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Ajith Abraham
Azah Kamilah Muda
Yun-Huoy Choo *Editors*

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Pattern Analysis, Intelligent Security and the Internet of Things

Springer

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Preface

Welcome to Melaka, Malaysia, and to the Parallel Symposiums of the 2014 Fourth World Congress on Information and Communication Technologies (WICT 2014) during December 8–11, 2014. In the past century, our society has been through several periods of dramatic changes, driven by innovations such as transportation systems, telephone. Last few decades have experienced technologies that are evolving so rapidly, altering the constraints of space and time and reshaping the way we communicate, learn, and think. Rapid advances in information technologies and other digital systems are reshaping our ecosystem. Innovations in ICT allow us to transmit information quickly and widely, propelling the growth of new urban communities, linking distant places and diverse areas of endeavor in productive new ways, which a decade ago was unimaginable. Thus, the theme of this World Congress is 'Innovating ICT for Social Revolutions'.

The four day World Congress is expected to provide an opportunity for the researchers from academia and industry to meet and discuss the latest solutions, scientific results and methods in the usage and applications of ICT in the real world. WICT 2014 is Co-Organized by Machine Intelligence Research Labs (MIR Labs), USA, and Universiti Teknikal Malaysia Melaka, Malaysia. WICT 2014 is technically co-sponsored by IEEE Systems, Man and Cybernetics Society Malaysia and Spain Chapters and Technically Supported by IEEE Systems Man and Cybernetics Society, Technical Committee on Soft Computing.

This year, we introduce additional academic activities, Editor-in-Chief's Panel Discussion, Student Symposium, Parallel Symposiums, and Research Product Exhibition. Editor-in-chiefs from world-renowned journals in ICT will be gathered in a special forum to facilitate sharing session for tips and advice on journal publication. The following five Parallel Symposiums were organized:

- Intelligent System and Pattern Analysis
- Emerging Computer Security Issues and Solutions
- Data Quality and Big Data Management
- Innovation in Teaching and Learning
- Requirements Engineering

Many people have collaborated and worked hard to produce a successful WICT-2014 conference. First and foremost, we would like to thank all the authors for submitting their papers to the conference, for their presentations and discussions during the conference. Our thanks to Program Committee members and reviewers, who carried out the most difficult work by carefully evaluating the submitted papers. The themes of the contributions and scientific sessions range from theories to applications, reflecting a wide spectrum of coverage of various data analysis topics covering big data, data quality, pattern recognition, computer security, etc. Each paper was reviewed by at least five reviewers in a standard peer-review process. Based on the recommendation by five independent referees, finally 31 papers were accepted for publication (43 % acceptance rate) in the proceedings published by Springer.

The General Chairs and the Program Chairs along with the entire team cordially invite you to attend the Parallel Symposiums of the 2014 Fourth World Congress on Information and Communication Technologies (WICT 2014).

General Chairs

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Program Chairs

Azah Kamilah Muda, University Teknikal Malaysia Melaka, Malaysia
Emilio Corchado, Universidad de Salamanca, Spain
Marina Gavrilova, University of Calgary, Calgary

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Comparing Features Extraction Methods for Person Authentication Using EEG Signals

Siaw-Hong Liew, Yun-Huoy Choo, Yin Fen Low, Zeratul Izzah Mohd Yusoh, Tian-Bee Yap and Azah Kamilah Muda

Abstract This chapter presents a comparison and analysis of six feature extraction methods which were often cited in the literature, namely wavelet packet decomposition (WPD), Hjorth parameter, mean, coherence, cross-correlation and mutual information for the purpose of person authentication using EEG signals. The experimental dataset consists of a selection of 5 lateral and 5 midline EEG channels extracted from the raw data published in UCI repository. The experiments were designed to assess the capability of the feature extraction methods in authenticating different users. Besides, the correlation-based feature selection (CFS) method was also proposed to identify the significant feature subset and enhance the authentication performance of the features vector. The performance measurement was based on the accuracy and area under ROC curve (AUC) values using the fuzzy-rough nearest neighbour (FRNN) classifier proposed previously in our earlier work. The results show that all the six feature extraction methods are promising. However, WPD will induce large vector set when the selected EEG channels increases. Thus, the feature selection process is important to reduce the features set before combining the significant features with the other small feature vectors set.

