ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014, i6doc.com publ., ISBN 978-287419095-7.
Available from http://www.i6doc.com/fr/livre/?GCOI=28001100432440.

Using Shannon Entropy as EEG Signal Feature for Fast Person Identification

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Abstract. Identification accuracy and speed are important factors in automatic person identification systems. In this paper, we propose a feature extraction method to extract brain wave features from different brain rhythms of electroencephalography (EEG) signal for the purpose of fast, yet accurate person identification. The proposed feature extraction method is based on the fact that EEG signal is complex, non-stationary, and non-linear. With this fact, non-linear analysis like entropy would be more appropriate. Shannon entropy (SE) based EEG features from alpha, beta, and gamma wave bands are extracted and evaluated for person identification. Experimental results show that SE features provide high person identification rates yet with a low feature dimension, thus better performance.

1 Introduction

Person identification is the process of recognising a person from a group. It recognises the identity of a given person out of a closed pool of N [1]. The applications of person identification are found in video surveillance (public places, restricted areas) and information retrieval (police databases) [1]. In general, there are three means of authentications: password based (something the individual knows), token based (something the individual possesses), and biometric based authentication (something the individual is, such as voice, face, iris, retina, and finger print). It has been shown that electroencephalogram (EEG) can also be used as biometrics for person authentication for its advantages of difficult (close to impossible) to fake, impossible to observe or intercept, unique, unintrusive, and alive [2]. Therefore, EEG signal can also be used for person identification.

EEG is a measurement of the brain signals containing information generated by brain activities [3]. EEG signal is captured by using multiple electrodes either from inside the brain (invasive methods), over the cortex under the skull, or certain locations over the scalp (non-invasive methods) [3]. EEG signal includes the following sub-bands: delta (0.5-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-26 Hz), and gamma (>30 Hz) [3]. A majority of Brain-Computer Interface (BCI) research has been focused on the alpha and beta bands [4]. However, other wave bands may contain useful information and features that are unique to individuals.

EEG signal carries genetic information; that is, there is a connection between genetic information and EEG of an individual [5]. Moreover, EEG features are universal as all living and functional persons have recordable EEG signal [6]. Therefore, EEG data can be suitably used for person identification [1, 5, 7, 8].

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The use of brain wave patterns as a new modality for person identification has several advantages [1]: a) It is confidential because it corresponds to a mental task; b) It is very difficult to mimic because similar mental tasks are person dependent; and c) It is almost impossible to steal because the brain activity is sensitive to the stress and the mood of the person, an aggressor cannot force the person to reproduce his/her mental pass-phrase.

The performance of a person identification system can be measured based on its accuracy and efficiency (identification speed). Feature extraction plays a decisive role in ensuring the classification accuracy, and one of the methods to reduce classifiers' computational complexity, thus to accelerate classification speed, is to decrease the number of features [9]. In this paper, we introduce Shannon Entropy (SE) as an feature extraction method aiming at improving the person identification speed yet still maintains a comparable accuracy to other popular methods such as Autoregressive (AR) modeling.

2 Entropy

One of the challenging problems for EEG data feature extraction is that EEG signal is complex, non-linear, non-stationary, and random in nature [3, 5, 8, 10, 11, 12, 13, 14]. They are considered stationary only within short intervals, i.e. "quasi-stationary", over longer periods of time, the signal characteristics are non-stationary [15]. As consequence, numerous linear feature extraction methods often apply short-time windowing technique to EEG signals to meet this requirement. However, this assumption holds during a normal brain condition, but during mental and physical activities this assumption is not valid [3]. Non-stationary EEG signal can be observed during the change in alertness and wakefulness, during eye blinking, during the transitions between various ictal states, and in the event-related potential (ERP) and evoked potential (EP) signals [3]. As a result, several approaches for non-linear analysis such as entropy have been proposed [8] as randomness of non-linear time series data is well embodied by by calculating entropies of the time series data [16].

Entropy is a measure of uncertainty. In brain-computer interface systems, entropy can be used to measure the level of chaos of the system [3]. It is a non-linear measure quantifying the degree of complexity in a time series [13]. Let X be a set of finite discrete random variables $X = \{x_1, x_2, ..., x_m\}, x_i \in R^d$, Shannon entropy, $H(X)$, is defined as [8]:

$$H(X) = -c \sum_{i=0}^{m} p(x_i) \ln p(x_i) \tag{1}$$

where c is a positive constant acting as a measuring unit and $p(x_i)$ is probability of $x_i \in X$ satisfying:

$$\sum_{i=0}^{m} p(x_i) = 1 \tag{2}$$

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Entropy reflects how well one can predict the behavior of each respective part of the trajectory from the other. Basically, higher entropy indicates more complex or chaotic systems, thus, less predictability [8].

So far, some entropy methods has been successfully used in EEG feature extraction for epilepsy detection, such as Sample, Approximate, Spectral entropy [13], and motor imagery such as Approximate [17], Kolmogorov [18], and Spectral entropy [19]. However, entropy has not been applied for person identification. We believe that entropy contains useful information and features that are unique to individuals, and hence entropy can be used for person identification.

