# USER AUTHENTICATION USING EEG SIGNALS

V. Sinthuja and B. Mayurathan

Department of Computer Science, Facuty of Science, University of Jaffna

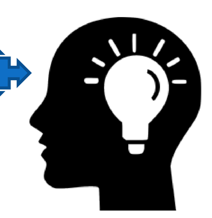
sinthu96vijaya@gmail.com, barathym@univ.jfn.ac.lk

## INTRODUCTION

The electrical activities and brain signals are different for each person and cannot faked or duplicated. The person must alive during the process of recording signals. EEG signals can vary based on person's mood so that even if the mental activity is same, the results is different for different persons.

The risk of personal data exposure through unauthorized access has never been as imminent as today's world. Faces, fingerprints, voiceprints, and irises are easy to steal and forge given their exposure to the external world.

Electroencephalography (EEG) has been suggested as a biometric credential due to its subject-specific and unbidden nature.

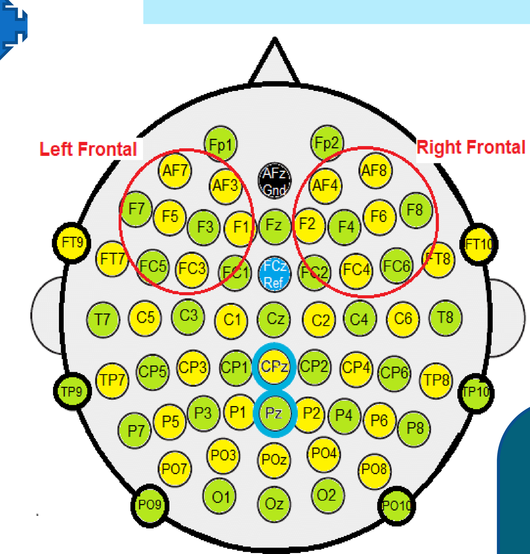


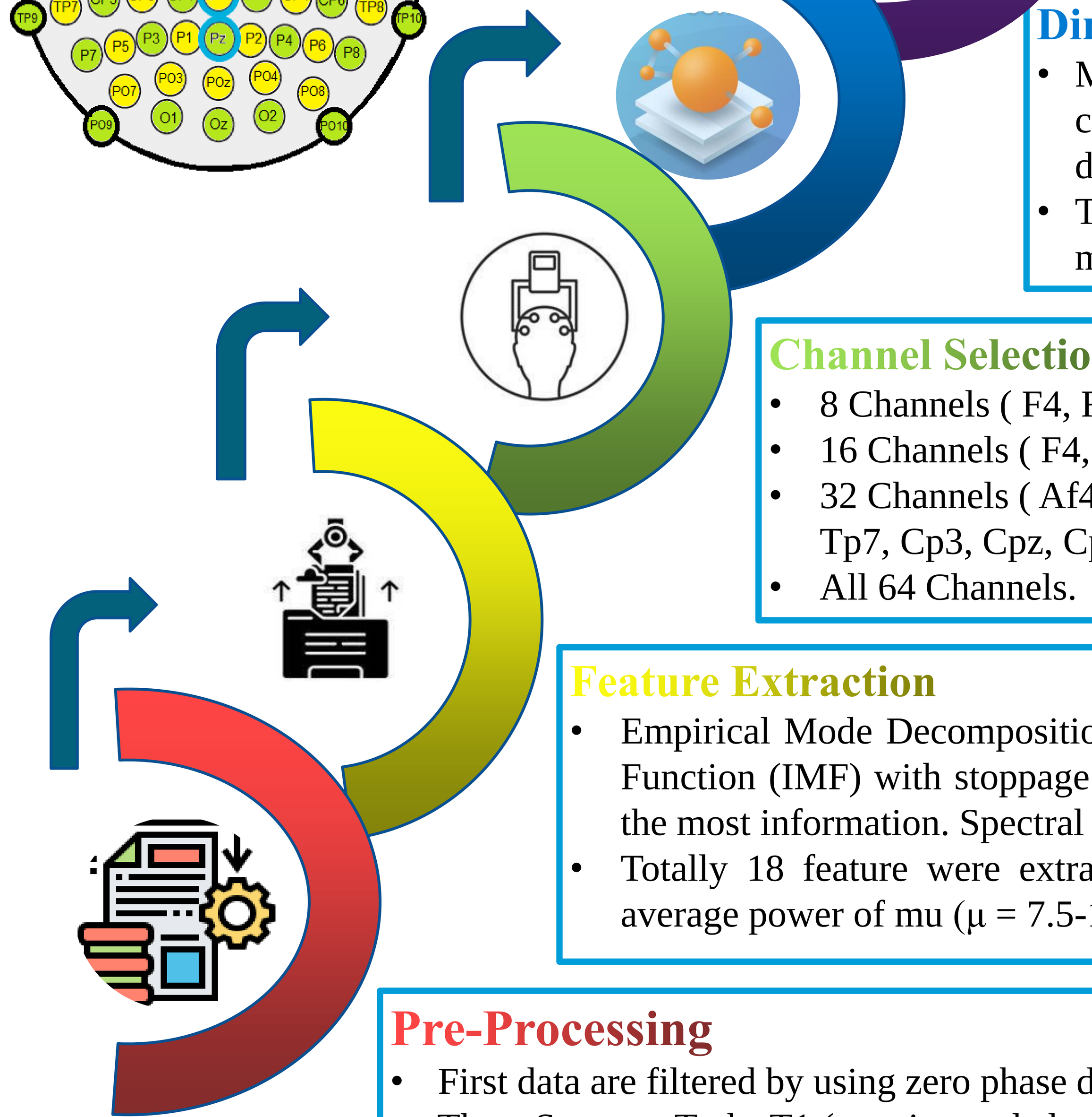
The main objective of this poster is to build a better accuracy EEG-based authentication system by using Dimensionality Reduction and compare various sub-groups of task-relevant electrodes channels(8,16,32 and 64).

