



# **EEG-based Person Authentication System Using A Self-paced Reaching Task**

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- **Introduction**
- **Experiment**
- **Methods**
- **Results**
- **Conclusions**



**Content**



# PART ONE INTRODUCTION

# Introduction|Biometrics

DNA Patterns

Fingerprints

Hand  
Shape

Iris

.....





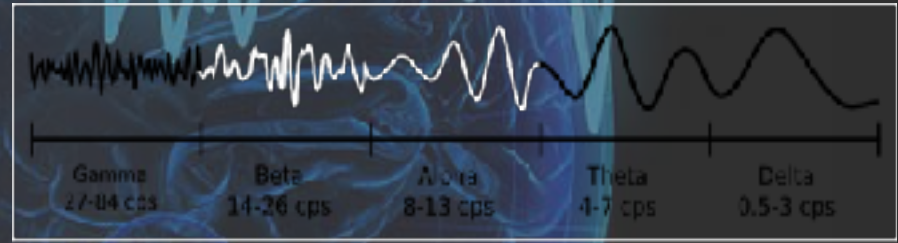
# Introduction|Electroencephalography(EEG)

Parietal Lobe

Frontal Lobe

Occipital Lobe

Temporal Lobe



## Introduction|Related Work



### Palaniapan et al.

Proposed a person authentication technique using gamma band visual evoked potentials from ten subjects when the individual is seeing a picture.



### APhuoc Nguyen et al.

Investigated EEG-based person authentication of 9 subjects during a motor imagery task and obtained a success rate of 94%.



### Pham et al.

Investigated the possibility of emotional states for person authentication using AR parameters and power spectral density features.

# Introduction | Motivation and Objects

## MOTIVATION

The stability and operability of the tasks used currently are still open to discussion.

A practicable person authentication system based a self-paced reaching task, which is a common and natural human daily task, was designed.

PSD features of delta, theta, alpha and beta bands were extracted as subject-specific features.

The time course characteristic of EEG signals of the self-paced reaching task for person authentication were investigated.



# PART TWO EXPERIMENT



## Experiment|Subjects



- Participants from SYSU
- Thirty healthy volunteers
- 20 years old around and Right-handed

## Experiment|Design



01

A gray screen was showed to indicate the beginning of each trial.

02

After two seconds, five colorful balls with one black ball were simultaneously presented on the screen. Subjects were required to hold the black ball using their forefinger for at least three seconds.

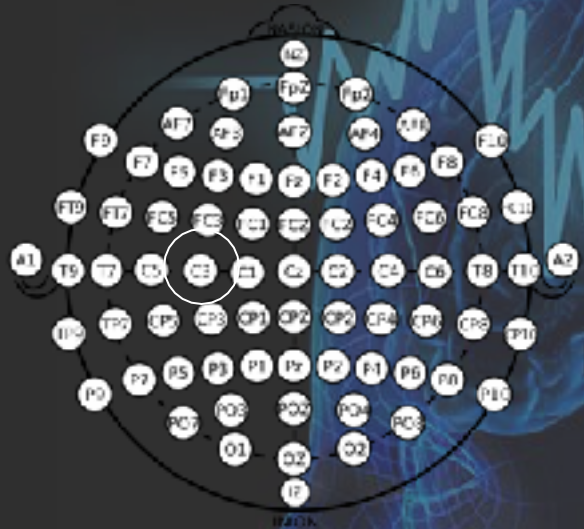
03

Then subjects self-paced released the black ball and touched each colorful ball in which order the subjects preferred to.

04

For each subject, the whole experiment contained ten blocks and each block had 10 trials, i.e. a total of 100 trials were finished.

## Experiment| EEG data collection and Preprocessing



EEG data in the opposite motor area were selected for analysis(Channel C3).

To improve the poor spatial resolution of EEG data, a large Laplacian filter was then applied, i.e. the average of EEG data of C1, C5, CP1, CP3, CP5, FC1, FC3 and FC5 was subtracted from the EEG data of C3.



# Experiment| EEG data collection and Preprocessing

01

The continuous EEG data were band-pass filtered in the frequency range of 1-30 Hz.