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1 Introduction

Person authentication using brainwaves particularly aimed to differentiate client from imposter based on the distinctive features hidden in the electroencephalograms (EEG) signals. EEG signals are unique but highly noisy, weak and difficult to process. Therefore, feature extraction plays an important role in extracting more relevant and meaningful information to facilitate better analysis. It is important to represent noisy, weak and non-stationary raw data such as EEG signals in a better manner. Features extraction stage involves the transformation of the raw data signal into a relevant data structure which is known as feature vector. A good feature vector tends to suppress noise, disclose important information and eliminate redundant data [1].

In the study of signal processing, feature extraction methods such as Fast Fourier Transform (FFT), autoregressive (AR) model and wavelet transform (WT) are widely used in many signal processing studies. Nevertheless, they are prone to different shortcomings, thus has jeopardized the performance in signal analysis. The FFT method provides useful information but only from frequency domain. Features with the combination of time domain and frequency information can improve the classification performance of EEG signals [2]. On the other hand, the AR model cannot capture transient features from the EEG signals [3]. The feature vectors of WT are rather complex and it will increase the difficulty to get accurate transcendent information.

Feature extraction methods such as FFT, AR and WT are not promising in non-stationary signals, i.e. the EEG signal. In our earlier work [4], some of the feature extraction methods were identified from the literature and were used in analysing EEG signals for person authentication purposes. No comparison was done on the selected feature extraction methods towards the classification performance. In recent studies, WPD, Hjorth parameter and mutual information are claimed to be good and appropriate for EEG signals analysis [5, 6]. Therefore, this study aimed to compare the feature extraction methods used in [4] and other methods recommended in the literature for person authentication analysis using the non-stationary EEG signals.

The rest of this chapter is organized as follows: Section 2 presents the proposed feature extraction methods in this study. Section 3 discusses the dataset, the experimental design, feature selection technique and the fuzzy-rough nearest neighbour (FRNN) classification technique. Section 4 depicts the results and discussion while Sect. 5 draws the conclusions and the direction of the future work.

2 The Proposed Feature Extraction Methods

Raw EEG data are non-stationary, noisy, complex and difficult to analyse. Therefore, feature extraction is needed to extract the relevant information or characteristics from the EEG signals. Features extracted from EEG signals are unique between subjects and sufficient for person authentication [7]. Different features provide different discriminative power for different subjects. Most of the authentication systems will make use of features combination architecture. The results were able to demonstrate the significant improvement in the system performance [8]. The feature extraction methods used in this study are as follows:

2.1 Wavelet Packet Decomposition (WPD) [3, 5]

In [5], the authors have demonstrated that WPD is an excellent feature extraction method for non-stationary signals such as EEG signals, and it is very appropriate for EEG signal analysis. WPD provides a multi-level time-frequency decomposition of signals, and it is able to provide more significant features. The wavelet decomposition splits the original signal into detail and approximation. After that, the approximation is split itself into next level approximation and detail. This process will be repeated until n-level. On the other hand, the detail also split itself into the next level to yield more than different ways to encode the signal. Figure 1 shows a complete decomposition tree of a signal.