3 Feature Extraction and Person Identification

We extract EEG features based on SE and AR methods. The AR is chosen as the baseline method so that we can compare the performance of the two methods. The AR modeling has been the popular feature extraction for EEG-based person identification as seen in [5, 20, 21]. EEG signals were firstly filtered into four wave bands including alpha (8-13 Hz), beta (14-26 Hz), gamma (30-45 Hz), and normal (8-45 Hz). Features were then extracted and classified separately for each sub-band. In particular, the filtered signals (about 1200 second length) was then segmented into one-second [13] sub-trials. Next, SE and AR features from sub-trials of each channel were extracted. SE features were calculated using the equation 1, in which the probabilities $p(x_i)$ contain normalized histogram counts of elements of an input EEG trial in 256 amplitude bins. The selected optimal order of AR was 16 (AR16). Consequently, one (by SE) feature or 16 (by AR16) features from each sub-trial were produced for one channel. All the features from 23 channels were joined together to form a feature vector for each sub-trial [22]. In brief, there were about 1200 vectors of 23 or 368 features regarding to the feature extraction method, SE or AR16, respectively. The extracted features were then used to train Linear Support Vector Machine (SVM) classifiers for person identification as described in [15, 22]. The person identification performance based on the two sets of features were finally compared for evaluation.

The person identification was experimented in two phases namely 3-fold cross validation and testing. The set of feature vectors was divided into two parts including 2/3 for 3-fold cross validation and 1/3 for testing. The SVM for person identification was performed in WEKA 3.6, 64 bits on a PC running Core i7 3.4GHz, 8GB RAM, and Windows 7, 64-bit OS.

4 Experimental Results

Our experiment was conducted on the Australian EEG (AEEG) dataset [23]. The dataset was collected in the John Hunter Hospital, New South Wales, Australia, over a period of 11 years. The recordings were made by using 23 electrodes (23 channels) placed on the scalp of a subject with the sampling rate of 167 Hz

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for about 20 minutes. Subset of the data used for our experiments consists of EEG data of 40 normal persons. The dataset is summarised in Table 1.

Group	Number of subjects	Number of channels	Number of trials	Number of sessions	Trial length (seconds)
Normal	40	23	1	1	1200

Table 1: AEEG dataset descriptions

Our experiments show that SE features extracted from individual wave bands provide much faster identification speed than AR16 in both 3-fold cross validation and testing phases yet with comparable accuracy. The identification speed comparisons for 3-fold cross validation are demonstrated in Figure 1, in which the identification speed of SE on Alpha band (54 secs) is much faster than that of AR16 (766 secs). The obvious reason is that SE's feature dimension (23) is lower than AR's (368).

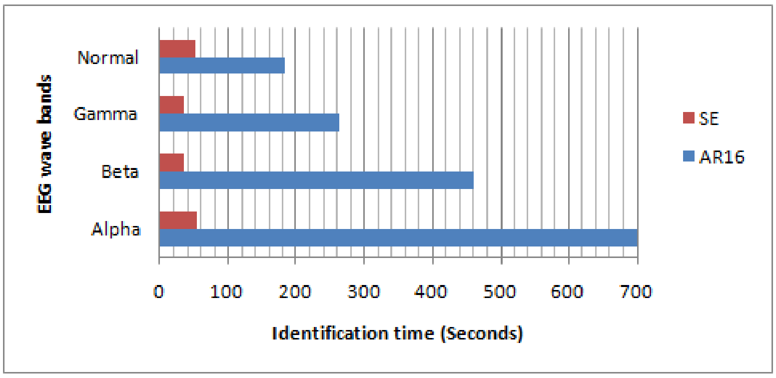

Fig. 1: Comparison of identification speed between SE and AR16

Band	SE		AR16	
	3-Fold Cross.(%)	Test(%)	3-Fold Cross.(%)	Test(%)
Gamma	91.7	87.1	95.2	91.9
Beta	73.6	73.1	94.4	91.6
Alpha	60.5	60.3	91.8	89.1
Normal	75.9	74.1	97.2	95.0

Table 2: Person identification rates on different wave bands

Although the accuracy of SE is not as high as AR16 on individual wave bands (as summarized in Table 2: the SE's highest identification rate is 91.7% on gamma band, while AR16 reaches 97.2% on normal band), we can improve the

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SE's identification rate by concatenating features from alpha, beta, and gamma to form 69-feature vectors. It is likely impossible to apply the same manner with AR16 as it results in vectors of 1104 features, while the number of training samples is about 1200. Therefore, this can cause the curse of dimensionality [22] as it is recommended in that the training samples per class should be at least five to ten times as many as the number of features.

Accordingly, the SE's improved classification rate is almost as same as that of AR16, that is, 97.1% versus 97.2% respectively. Although the number of features of SE increases by three times(69), it is 5.33 times smaller than AR16's, and the identification speeds of SE are still 2.3 and 2.6 times faster than AR16 in 3-fold cross validation and testing modes respectively (see Table 3).

Feature	3-Fold Cross.		Test	
	Rate(%)	Time(s)	Rate(%)	Time(s)
Shannon Entropy	97.1	80	94.9	18
AR16	97.2	184	95.0	47

Table 3: SE's improved person identification rate

5 Conclusions

We have demonstrated that using SE features yields very fast person identification, yet with comparable accuracy because the feature dimension is low. This not only helps to avoid the curse of dimensionality [22], but also reduces SVM's computational complexity, thus increases the speed of the classifiers. In real life security operation, timely response is critical. In the future, we will investigate other entropy methods as well as conduct experiments on a larger scale of datasets for person identification. In addition, we will also investigate, from the theory point of view, on the information content carried by different features and prove its impact on the accuracy and performance.

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