02

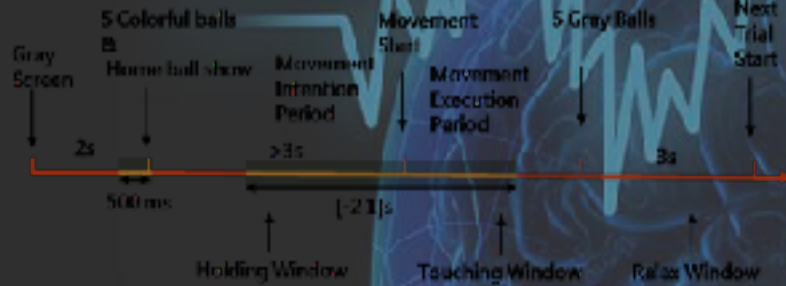
A common average reference was computed as the average voltage amplitude of the EEG data from all EEG channels.

03

EEG signals were segmented into epochs of  $[-2\ 1]$  s time-locked to the onset of the movement.

04

Each epoch was baseline corrected to the EEG data in time window  $[-500\ 0]$  ms time-locked to the onset of the five colorful circles and two black balls.







# PART THREE METHODS

## Methods| Features



### POWER SPECTRAL DENSITY

The discrete time fourier transform of the covariance sequence:

$$\Phi(\omega) = \sum_{k=-\infty}^{\infty} r(k) e^{-i\omega k}$$
$$r(k) = E\{s(k)s(t-k)\}$$
$$\{s(t); t = 0, \pm 1, \pm 2, \dots\}$$

Welch's method using periodogram was used for estimating the power of a timeseries at different frequencies. A Hamming window with 50% overlap was applied.



### AUTOREGRESSIVE MODEL

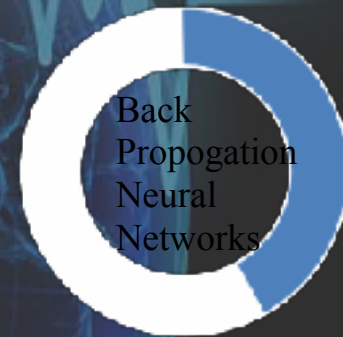
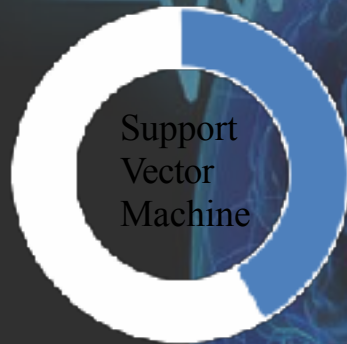
A linear prediction formulas that best describe the signal generation system:

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

AIC was used to determine the order of the model.

$$AIC(p) = (N - m) \log \hat{\sigma}_e^2 + 2p$$
$$\hat{\sigma}_e^2 = \frac{1}{N-m} \sum_{n=m}^N \hat{e}_n^2$$

