EEG FOR BIOMETRIC VERIFICATION

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Abstract: This paper describes various approaches to use of brain waves in biometric verification. Existing possibilities of EEG data acquisition are introduced in the Data Collection section. A list of basic methods for analysing EEG signal, feature size reduction and classification are given in next three sections. A new method for EEG measuring is suggested in the Conclusion.

Keywords: electroencephalography, EEG, biometric system, signal analysis, classification.

1. INTRODUCTION

Electroencephalography [1] is a medical and scientific method of measuring and recording of brain electricity generated by neurons during communication between brain cells in the scalp of the subject. Scientists confirm that EEG signal is a universal feature and every living person has unique individual brain waves. The EEG signal characteristic is changing with stress and mood and therefore it is impossible to get the signal without subject permission. All these properties make EEG convenient for using it in person authentication in biometric systems [2].

2. DATA COLLECTION

The first important decision to make is to choose an appropriate brain rhythm, or (to be specific) frequency band. The most common choice is an alpha rhythm (8-13 Hz [1]). The alpha rhythm of adults forms a unique pattern for every individual and its amplitude depends on measured brain region. The alpha rhythm is physiologically present in EEG signal when person is awake, but with closed eyes. For appropriate alpha rhythm acquisition, subject has to relax, while sitting without a moving or talking in a dark room with closed eyes. A number of used EEG electrodes is varying among researchers. Their studies are based on typical 10-20 system with 41 electrodes [3] or 2 forehead electrodes [4, 5]. Another approach used eight-channel EEG despite the fact it analysed only one parietal electrode at the end [2]. Sometimes the combination of more rhythm acquisition during relaxing with closed eyes is used (for example theta and SMR) [6].

Next wide area of measuring EEG signal for personal identification is based on imagination. First option is so-called motor imagery. The task is usually to sit and perform imagery moves of left and right hand, foot or tongue according to a cue. For analysis of EEG usually central, parietal and occipital electrodes are used [7, 8]. Another approach is to use imagined speech. A person again relaxes, while sitting and is not moving and is only imagining saying syllables without semantic meaning [9]. Next idea is to imagine own name which should imitate a password [10]. There are also studies containing publicly available database of EEG signal. Data were collected by six electrodes placed in the central, parietal and occipital region during five different thought activities which involved hemispheric brainwave asymmetry. It involved relaxing without thinking of anything in particular, non-trivial multiplication of big numbers, visualizing rotation of three-dimensional block object, mentally compose a letter to a friend and visualizing numbers being written on the blackboard [11, 12].

The third large topic is visual evoked potential (VEP) [1]. VEP is response of the brain to a visual stimulus. The Snodgrass and Vanderwart pictures [13] are the most using stimulus, standardized black and white line drawings. The task is to name and remember the picture. The response to this picture is believed to be unique for every individual and it is located in gamma frequency band (22-30 Hz [1]). It is measured by 61-channel EEG device [14]. A special class of VEP is so-called Rapid VEP [15]. They are based on presenting pictures from different sets, for example faces and cars. The task is not to name but categorize the pictures; the response is faster than VEP. One from the last papers [16] presented a method based on interesting fact, that person brain response to the photograph of own face is markedly different from response to familiar or unfamiliar face and it can be utilized for person recognition even among monozygotic twin. It is measured in the inferior temporal and posterior areas.

3. SIGNAL ANALYSIS

The second important step of biometric system based on EEG is to analyse the EEG signal to get parametric vector of features for further classification. We can differentiate between two major types of features: single channel features and synchronicity features, extracted from two (or more) different channels [5].

Autoregression (AR) [11] and Power Spectrum (PS) [5] are examples of single channel features. Autoregressive model assumes that the EEG signal can be considered stationary random signal in short time and therefore it can be modelled by passing white-noise random process into a linear filter. AR model attempts to predict the current time sample from previous one. Autoregressive coefficients are features extracted from every EEG channel using AR modelling [11]:

$$x(n) = -\sum_{k=1}^{p} a_k \cdot x(n-k) + e(n), \tag{1}$$

where p is the model order (the higher order we choose, the more coefficients we get), $x(n)$ is the signal at the sampled point n, a_k are the real valued AR coefficients and $e(n)$ represents the white noise random process. The Burg [11] or Yule-Walker [5] method is usually used to estimate the feature vector. Instead of AR model it is also possible to use another parametric model, for instance Auto-Regressive and Moving Average model (ARMA) [8].

It is possible to calculate the Power spectrum of EEG signal by different methods, such as Discrete Fourier Transform (DFT), Welch method and AR model method [6]. Coefficients of power spectrum are features extracted also from every EEG channel. For example DFT can be described by the following equation [5]:

$$X(k) \ = \sum_{j=1}^{N} x(j)\, w_N^{(j-1)(k-1)}, \tag{2}$$

where $w_N = e^{(-2i)/N}$. N is the number of samples, $X(k)$ is spectral power at frequency bin $k, x(j)$ is an input signal amplitude in time j, w is circular frequency. More parameters can be derived from the power spectrum, e.g. central frequency, variance of spectral power or non-dominant region of the power spectrum.

