Motor Imagery EEG-Based Person Verification

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Abstract. We investigate in this paper the activity-dependent person verification method using electroencephalography (EEG) signal from a person performing motor imagery tasks. Two tasks were performed in our experiments were performed. In the first task, the same motor imagery task of left hand or right hand was applied to all persons. In the second task, only the best motor imagery task for each person was performed. The Gaussian mixture model (GMM) and support vector data description (SVDD) methods were used for modelling persons. Experimental results showed that lowest person verification error rate could be achieved when each person performed his/her best motor imagery task.

Keywords: EEG, Person Verification, Brain Computer Interface, SVDD, GMM.

1 Introduction

Beside the popular person characteristics such as face, voice, fingerprint, signature and iris, researchers have been investigated other types of biometrics such as ear, gait, hand and dental [1]. Those biometric traits are not universal, and can be subject to physical damage such as dry skin, scars, loss of voice, etc. [2]. In addition, static physical characteristics can be digitally duplicated, such as a photo of a face or a voice recording [3]. On the other hand, brain electrical signals can avoid those limitations, it is hardly 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 [4] and it requires living person recording, spontaneous signal, individual uniqueness due to different brain configurations [2].

Brain electrical signal is usually used in diagnosing brain related diseases, but there are very few reported studies on brain electrical activity-based biometrics [5]. Measuring the EEG is a simple non-invasive way to monitor electrical brain activity, but it does not provide detailed information on the activity of single neurons (or small brain areas). Moreover, it is characterized by small signal amplitudes (a few Volts) and noisy measurements [4].

The main applications of authentication systems are access control systems, building gate control, digital multimedia access, transaction authentication, voice mail, or secure teleworking. A research at the Canada's Carleton University uses

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the brains response to stimuli, such as sounds or images, as the authentication method called pass-thought. Users will access a protected computer system or building by thinking of their pass-thought. Their brain signals are recorded and features are extracted for matching with authorized users models [6].

Several techniques have been used for brain-wave-based person verification. In [7], Manhattan distances on autoregressive (AR) coefficients with PCA were used to compute thresholds for determining test patterns were clients or impostors, the person verification task from 5 subjects were done in 2 stages. In [8], Independent Component Analysis (ICA) was used to determine dominating brain regions to extract AR features, then a Naive Bayes probabilistic model is employed for person authentication of 7 subjects with Half Total Error Rate (HTER) of 2.2%. In [4], Gaussian mixture models has been applied for person verification task on EEG signal from 9 subjects. Half total error rate of 6.6 % was achieved for imagination left task.

In this paper, we investigate the person verification system using EEG signals of motor imagery tasks. The subjects were required doing the same motor imagery tasks in enrolment and test phases. Experiments were done first using the same task for all subjects, namely motor imagery of left hand or right hand, then they were done using the best motor imagery task for each subjects that can distinguish them. The GMM and SVDD methods were used for modelling the individuals. The rest of the paper is organized as follows: Section 2 describes the brainwave features, Section 3 describes SVDD and GMM modelling techniques, Section 4 depicts the dataset used and parameter setup, finally Section 5 represents person verification results and Section 6 concludes the paper.

2 Brainwave Features

2.1 Autoregressive (AR) Features

Autoregressive model can be used for a single-channel EEG signal. It is a simple linear prediction formulas that best describe the signal generation system. Each sample in an AR model is considered to be linearly related with respect to a number of its previous samples [9]:

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

where a_k, $k = 1, 2, \ldots, p$, are the linear parameters, n denotes the discrete sample time, and $x(n)$ is the noise input. The linear parameters of different EEG channel were taken as the features.

2.2 Power Spectral Density (PSD) Features

Power spectral density (PSD) of a signal is a positive real function of a frequency variable associated with a stationary stochastic process. The PSD is defined as the discrete time Fourier transform (DTFT) of the covariance sequence (ACS) [10]

$$\phi(\omega) = \sum_{k=-\infty}^{\infty} r(k) e^{-i\omega k} \tag{2}$$

where the auto covariance sequence $r(k)$ is defined as

$$r(k) = E\{y(t)y^*(t-k)\} \tag{3}$$

and $y(t)$ is the discrete time signal $\{y(t); t = 0, \pm 1, \pm 2, \ldots\}$ assumed to be a sequence of random variables with zero mean.

In this paper, the Welch's method using periodogram is used for estimating the power of a signal at different frequencies. 12 frequency components in the band 8-30 Hz of different channels was estimated as features. Welch's method can reduce noise but also reduce the frequency resolution as compare to the standard Bartlett's method, which is desirable for this experiments.

