4 3), (4-4), (4-5), (4-6), and (4-7) are extracted and used to compute above statistics. This feature will be used for performance comparison with the proposed features.

D. Classification

Classification is the process to check the identity of input EEG feature vectors to the EEG vectors of the persons that were stored in the database. Artificial Neural Networks (ANNs) and support vector machine (SVM) are two widely used methods in supervised classification. In this study, we applied error-correcting output code multiclass model (ECOC), which uses SVM classifier to solve multiclass problem [8]. It requires a coding design, which determines the classes that the binary learners train on, and a decoding scheme, which determines how the results (predictions) of the binary classifiers are aggregated.

III. Experimental Evaluation

We did experiment on a set of nine ECG signals, recorded from nine female subjects with “eye-close” condition. To eliminate the instability, we discarded initial part from each EEG signal and chose a length of 5001 samples for each signal per channel. Each signal is then divided into five equal segments (i.e., each has approximately 8 sec.) and features were extracted from them. Daubechies db5 wavelet is used to compute the wavelet packet feature in the time-frequency domain. Extracted features corresponding to three segments were used for training the classifier, while the rest two segments were used for testing. Classification results were evaluated using following criteria.

$$TPR = \frac{TP}{TP + FN} \times 100\% \qquad (8)$$

$$FNR = \frac{FN}{TP + FN} \times 100\% = 1 - TPR, \qquad (9)$$

where TP and FN are the true positive and false negative, respectively. Table 1 shows the various parameters in our experiment, while identification results were shown in table 2. Results clearly showed that WPS and WPES features (red and light green bars) consistently perform better identification of humans compared to the MSD feature (blue bars) in all five channels. The highest accuracy obtained by the WPS feature is 94.44% on channel-3 and channel-5 data, while the same is obtained by WPES feature on channel-5 data (Please refer to Fig. 5). This observation indicates the dependency of features on particular channel data. A future study can therefore be done to fuse multiple channels that may lead to better accuracy. We have performed a comparative study of the proposed features with the brainwave statistics, i.e., ABS feature. Results are shown in the table II as well as in Fig. 5. It shows that this feature (pink bars) performs slightly better than the MSD feature (blue bars) in almost all channels. On the other hand, it shows poor performance against the proposed WPS and WPES features, which produce higher accuracies in all channels. Whatsoever, this feasibility study clearly indicates the potential of these features (red & green bars) in combination with the ECOC based SVM classifier.

TABLE I: VARIOUS EXPERIMENTAL PARAMETERS

Parameters	**Value**
Device	Five channel Mobile Neuro headset (EMOTIV INSIGHT)
Subjects	9 (Ages: 20 to 24)
Sampling rate	128 Hz per channel
Minimum Voltage Resolution	0.51 µV
EEG length	5001 samples on average
Filter parameters (Bandpass FIR filter)	Order=8; Lower cutoff frequency=0.5 Hz, Upper cutoff frequency=59 Hz.
Multiscale window sizes	3, 5, 7, 9, 11, 13, 15 samples
EEG segments	5

TABLE II: HUMAN IDENTIFICATION RESULTS

Features	**Recognition Accuracy [*TPR* (*FNR*)] (%)**				
	Ch-1	***Ch-2***	***Ch-3***	***Ch-4***	***Ch-5***
MSD	50.00 (50.00)	44.44 (55.56)	50.00 (50.00)	61.11 (38.89)	61.11 (38.89)
WPS	66.67 (33.33)	72.22 (27.78)	94.44 (5.56)	72.22 (27.78)	94.44 (5.56)
WPES	83.33 (16.67)	72.22 (27.78)	83.33 (16.67)	72.22 (27.78)	94.44 (5.56)
ABS	61.11 (38.89)	61.11 (38.89)	61.11 (38.89)	44.44 (55.56)	61.11 (38.89)

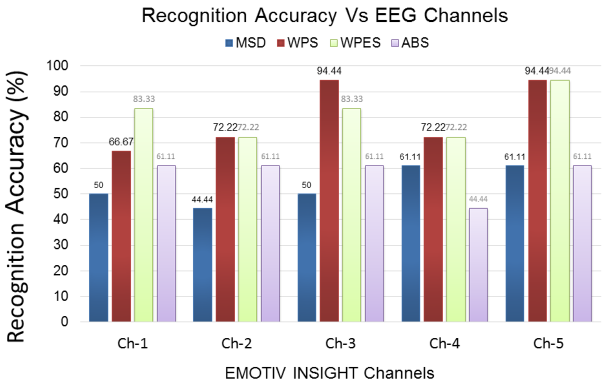

Fig.5 Human Recognition results. Blue, red, light green, and pink bars indicate the authentication results using MSD, WPS, WPES, and ABS features.

A. Discussion

While the proposed WPS/WPES features are efficient compared to the MSD or ABS features, we have yet to consider other potential features in future. At the moment, disjoint EEG segments from the same EEG signal are used for training and testing the classifier. In future, we will consider "Holdout" validation method subject to having large EEG database. Moreover, the individual channel data is used independently in the current study. Fusing multi-channel information may produce better classification accuracy. A multi-channel fusion strategy will therefore be explored. Biometric fusion is a recent trend towards the development of robust recognition system. Therefore, the fusion technology in both mono-modal and the multi-modal biometric will also be explored along with the incorporation of the large databases.

We observe that the classification accuracy varies with the variation of the type of preprocessing filters. A multichannel combination of features may be useful to stabilize the classifier performance. A further study can also be done with extended feature sets and prediction algorithms in order to identify their best combination. In this study, Daubechies d5 wavelet is used. Other wavelets may also be investigated to find their potential towards human recognition.

IV. CONCLUSION

A feasibility study on the human detection using low-cost EEG device (EMOTIV INSIGHT) has been proposed. Three feature extraction methods, namely multiscale local shape descriptors (MSD) in the time domain and multiscale wavelet packet statistics (WPS) and multiscale wavelet packet energy statistics (WPES) in the time-frequency domain have been applied with the supervised ECOC model using SVM classifier. An experiment with nine EEG records from nine individuals showed the potential of the proposed method. WPS and WPES features consistently showed better recognition accuracies compared to the MSD in all five data channels with the highest accuracy of 94.44%. While the proposed WPES or WPS based method is efficient, we have yet to consider large databases. More features need to be investigated for finding an optimal combination of the features and the prediction algorithms in our future study. A method for multi-channel data fusion and the possibility of multimodal biometric will also be explored.

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