Research work in [3] has proven that Daubechies with order 4 (DB4) wavelet and sixth level of wavelet packet decomposition is appropriate parameter in order to analyse the EEG signals with 256-Hz sampling rate. Since the frequency of useful EEG signals is lower than 50-Hz, therefore, we use 25 sub-bands in each channel. The combination with the time domain and frequency domain can provide more significant features; we characterized the time–frequency distribution of EEG signals by combining the features below:

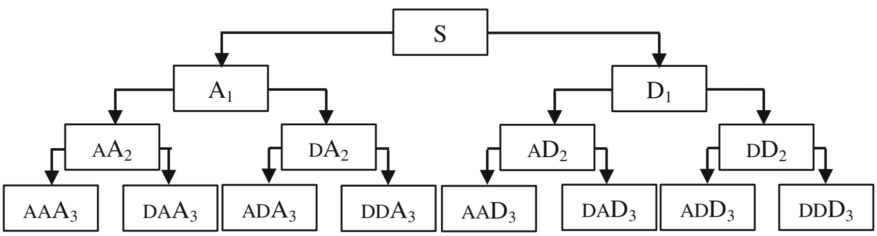

Fig. 1 Level 3 of wavelet packet decomposition tree [9]

Average coefficients in sixth sub-band. A total of 9 channels were selected from 64 available channels in the dataset and the sampling rate for each channel is 2^8, the sub-band means (*Mj*) at *j*th level is defined as in Eq. (1):

$$M_j = \frac{1}{2^j} \sum_{k}^{2^8} d_j(k) \tag{1}$$

where $d_j(k)$ represents the coefficient of WPD at jth level and kth sample. 25 sub-bands were used for WPD as the frequency of useful EEG signal is lower than 50 Hz. Therefore, the dimensions of feature vector for average coefficients are 225.

Wavelet packet energy in each sub-band. In the perspective of wavelet packet energy, WPD decomposes signal energy on different time–frequency plain; the integration of square amplitude of WPD is proportional to signal power. The sub-band entropy is defined as in Eq. (2):

$$E(j,n) = \int |S(t)|^2 \mathrm{d}t = \sum_k \left(d_j^n(k)\right)^2 \tag{2}$$

where $n = 0, 1, 2, \ldots, 2^j$. Since we were selected 9 channels in this research, the dimension of feature vector for wavelet packet energy is 225.

2.2 *Hjorth Parameter [6, 10]*

Hjorth parameter is essential to analyse EEG signals in both time and frequency domains. It can extract the property of EEG signals efficiently [6]. Hjorth parameters are used to compute the quadratic mean and the dominant frequency of EEG signals on each side of the brain, we used the first two Hjorth descriptors in 1970 and 1973, namely activity and mobility. From the activity and mobility in the EEG signals, it reflects the global trend of a signal, for visual analysis. Hjorth parameters were used in various online EEG analyses, such as in sleep staging in order to compute the amplitude and the main frequency of a signal. These descriptors are chosen because they have a low calculation cost [10].

Let us consider the spectral moment of order zero and two

$$m_0 = \int_{-\pi}^{\pi} S(w)\mathrm{d}w = \frac{1}{T} \int_{t-T}^{t} f^2(t)\mathrm{d}t \tag{3}$$

$$m_2 = \int_{-\pi}^{\pi} w^2 S(w) \mathrm{d}w = \frac{1}{T} \int_{t-T}^{t} \left(\frac{\mathrm{d}f}{\mathrm{d}t}\right)^2 \mathrm{d}t \tag{4}$$

where $S(w)$ represents the power density spectrum and $f(t)$ represents the EEG signal within an epoch of duration T. The first two of Hjorth parameters is given by

$$\text{Activity} : h_0 = m_0 \tag{5}$$

$$\text{Mobility} : h_1 = \sqrt{\frac{m_2}{m_0}} \tag{6}$$

h_0 is the square of the quartic mean and h_1 reflect that frequency of dominant. These quantities that are in discrete forms, where $h_0(k)$ and $h_1(k)$ at a sampled time of k, are calculated within a sliding window of 1 s length using the open-source software library BioSig.