3 Modelling Techniques

3.1 Support Vector Data Description (SVDD)

Let $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$ be the normal data set. SVDD [11] aims at determining an optimal hypersphere that encloses all normal data samples in this data set $\mathbf{X}$ while abnormal data samples are not included. The optimisation problem is formulated as follows

$$\min_{R,c,\xi} \left(R^2 + C \sum_{i=1}^{n} \xi_i \right) \tag{4}$$

subject to

$$\begin{array}{ll} ||\phi(\mathbf{x}_i) - \mathbf{c}||^2 \leq R^2 + \xi_i & \quad i = 1, \ldots, n \\ \xi_i \geq 0, \quad i = 1, \ldots, n & \end{array} \tag{5}$$

where R is radius of the hypersphere, C is a constant, $\xi = [\xi_i]_{i=1,\ldots,n}$ is vector of slack variables, $\phi(.)$ is the nonlinear function related to the symmetric, positive definite kernel function $K(\mathbf{x}_1, \mathbf{x}_2) = \phi(\mathbf{x}_1) \cdot \phi(\mathbf{x}_2)$, and $\mathbf{c}$ is centre of the hypersphere.

For classifying an unknown data sample $\mathbf{x}$, the following decision function is used: $f(\mathbf{x}) = sign(R^2 - ||\phi(\mathbf{x}) - \mathbf{c}||^2)$. The unknown data sample $\mathbf{x}$ is normal if $f(\mathbf{x}) = +1$ or abnormal if $f(\mathbf{x}) = -1$.

In person verification enrolment phase, a smallest hyper sphere is trained to enclose the individual feature vectors. In test phase a feature vector will be accepted belonging to a claimed identity if its distances to the sphere center less than the sphere radius R and rejected otherwise. The radius R can be changed larger or smaller as a threshold.

3.2 Gaussian Mixture Model (GMM)

Since the distribution of feature vectors in X is unknown, it is approximately modelled by a mixture of Gaussian densities, which is a weighted sum of K component densities, given by the equation

$$p(x_t|\lambda) = \sum_{i=1}^{K} w_i N(x_t, \mu_i, \Sigma_i) \tag{6}$$

where λ denotes a prototype consisting of a set of model parameters $\lambda = \{w_i, \mu_i, \Sigma_i\}$, w_i , $i = 1, \ldots, K$, are the mixture weights and $N(x_t, \mu_i, \Sigma_i)$,$i = 1, \ldots, K$, are the d-variate Gaussian component densities with mean vectors μ_i and covariance matrices Σ_i

$$N(x_t, \mu_i, \Sigma_i) = \frac{\exp\left\{-\frac{1}{2}(x_t - \mu_i)' \Sigma_i^{-1} (x_t - \mu_i)\right\}}{(2\pi)^{d/2} |\Sigma_i|^{1/2}} \tag{7}$$

In training the GMM, these parameters are estimated such that in some sense, they best match the distribution of the training vectors. The most widely used training method is the maximum likelihood (ML) estimation. For a sequence of training vectors X, the likelihood of the GMM is

$$p(X|\lambda) = \prod_{t=1}^{T} p(x_t|\lambda) \tag{8}$$

The aim of ML estimation is to find a new $\bar{\lambda}$ parameter model such that $p(X|\bar{\lambda}) \geq p(X|\lambda)$. Since the expression in 8 is a nonlinear function of parameters in λ its direct maximisation is not possible. However, parameters can be obtained iteratively using the expectation-maximisation (EM) algorithm [12]. An auxiliary function Q is used

$$Q(\lambda, \bar{\lambda}) = \sum_{i=1}^{T} p(i|x_t, \lambda) \log[\bar{w}_i N(x_t, \bar{\mu}_i, \bar{\Sigma}_i)] \tag{9}$$

where $p(i|x_t, \lambda)$ is the a posteriori probability for acoustic class $i, i = 1, \ldots, c$ and satisfies

$$p(i|x_t, \lambda) = \frac{w_i N(x_t, \mu_i, \Sigma_i)}{\sum\limits_{k=1}^{c} w_k N(x_t, \mu_k, \Sigma_k)} \tag{10}$$