## Methods| Classification Models

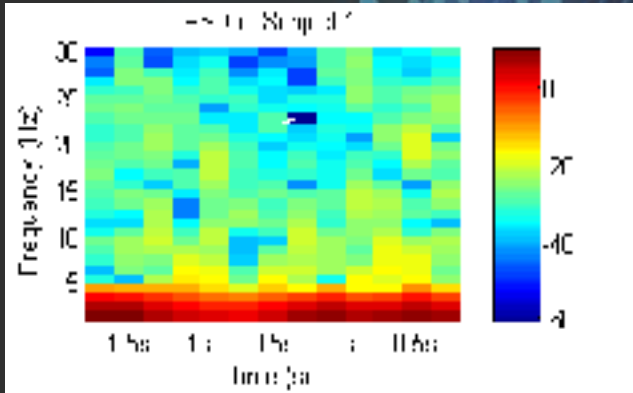




# PART FOUR RESULTS



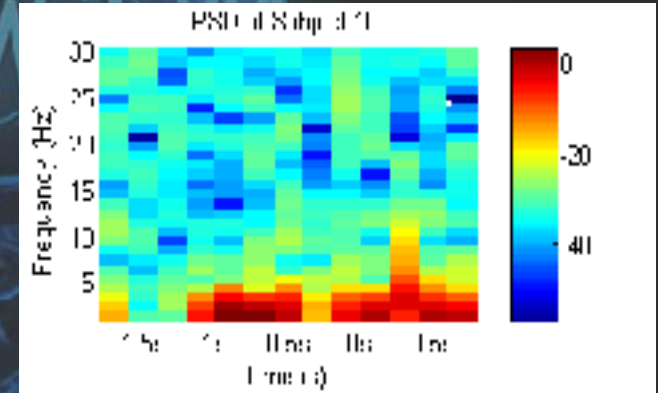
## Results|PSD Analysis



Time-frequency representation for Subject 1.



PSD distributions vary between subjects during the movement intention and execution periods.

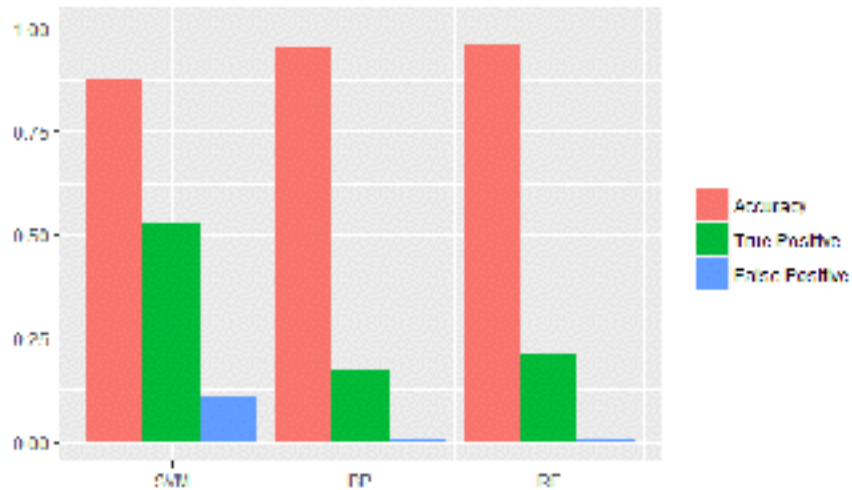


Time-frequency representation for Subject 10.

# Results|Authentication Performance Comparison of Different Algorithms

## - SVM/RF/BP

Performance Comparison of SVM/BP/RF using PSD Features

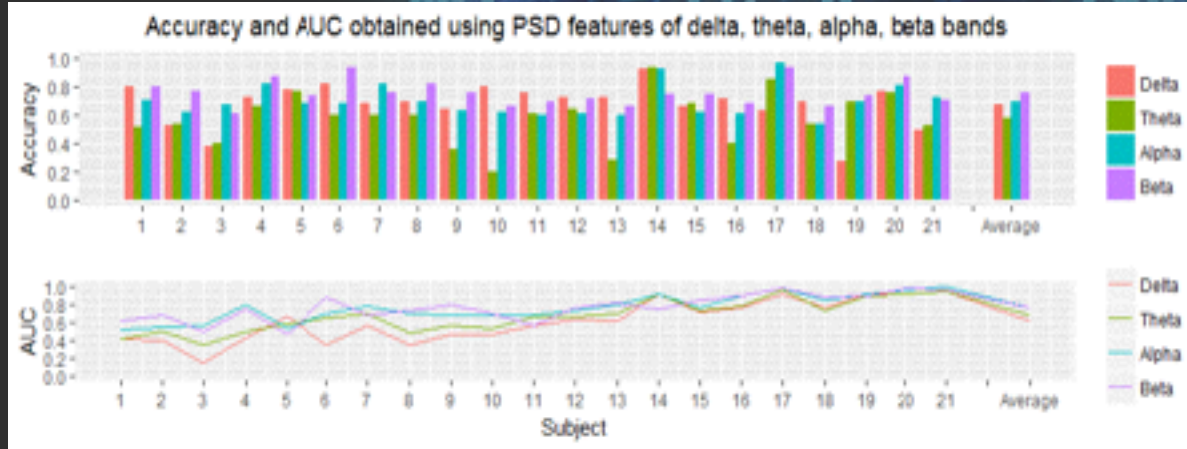


Although the accuracy of Random Forest and Backpropagation Neural Network methods are higher than that of Support Vector Machine, their true positive rates are far lower than that of the later.