Besides that, Hjorth parameter has also used the fourth-order spectral moment m_4 to define a measure of the bandwidth of the signal, called complexity.

$$\text{Complexity} : h_2 = \sqrt{\frac{m_4}{m_2} - \frac{m_2}{m_0}} \tag{7}$$

The first parameter is activity which represents the signal power, mobility represents the mean frequency, and complexity represents the change in frequency.

2.3 Mean [4]

Mean, also known as average, can be obtained by summing up of all EEG potential value and divides by the number of samples. The expression of the mean is given in Eq. (2) as follows:

$$\bar{x} = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i \tag{8}$$

where, n is the number of data and x_i is the value of the data.

2.4 Coherence [11]

Coherence is used to measure the degree of linear correlation between two signals. The correlation between two time series at different frequencies can be uncovered by coherence. The range value for the magnitude of the squared coherence estimate is between 0 and 1. The value of 0 for the coherence function means the independence between two signals while a value of 1 for the coherence function means the complete linear dependence. The formula of coherence is given as follows:

$$C_{xy}(f) = \frac{\left|P_{xy}(f)\right|^2}{P_{xx}(f)P_{yy}(f)} \tag{9}$$

where $C_{xy}(f)$ is a function of the power spectral density, (P_{xx} and P_{yy}) of x and y and the cross-power spectral density (P_{xy}) of x and y.

2.5 Cross-correlation [12]

The main purpose of the cross-correlation is to measure the similarity between two channels. Cross-correlation is also known as sliding dot product, which is used to find occurrences of a known signal in unknown one. Furthermore, it is a function of the relative delay between the signals which can be applied in pattern recognition and cryptanalysis. Two input signals will be used to compute the cross-correlation:

- Channel 1 with itself: ρ_X;
- Channel 2 with itself: ρ_Y;
- Channel 1 with channel 2: ρ_{XY}.

The correlation ρ_{XY} between two random variables x and y with expected values, μ_X and μ_Y, and standard deviation, σ_X and σ_Y is given as:

$$\rho_{XY} = \frac{\mathrm{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E((X - \mu_X)(Y - \mu_Y))}{\sigma_X \sigma_Y} \tag{10}$$

where $E(\cdot)$ is the expectation operator, and $\mathrm{cov}(\cdot)$ is the covariance operator.

2.6 Mutual Information (MI) [7, 8]

Mutual information theory represents the quantity that can measure the mutual dependence of the two signals. It is defined as the difference between the sum of entropies within the time series of two channels and their mutual entropy. Logarithms of base 2 were used in the experiment to measure MI in bit.

3 Materials and Methods

3.1 Data Description and Data Preparation

In this study, an EEG dataset from UCI Machine Learning Repository were used in the experiments. The full dataset consists of three versions of data with different subject size, i.e. small (1 subject), large (10 subjects) and full dataset (122 subjects). Large dataset were used in this research and it consists of 10 subjects with 64 channels electrode placement. Each individual is completed with a total number of 60 trials and sampled at 256 Hz (3.9-ms epoch). Due to many redundant trials in one of the subjects, it was replaced by another subject from the full dataset. The swap was performed to ensure that the prediction ability is not biased due to the redundant data in both training and testing phase in a particular subject.

Instead of treating the classification as a ten-class problem, the classifier was trained with only two outputs, i.e. the client and the imposter. The data were split into 80 % of training and 20 % of testing. For training data, 16 trials of S1 object and 32 trials of S2, both match and not match will be selected. On the other hand, there are 4 trials of S1 object and 8 trials of S2 object, both match and not match cases were selected for testing data. It is because the amplitude of the EEG signals will be different when the subject performed different task. The signal data in S2, both match and not match, involve analysis of the picture whether it is match or not match with the previous picture. This is different from the EEG signals as S1 object does not involve analysis as such.

Only the lateral and midline electrodes were used in this study because they have been proven good and able to provide stronger signals in response to visual stimuli [13]. The O1, OZ, O2, PO7 and PO8 are the selected lateral active electrodes, while the FPZ, FZ, OZ, CZ and PZ are the selected midline active electrodes.