The proposed methodology in this poster, Principal Component Analysis (PCA) [1] is used for dimensionality reduction and Support Vector Machine (SVM) is used for binary classification.

Motor Imagery / Movement dataset is used to evaluate the performance of the proposed methodology. This study focused on the various sub-group of task-relevant electrodes (8, 16,32,64) and 64 channel system gives better classification performance with an accuracy 95.41%.

## METHODOLOGY



**Classification**

- Data divided into 5 groups ( 20% testing, 80% training).
- Model accuracy is calculated by 5-fold cross validattion.
- In SVM - RDF kernal, Standardization and automatic scaling were used.

**Dimensionality Reduction**

- Multichannel analyses conducted using the cross-correlation method and noted 2 clusters of channels. For each feature, we calculated the mean and standard deviation of the cross-correlation between all pairs of channels.
- Then, PCA is used for transfer 18 features into 2 for each of the channel. 18 x 2 matrix then transformed into a 36 x 1 matrix by concatenation of channels.

**Channel Selection**

- 8 Channels ( F4, Fp1, Fp2, C1, C2, Fc1, Fc2, F3).
- 16 Channels ( F4, Fp1, Fp2, C1, C2, Fc1, Fc2, F3, Fz, Fcz, C3, C4, F1, F2, Af3, Af4).
- 32 Channels ( Af4, Af3, F4, Fp1, Fp2, C3, C4, Fc3, Fcz, F3, F7, Fz, F8, Ft7, Fc4, Ft8, T7, Cz, T8, Tp7, Cp3, Cpz, Cp4, Tp8, P7, P3, Pz, P4, P8, O1, O2, Oz).
- All 64 Channels.

**Feature Extraction**

- Empirical Mode Decomposition [2] used to get complete and finite set of components called Intrinsic Mode Function (IMF) with stoppage criteria as 40dB resolution and 60dB residual energy. The first 4 IMFs carries the most information. Spectral Density (PSD) calculated by using multi-taper method of Chronux toolbox.
- Totally 18 feature were extracted including Shannon, log, approximate and sample entropies.In addition, average power of mu (μ = 7.5-12.5Hz) and beta (β = 16-31 Hz) frequency features were extracted using PSD.

**Pre-Processing**

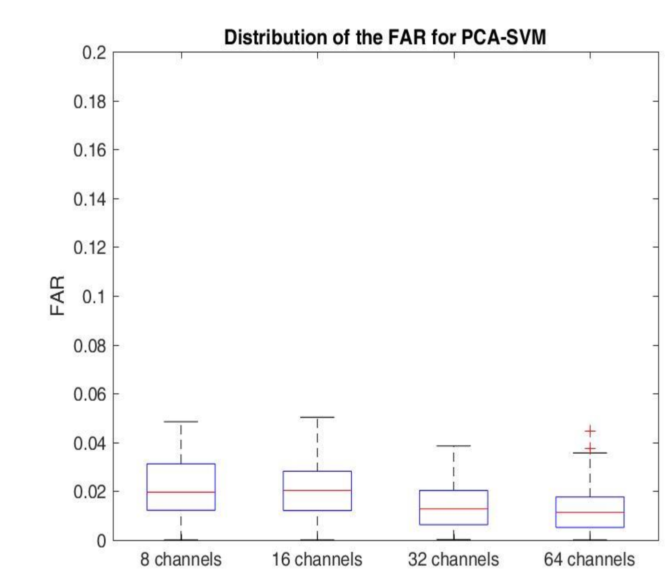
- First data are filtered by using zero phase delay filter with cutoff frequencies at 1Hz and 50 Hz.
- Then, Separate Tasks T1 (opening and closing the left hand) and T2 (opening and closing the right hand).
- After separating T1 and T2, Sliding windows with a length of 2 seconds and 75% overlap applied to get around 105 trials per subject for each task T1 and T2 and then merge them as one file.