Therefore we have adopted the Support Vector Machine as the classifier of the authentication system.

# Results|Authentication Performance of PSD Features using SVM

## Authentication Results for PSD Features of Four Frequency Bands

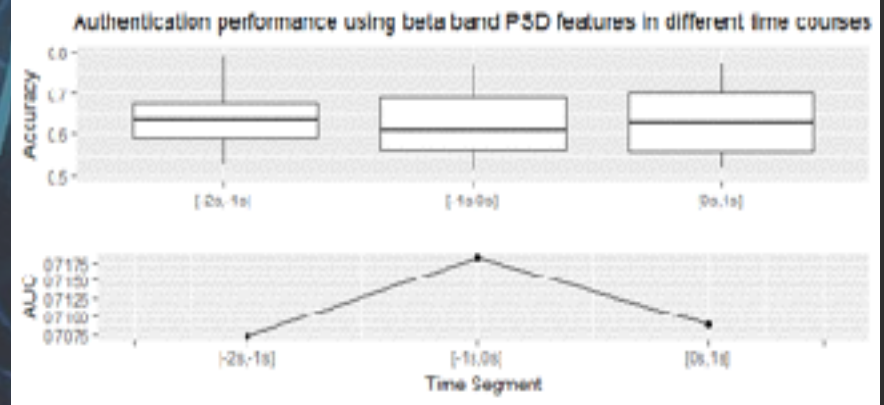
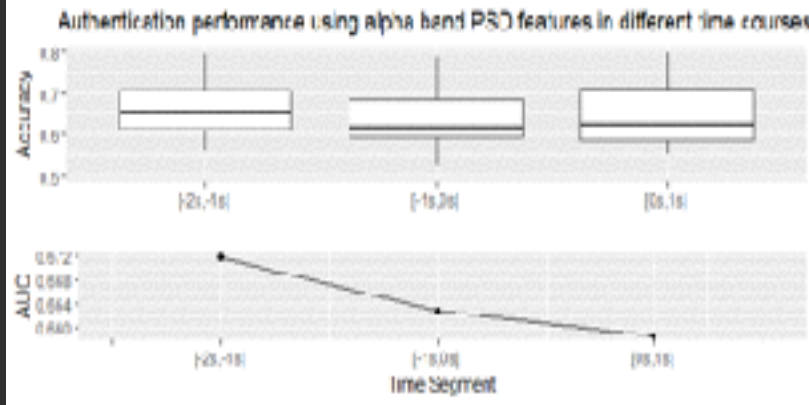


The alpha and beta bands achieve better authentication performances than delta and theta bands.

As the bandwidth is much larger in beta band (14-30Hz), the beta band power spectral densities were averaged in each frequency range (14-17) Hz, (18-21) Hz, (22-25) Hz and (26-30) Hz to derive 4 features for each subject.