3.2 Feature Selection

The WPD method tends to induce large vector set especially when the selected EEG channels increases. Thus, the feature selection process is important to reduce the features set before combining the significant features with the other small feature vectors set. Three common models for feature selection are the filter model, the wrapper model and the embedded model. Correlation-based feature selection (CFS) is a good feature selection method which is able to reduce dimensionality without affecting accuracy [14]. It is a fast and correlated-based filter algorithm that is applicable in discrete and continuous problems [14]. The CFS algorithm evaluates the feature subset according to the correlation-based heuristic merit. A good feature subset contains high correlation between features and the class [15]. In this study, the experiments were designed in two levels, i.e. select the attributes from WPD feature vectors using CFS algorithm before combining with other feature vectors;

and to apply the CFS feature selection across all feature vectors at the same time. The results in Sect. 4 show the influence of different feature vectors on the classification performance.

3.3 Fuzzy-Rough Nearest Neighbour (FRNN) Classification

The performance quantification in this study was based on the accuracy and area under ROC curve (AUC) measurements using the FRNN classifier proposed previously in our earlier work. FRNN classifier introduced by Jensen and Cornelis [16] is an algorithm which combined the strength of fuzzy sets, rough sets and nearest neighbour classification approach motivated by human decision making. The implementation of FRNN algorithm was carried out using the fuzzy-rough version of WEKA data mining tools. In FRNN algorithm, the nearest neighbours are used to construct the fuzzy lower and upper approximations to quantify the membership value of a test object to determine its decision class, and test instances are classified based on their membership to these approximations. FRNN classification approach outperformed various nearest neighbours' approaches such as support vector machine and Naïve Bayes prediction models. FRNN was used in [4] and has gained good results for person authentication using EEG signals. The accuracy and AUC were recorded at 90.17 % and 0.904, respectively.

4 Result and Discussion

The experimental data were preprocessed in the same way as mentioned in Sect. 3. The same classification method and performance measures were used to ensure a fair comparison on different feature extraction methods. The extracted data were also further tested in the two experiment settings to investigate the effect of feature selection process. Table 1 shows the comparison of classification performance using 3 features extraction methods as reported in [4] and 6 features extraction methods as proposed in this study. The 3 feature extraction methods are mean, cross-correlation and coherence while the 6 feature extraction methods are mean, cross-correlation, coherence, Hjorth parameter, mutual information and WPD. The mutual information feature values were normalized to the interval of [0, 1] since the extracted values were relatively small compared with other features.

The average classification accuracy for 3 features set is slightly lower than the result using 6 features set while the AUC shows contrary result where the 3 features set is slightly outperform the 6 features set. It might due to the large number of feature vectors (567 features) which have affected the classification performance. Feature selection was proposed and implemented in the second stage of the experiments. Apart from that, it is obvious that person 7 has obtained the highest accuracy and AUC while person 4 has gained the lowest accuracy and AUC for

Table 1 Comparison of classification performance using 3 feature extraction methods versus 6 features extraction methods

Person	3 feature extraction methods		6 feature extraction methods	
	Accuracy (%)	AUC	Accuracy (%)	AUC
Person 1	87.50	0.924	96.67	0.981
Person 2	86.67	0.788	89.17	0.843
Person 3	88.33	0.922	85.83	0.909
Person 4	80.83	0.704	78.33	0.681
Person 5	93.33	0.954	91.67	0.993
Person 6	88.33	0.924	88.33	0.854
Person 7	99.17	1.000	97.50	1.000
Person 8	90.83	0.895	88.33	0.826
Person 9	90.00	0.936	92.50	0.934
Person 10	96.67	0.990	95.00	0.992
Average	90.17	0.904	90.33	0.901

both 3 features and 6 features. The results are in line with the earlier work reported in [4] where most of the VEP signals for person 7 are more consistent and hence the results are the best compared with others. In contrast, the EEG data of person 4 are incomplete and thus have influenced the classification performance.