Mutual Information (MI), coherence (CO) and cross-correlation (CC) are examples of two-channel features. Mutual Information (MI) is a scale factor of the mutual dependence of two variables. Definition of the mutual information I of discrete variables X and Y is [17]:

$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x) \cdot p(y)}, \tag{3}$$

where $p(x, y)$ is joint probability distribution function of X and $Y, p(x)$ and $p(y)$ are marginal probability distribution functions of X and Y.

Coherence (CO) is used to discover the correlation between two time series at different frequencies. The coherence C between two signals $x(t)$ and $y(t)$ is defined [5]:

$$C_{xy}(f) = \frac{\left|P_{xy}(f)\right|^2}{P_{xx}(f) \cdot P_{yy}(f)}, \tag{4}$$

where P_{xx} and P_{yy} are functions of the power spectral density of x and y and P_{xy} is the cross-power spectral density of x and y.

Cross-correlation (CC) is a measure of similarity of two signals, commonly used to find occurrences of a known signal in an unknown one. The correlation [5]:

$$\rho_{X,Y} = \frac{cov(X, Y)}{\sigma_X \cdot \sigma_Y} = \frac{E((X - \mu_X), (Y - \mu_Y))}{\sigma_X \cdot \sigma_Y}, \tag{5}$$

where μ_X and μ_Y are expected values of x and y, σ_X and σ_Y are standard deviations of x and y, E is the expectation operator and cov is the covariance operator.

The spectral power comparison between channels can be also used as two-channel feature. The inter-hemispheric channel spectral power differences in each spectral band are computed [11]:

$$Power_{difference} = \frac{P_1 - P_2}{P_1 + P_2}, \tag{6}$$

where P_1 is the power in one EEG channel and P_2 is the power in another channel in the same spectral band but in opposite hemisphere. Other features could be for example inter-hemispheric channel linear complexity, non-linear complexity etc.

The third option to analyze EEG signal is to calculate parameters which depend on all channels, e.g. by SOBI. Second-order Blind Identification (SOBI) [8] is based on presumption that every sample $x_i(t)$ of every channel i in time t can be assumed to be an instantaneous mixture of unknown components (number of components is equal to number of channels) or sources $s_i(t)$, via unknown mixing matrix A:

$$x(t) = A \cdot s(t). \tag{7}$$

The mixing matrix is generated only from EEG measurement.

4. FEATURE SIZE REDUCTION

Sometimes the size of the feature vector is too large, and then it is desirable to use techniques for picking the most important parameters to reduce the vector. Principal Component Analysis (PCA) [11] is statistical method that transforms original variables (in our case features) by orthogonal transformation to a set of linearly uncorrelated variables called principal components. The count of principal components is, in ideal case, less than number of the original variables. Principal components are defined by variance, in other words amount of variability between original data they describes.

5. CLASSIFICATION

The next step in every biometric system is the classification. It is used for feature vectors comparison. We assume that the most similar vectors come from the same person. In most cases part of retrieved vectors serves for training, the rest is for testing of accuracy. The neural networks and k-nearest neighbour method are used.

The k-Nearest-Neighbour (kNN) Classifier [6, 9, 14] is non-parametric method. Its input is the feature vector and the output is a class membership. The training phase of the algorithm consists of storing the feature vectors in a multidimensional feature space, each with a class label. In the second phase an unlabeled vector is located into feature space and it is marked by the class which is the most frequent among the k training samples nearest to that searched vector. The distance metric is used for assessment of distance between vectors in features space, the most commonly used metrics are Hamming distance, Manhattan distance, etc. [6, 9, 14].

The neural networks [3, 7, 8] are inspired by human brain. It consists of neurons with weighted inputs and a function that transforms them into output. Neurons are organized into layers, most of them are hidden. The number of outputs from the last layer is equal to the count of classes. We know the right class of the feature vector in the training phase of the algorithm, we assign the value to every classification the neural networks did to adjust the weights in the hidden layers so the next time the resulting output will be closer to the correct solution. After training of the neural network we can start to classify training feature vectors.

After the classification a very important step follows - assessment of the accuracy of the designed biometric system. The most frequently used technique is the ratio of the number of correct identification persons to all classified subjects.

6. CONCLUSIONS

All current research groups are focused on improving the classification and identification of persons based on available methods of EEG data measuring. The EEG signals are acquisited under strict experimental condition, in the dark, soundproofed and shielded rooms. They work with a small number of test subjects, mostly less than 20 individuals. Despite the fact, they analysed a few electrodes, they often measured with 61-channel EEG device. Although there are studies from other fields suggesting that EEG signal changes with emotion, stress and time, there are very few articles in the area of biometrics, in which this changes are included.

My goal is to design a new method for EEG data acquisition. I will set an experiment for measuring alpha activity caused by emotion. Test subject will sit in a relaxed position and watch and hear emotional stimulus in form of pictures, movies or music. This stimulus were already designed by different authors [18], however they were focused on emotion classification not on biometry.

My second aim is to create an alpha rhythm database with a large number of individuals. Besides emotionally changed alpha activity, it will contain a normal alpha rhythm while closed eyes. The database allows to confirm existing studies on a bigger sample and will help to prove my new method. It can be also used for observing time changes in individual EEG data, by repeating experiment in a longer time interval.

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