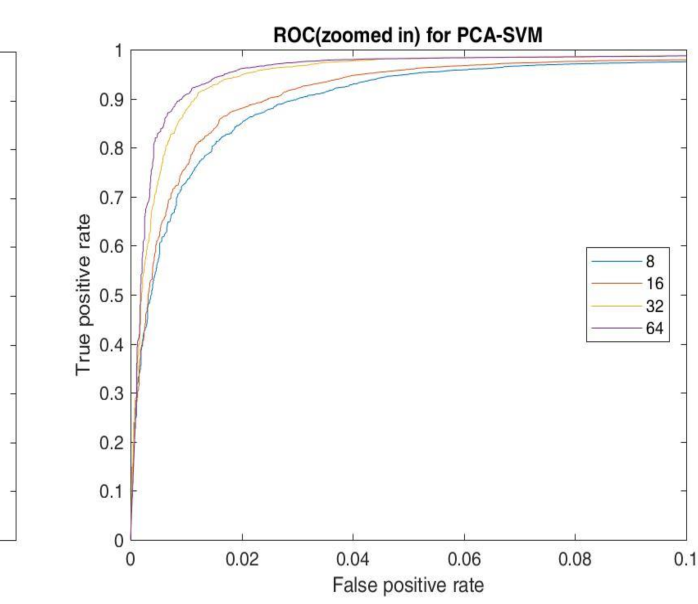
## RESULTS

- False Acceptance Rate (FAR) and False Rejection Rate (FRR) is used to predict the performance of the proposed methodology. ( FN- False Negative, FP- False Positive, TP- True Positive, TN- True Negative, AUC - Area Under Curve).
- The FAR of the PCA-SVM decreases significantly with the number of channels.

$$FAR = \sum_{ij} \frac{FP_{ij}}{TN_{ij} + FP_{ij}} \qquad FRR = \sum_{i,j} \frac{FN_{ij}}{TP_{ij} + FN_{ij}}$$

| Channel | Accuracy | FRR | FAR | AUC |
|---|---|---|---|---|
| 8 channel | 0.9220 | 0.1332 | 0.0222 | 0.9836 |
| 16 channel | 0.9270 | 0.1229 | 0.0212 | 0.9849 |
| 32 channel | 0.9513 | 0.0838 | 0.0139 | 0.9896 |
| 64 channel | 0.9541 | 0.781 | 0.0136 | 0.9911 |

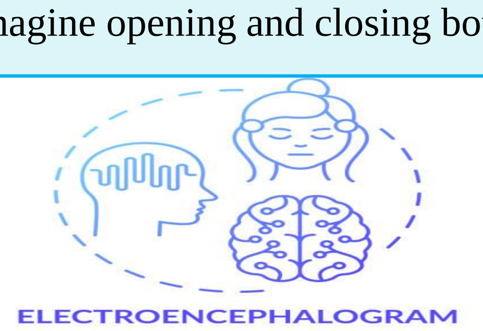



## DATASET

Motor movement/imagery EEG dataset [3] is used to calculate the performance of the proposed methodology. This dataset consists of 1500 EEG recordings collected from 109 subjects. Each subject performed 14 experimental runs including :

- Open and closed left or right fist.
- Imagine opening and closing left or right fist.
- Open and close both fist or both feet.
- Imagine opening and closing both fist or both feet.




## DISCUSSION

- User must pass two task such as, opening and closing the left hand (T1) and opening and closing the right hand (T2).
- As per the results, 64 channel system obtained highest accuracy with 95.41% and FAR with 1.36 %. The second highest accuracy obtained from 32 channel system with 95.13% and FAR with 1.39%. The third Highest accuracy obtained from 16 channel system with 92.7% and FAR with 2.12%. Finally the lowest accuracy compared to others obtained from 8 channel system with 92.2% and FAR with 2.22%.
- Based on the experimental results, it can be easily concluded that, performance of this method depends on the total number of channels.

## CONCLUSION

- Dimensionality reduction and channel selection are the important component in this proposed methodology. PCA helps to improve the performance of the system. It reduces the computational time and also it helps to increase the accuracy.
- Secondly, 4 channel systems were used to authenticate the user such as 8, 16, 32 and 64 channels. Comparatively the 64 channel system works better than others.
- It can be concluded that the highest accuracy 95.41% is achieved by PCA-SVM with 64 channel system.

## REFERENCES

[1] Li, Feng, X. Li, F. Wang, D. Zhang, Y. Xia, and F. He. 2020. "A Novel P300 Classification Algorithm Based on a Principal Component Analysis-Convolutional Neural Network" Applied Sciences 10, no. 4: 1546.

[2] A. Zeiler, R. Faltermeier, I. Keck, A.M. Tomé, C.G. Puntonet, E.W. Lang, Empirical mode decomposition—An introduction. In Proceedings of the 2010 International Joint Conference on Neural Networks (IJCNN), Barcelona, Spain, 18–23 July 2010.

[3] A.L. Goldberger, L.A. Amaral, L. Glass, J.M. Hausdorff, P.C. Ivanov, R.G. Mark, J.E. Mietus, G.B. Moody, C.K. Peng, and H.E. Stanley, Components of a new research resource for complex physiologic signals. PhysioBank, PhysioToolkit, and PhysioNet, p. E215–E220 , 2000.