# Results|Authentication Performance of PSD Features using SVM

## Time Course Authentication Performances for Alpha and Beta Band PSD Features

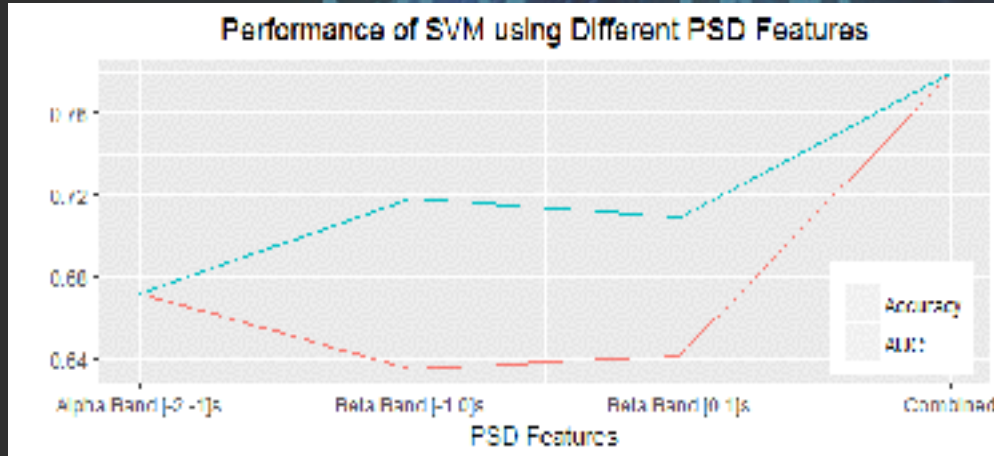


Alpha band PSD features in the time period of  $[-2 -1]$  s and the beta band PSD features in the time period of  $[-1 0]$  s and  $[0 1]$  s achieve a better result than in other time segments.



# Results|Authentication Performance of PSD Features using SVM

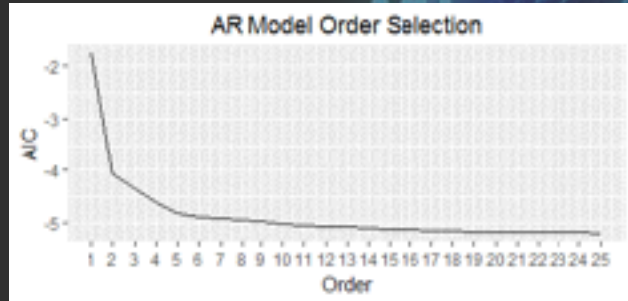
## Authentication Performances of Combined Alpha and Beta Band PSD Features



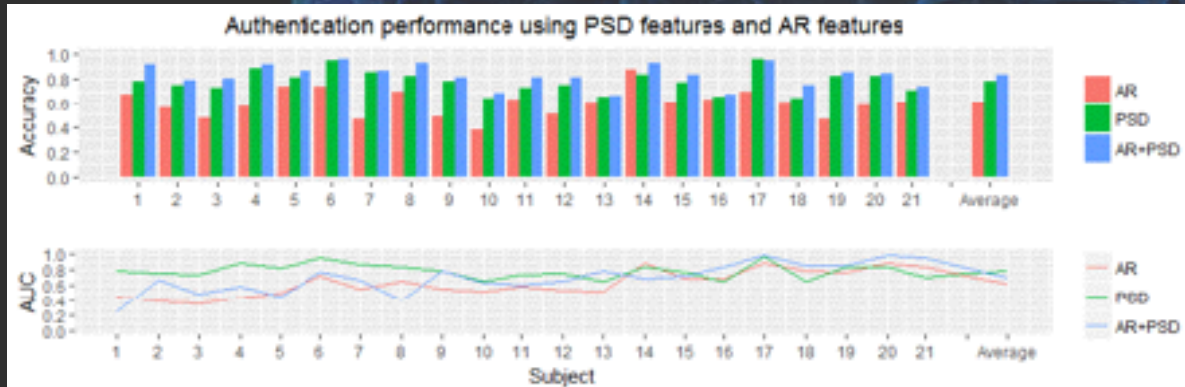
The combined features achieved a better authentication performance.

# Results|Authentication Performance of PSD Features using SVM

## Authentication Results for Combined PSD and AR Features using SVM



Compared to AR parameters, PSD features gives better performance.



AUC decreased when combining the features of AR and PSD features.

## Conclusions



In this study, a practicable EEG based biometric authentication system is designed. The self-paced reaching task is applied as it is a natural and common human daily task, compared to visual evoked tasks, motor imagery tasks, emotional tasks, etc. The best average accuracy of our person authentication is 78.0%. And the average AUC is 0.751.



Our experiment validates the usage of self-paced reaching task for EEG person authentication.



Further investigation is necessary to optimize the performance of the proposed method in larger populations.

