

# On EEG-based Person Recognition and Human Characteristics Classification

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# Summary of Thesis

The brainwave signal has recently been investigated for person identification and verification due to its advantages over traditional means. Most research on brain signals focuses on BCI or clinical applications. However little work has been done in brainwave-based person recognition or emotion recognition, and none has been done in brainwave-based human characteristics classification. Although numerous pre-processing, feature extraction and classification methods have been proposed and explored for BCI systems, none of them has been accepted as the best method.

This research project focuses on using Electroencephalography (EEG) as a new biometric to build person recognition systems. These systems include EEG-based person recognition that can identify or verify a person using a given unknown EEG signal, and EEG-based human characteristics classification that can classify a person in to an age group, gender group, or emotion group based on his/her EEG signal. This research also proposes a new feature extraction method based on speech analysis, and a new modelling method based on support vector machines to enhance the performance of those EEG-based recognition systems.

The following feature extraction methods from the speech domain are proposed: speech recognition features, speaker recognition features, and speaker characteristics features. Models proposed for human characteristics classification include D-SVDD, TD-SVDD, MTD-SVDD, R-SVDDs and MR-SVDDs. Models proposed for person verification are MS-SVDD UBM, FMS-SVDD UBM, M3S-SVDD UBM and FM3S-SVDD UBM.

Evaluation experiments performed on the Australian EEG, EEGMMIDB, Alcoholism, Graz and DEAP datasets show better results for most of the proposed techniques than do traditional techniques.

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# Abbreviation

PSD	Power spectral density
AR	Auto regressive
MFCCs	Mel-frequency ceptral coefficients
GMM	Gaussian mixture models
SVM	Support vector machine
SVDD	Support vector data description
D-SVDD	Distant SVDD
TD-SVDD	Translated distant SVDD
MTD-SVDD	Maximal-margin translated distant SVDD
R-SVDDs	Repulsive SVDDs
MR-SVDDs	Maximal-margin repulsive SVDDs
MS-SVDD	Multi-sphere SVDD
FMS-SVDD	Fuzzy multi-sphere SVDD
M3S-SVDD	Maximal-margin multi-sphere SVDD
FM3S-SVDD	Fuzzy Maximal-margin multi-sphere SVDD