The basis of the EM algorithm is that if $Q(\lambda, \bar{\lambda}) \geq Q(\lambda, \lambda)$ then $p(X|\bar{\lambda}) \geq p(X|\lambda)$ [23][24][25]. The following re-estimation equations are found

$$\bar{w}_i = \frac{1}{T} \sum_{t=1}^{T} p(i|x_t, \lambda) \tag{11}$$

$$\bar{\mu}_i = \frac{\sum_{t=1}^{T} p(i|x_t, \lambda) x_t}{\sum_{t=1}^{T} p(i|x_t, \lambda)} \tag{12}$$

$$\bar{\Sigma}_i = \frac{\sum_{t=1}^{T} p(i|x_t, \lambda)(x_t - \bar{\mu}_i)(x_t - \bar{\mu}_i)'}{\sum_{t=1}^{T} p(i|x_t, \lambda)} \tag{13}$$

3.3 Hypothesis Testing

The verification task can be stated as a hypothesis testing between the two hypotheses: the input is from the hypothesis person, (H_0) or not from the hypothesis person (H_1).

Let λ_0 be the claimed person model and λ be a model representing all other possible people, i.e. impostors. For a given input x and a claimed identity, the choice is between the hypothesis H_0: x is from the claimed person λ_0, and the alternative hypothesis H_1: x is from the impostors λ. A claimed person's score $L(x)$ is computed to reject or accept the person claim satisfying the following rules

$$L(x) \begin{cases} > \theta_L & \text{accept} \\ \leqslant \theta_L & \text{reject} \end{cases} \tag{14}$$

where θ_L are the decision thresholds.

The score used in person verification using GMM models is

$$L_0(x) = \log P(x|\lambda_0) - \log P(x|\lambda) \tag{15}$$

And the score used in person verification using SVDD models is

$$L_0(x) = R - \|x - c_S\| \tag{16}$$

The score (16) with a radius threshold R checks whether x is inside or outside the sphere

4 Experimental Setup

4.1 Datasets

The Graz dataset B in the BCI Competition 2008 comes from the Department of Medical Informatics, Institute of Biomedical Engineering, Graz University of Technology for motor imagery classification problem in BCI Competition 2008 [13]. The Graz B 2008 dataset consists of EEG data from 9 subjects. The subjects were right-handed, had normal or corrected-to-normal vision and were paid for participating in the experiments. The subjects paticipated in two sessions contain training data without feedback (screening), and three sessions were recorded with feedback. It consisted of two classes: the motor imagery (MI) of left hand and right hand. Three bipolar recordings (C3, Cz, and C4) were recorded at sampling frequency of 250 Hz.

4.2 Feature Extraction

The signals from electrodes C3, C4 and Cz were selected to extract features. The autoregressive (AR) linear parameters and power spectral density (PSD) components from these signals are extracted as features. In details, the power spectral density (PSD) in the band 8-30 Hz was estimated. The Welch's averaged modified periodogram method was used for spectral estimation. Hamming window was 1 second 50% overlap. 12 power components in the frequency band 8-30 Hz were extracted. Besides PSD features, autoregressive (AR) model parameters were extracted. In AR model, each sample is considered linearly related with a number of its previous samples. The AR model has the advantage of low complexity and has been used for person identification and authentication [14] [15] [7]. Burg's lattice-based method was used with the AR model order 21, as a previous study [15] suggested when there were many subjects and epochs.

The resulting feature set consists of 3*(12+21)=99 features.

5 Experimental Results

For SVDD method, eperiments were conducted using 5-fold cross validation training and the best parameters found were used to train models on the whole training set and test on a separate test set. the RBF kernel function $K(x, x') = e^{-\gamma||x-x'||^2}$ was used. The parameters for SVDD training are γ and ν. The parameter γ was searched in $\{2^k : k = 2l+1, l = -8, -7, \ldots, 2\}$. The parameter ν was

Table 1. Equal error rate in training phase of 9 subjects using the left, right or the best motor imagery task of SVDD and GMM methods

	SVDD			GMM		
Subject	Left	Right	Best	Left	Right	Best
B01	0.0471	0.0466	0.0466	0.0998	0.1402	0.0371
B02	0.0502	0.0367	0.0342	0.0571	0.0404	0.0341
B03	0.0310	0.0113	0.0054	0.0013	0.0038	0.0013
B04	0.0912	0.0736	0.0855	0.1054	0.1179	0.0524
B05	0.1699	0.0620	0.0682	0.1964	0.1541	0.0805
B06	0.0857	0.0413	0.0413	0.0497	0.0438	0.0400
B07	0.0528	0.0692	0.0301	0.0313	0.0277	0.0630
B08	0.0746	0.0679	0.0546	0.0608	0.0529	0.0129
B09	0.0742	0.0978	0.0025	0.0625	0.0968	0.0758
Average:	0.0752	0.0563	0.0409	0.0738	0.0753	0.0441

searched in $\{0.001, 0.01, 0.1\}$. The best parameters found are ($\nu = 0.1, \gamma = 2^{-3}$) for left and right hand motor imagery and ($\nu = 0.1, \gamma = 2^{-5}$) for the best motor imagery of each subjects. For the GMM method, the number of mixtures are set to 64 in model trainings.

