



**UNIVERSITY OF  
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## **PhD Thesis**

# **Robust EEG Channel Set for Biometric Application**

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# Terms and abbreviations

$DB_x$	Between Person Distance.
$DW_x$	Within Person Distance.
$S_x$	Stability Index.
$T_e$	Enhancement Threshold.
AI	Artificial Intelligence.
AR	Autoregression.
ARMA	Autoregressive Moving Average.
BCI	Brain Computer Interface.
BPFNN	Backpropagation Feedforward Neural Network.
CAR	Common Average Reference.
CSD	Current Source Density.
DBI	Davies Bouldin index.
DET	Detection Error Tradeoff.
ECG	Electrocardiogram.
EEG	Electroencephalogram.
EM	Expectation Maximization.
EOG	Electrooculography.
EST	Equivalent Source Technique.

FAR	False Acceptance Rate.
FD	Fractal Dimension.
FDR	Fisher Discriminant Ratio.
FFT	Fast Fourier Transform.
fMRI	Functional Magnetic Resonance Imaging.
FRR	False Rejection Rate.
GA	Genetics Algorithm.
GMM	Gaussian Mixture Model.
HTER	Half Total Error Rate.
ICA	Independent Component Analysis.
KNN	K-Nearest Neighbour.
LDA	Linear Discriminant Analysis.
LF	Lead Field matrix.
LVQ	Learning Vector Quantization.
MAP	Maximum A Posteriori.
ML	Maximum Likelihood.
MSE	Mean Square Error.
NN	Neural Network.
PCA	Principal Component Analysis.
PDF	Probability Density Function.
PLV	Phase Locking Value.
PSD	Power Spectral Density.
R-LOWESS	Robust Locally Weighted Regression and Smoothing Scatterplots.

REST	Reference Electrode Standardization Technique.
RMS	Root Mean Squared.
SFS	Sequential Forward Selection.
SL	Surface Laplacian.
SMA	Supplementary Motor Area.
SNR	Signal-To-Noise Ratio.
SS	Spherical Splines.
SVD	Singular Value Decomposition.
SVM	Support Vector Machine.
SVM-RFE	SVM Recursive Feature Elimination.
TDPS	Time Domain Power Spectrum.
UBM	Universal Background Model.
VEP	Visually Evoked Potentials.

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# Abstract

As a biometric modality for person recognition, electroencephalogram (EEG) has many benefits compared to other biometric modalities. However, studies show that EEG signals are highly affected by the mental task the participant is engaging at the time of EEG recording, as well as being quite sensitive to the applied montage method and the choice of reference point, and also being quite sensitive to the selected segment length. The main goal of this research is to find **EEG robust channel set** that are least affected by the change of mental task and can be used in biometric applications. Also, since there is so far no consensus on the used montage method or reference point for the EEG recording, so the effect of the EEG montage method or reference point on the selected **robust channel set** and its recognition performance was analysed. Finally, the effect of the EEG signal segment length on the selected **robust channel set** and the resulting performance was also analysed. The contribution of this research was to develop a method to analyze stability of the EEG channels and select the **robust channel set** which will be used in biometric application regardless of the user mental task, also to suggest the best montage method and segment length to be used with this **robust channel set**. The final outcomes was to propose an optimal EEG channel set, montage method or reference point, and

a segment length for the EEG signal for the purpose of biometric applications.