In the second stage of experiment, feature selection method, i.e. CFS, was used to select the important attributes before the classification process. From a total of 567 attributes, only 21 attributes are selected. The performance of the selected attributes demonstrated using FRNN classifier is as shown in Table 2.

Commonly, the results are generally more promising when implementing feature selection process. However, in this experiment, both the classification accuracy and AUC values were worse than the results without feature selection. The average accuracy was recorded at 87.00 % while the AUC was recorded at 0.760. The dominating feature, i.e. WPD, has causing the bias in feature selection process, thus resulting in lower accuracy and AUC readings.

In order to avoid bias on the large feature vector, i.e. the WPD features, feature selection was applied to identify significant attributes among the WPD features before combining with the Hjorth parameter, mean, coherence, cross-correlation and mutual information. The classification results are as shown in Fig. 2. From the results, it is proven that a better way of avoiding bias by large feature vectors is to apply separate feature selection process on individual large feature vector before combining with other small feature vectors. Refer to Table 2 for the comparison of feature selection on WPD feature vector.

The classification accuracy and AUC with the feature selection applied on WPD only are both better than applying feature selection across all feature vectors at the same time. The average accuracy and AUC were reported an increase of 4.67 % and

Table 2 Comparison of classification performance without feature selection (FS), with feature selection (FS) and feature selection (FS) on WPD only for 6 feature extraction methods

Person	Without FS		With FS		FS on WPD only	
	Accuracy (%)	AUC	Accuracy (%)	AUC	Accuracy (%)	AUC
Person 1	96.67	0.981	85.83	0.827	98.33	0.991
Person 2	89.17	0.843	85.83	0.618	93.33	0.902
Person 3	85.83	0.909	84.17	0.715	94.17	0.968
Person 4	78.33	0.681	86.67	0.690	92.50	0.937
Person 5	91.67	0.993	90.83	0.693	99.17	0.999
Person 6	88.33	0.854	80.00	0.678	91.67	0.944
Person 7	97.50	1.000	92.50	0.959	98.33	1.000
Person 8	88.33	0.826	87.50	0.725	94.17	0.975
Person 9	92.50	0.934	86.67	0.734	90.00	0.949
Person 10	95.00	0.992	90.00	0.962	98.33	0.999
Average	90.33	0.901	87.00	0.760	95.00	0.966

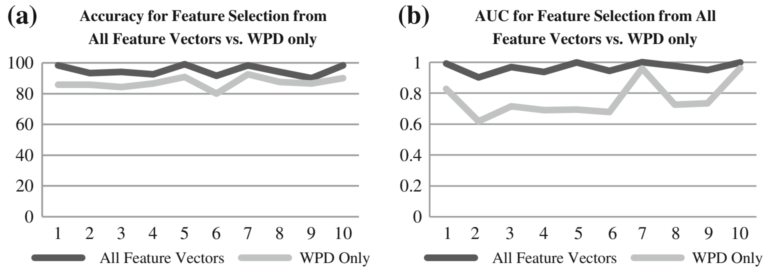

Fig. 2 The comparison of classification accuracy (**a**) and AUC (**b**) for implementing feature selection on all feature vectors versus on only the WPD feature vector

0.065, respectively. Therefore, appropriate feature selection process has proven to be good in person authentication analysis especially when many EEG channels are used and the extracted feature vectors are large in quantity.

5 Conclusion

In this chapter, we have compared and discussed on few well-known feature extraction methods. It can be concluded that WPD cannot perform well in person authentication classification. It must combine with other feature extraction methods in order to get higher accuracy and AUC. Apart from that, feature selection also plays important roles. Last but not least, WPD, Hjorth parameter, mean, coherence, cross-correlation and mutual information are good to extract important attributes for person authentication, and feature selection is needed if the size of feature vectors is large.

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