Table 1 shows the equal error rate (EER) in training phase of 9 subjects using the left, right or the best motor imagery task of SVDD and GMM methods. Overall the EER is the lowest using the best motor imagery task. The subject B09 can be recognized best with left hand motor imagery task.

Figures 1 and 2 show the DET curves in test phase of person verification task using EEG signal of left, right and best motor imagery task of SVDD method

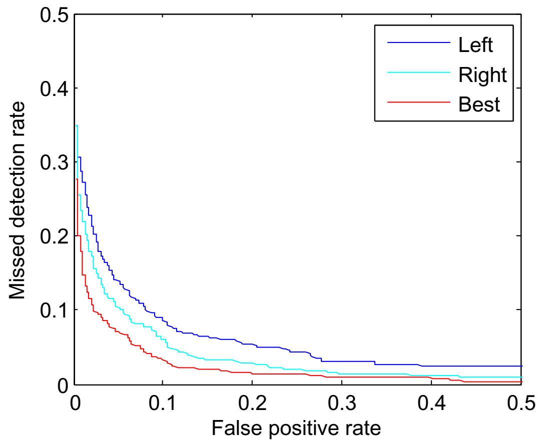

Fig. 1. DET curves of person verification task using EEG signal of left, right and best motor imagery task of SVDD method

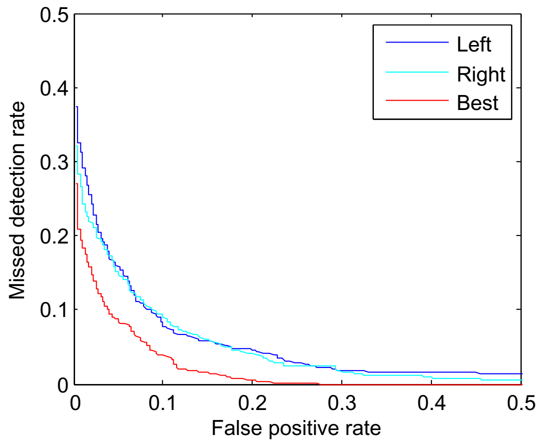

Fig. 2. DET curves of person verification task using EEG signal of left, right and best motor imagery task of GMM method

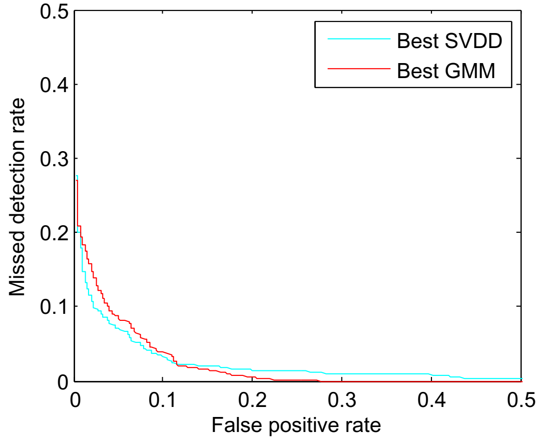

Fig. 3. DET curves of person verification task using EEG signal using the best motor imagery task of SVDD and GMM methods

for SVDD and GMM person verification methods respectively. The curves are averaged across targets from DET curves of each target person [16]. Overall, the equal error rate is the lowest using the best motor imagery task.

Figure 3 shows the comparison of DET curves in test phase between SVDD and GMM methods using the best motor imagery task. The SVDD method show slightly lower EER than the GMM method.

6 Conclusion

We have investigated the activity-dependent person verification method using brain wave features extracted from EEG signals of motor imagery tasks. The left, right and best motor imagery tasks were used for each subject. The GMM and SVDD methods were used for modelling the individuals. Experimental results have showed that we can use EEG signals of persons performing motor imagery tasks to verify persons and that different motor imagery tasks can be performed by different persons to reduce person verification error rate. For future investigation, more data sets and brain activities will be investigated.

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