High-Accuracy User Identification Using EEG Biometrics

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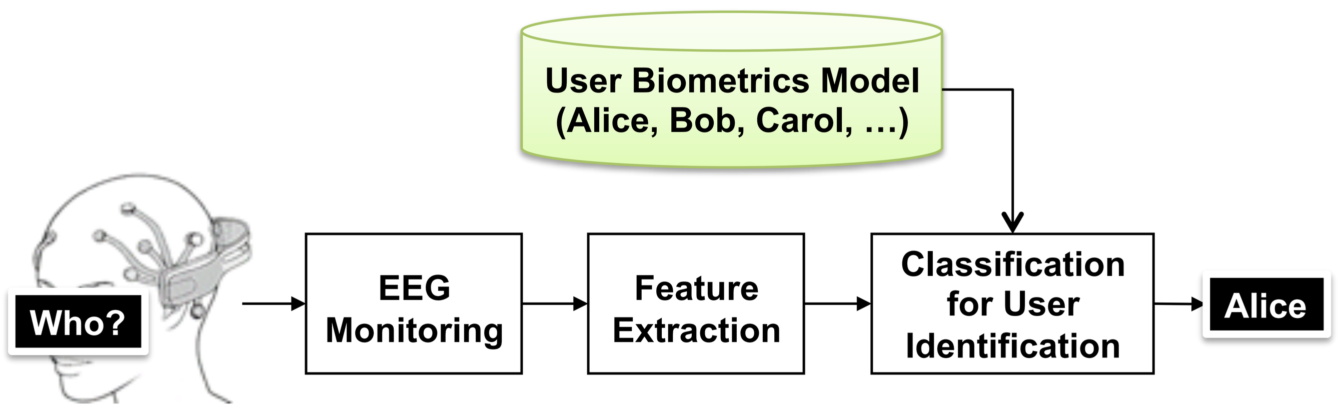
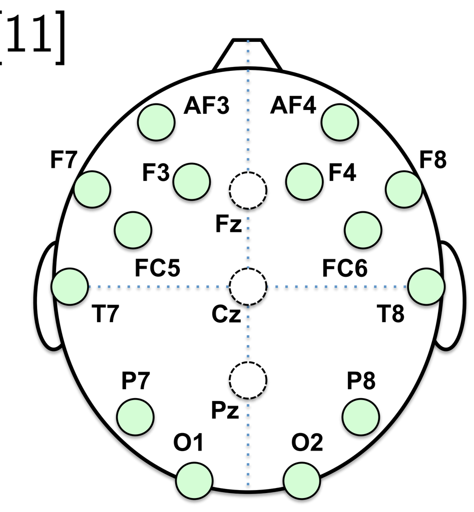
Abstract

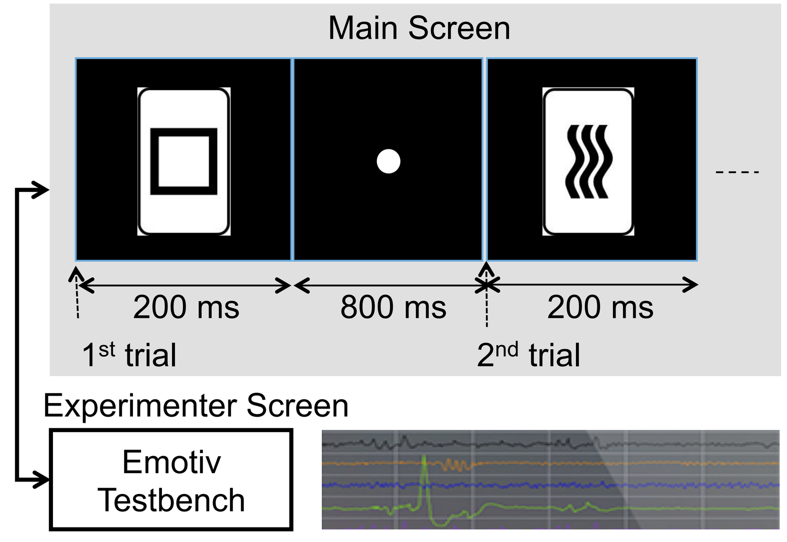
- We analyze brainwave biometrics, measured by a consumer-grade EEG device
- We show that 97% accuracy can be achieved by multi-epoch classification

EEG Brainwave Biometrics

- EEG signals are used for biometrics[3, 4, 5, 6], alternative to fingerprints, palm vein, and iris recognition
- Clinical-grade sensors: AR feature[7], GMM[2], LDA[8], SVM[9]
- Consumer-grade sensors: AR feature[10], eye blinks[1], breathing[11]

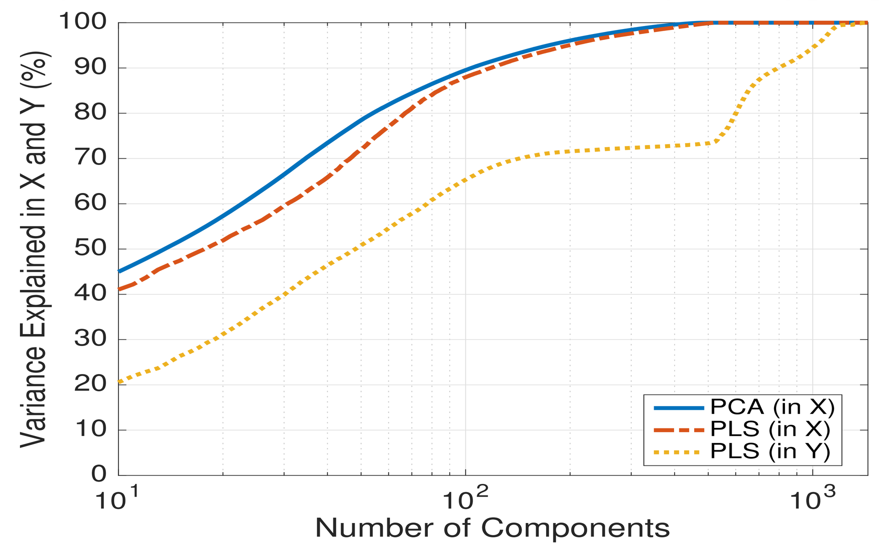






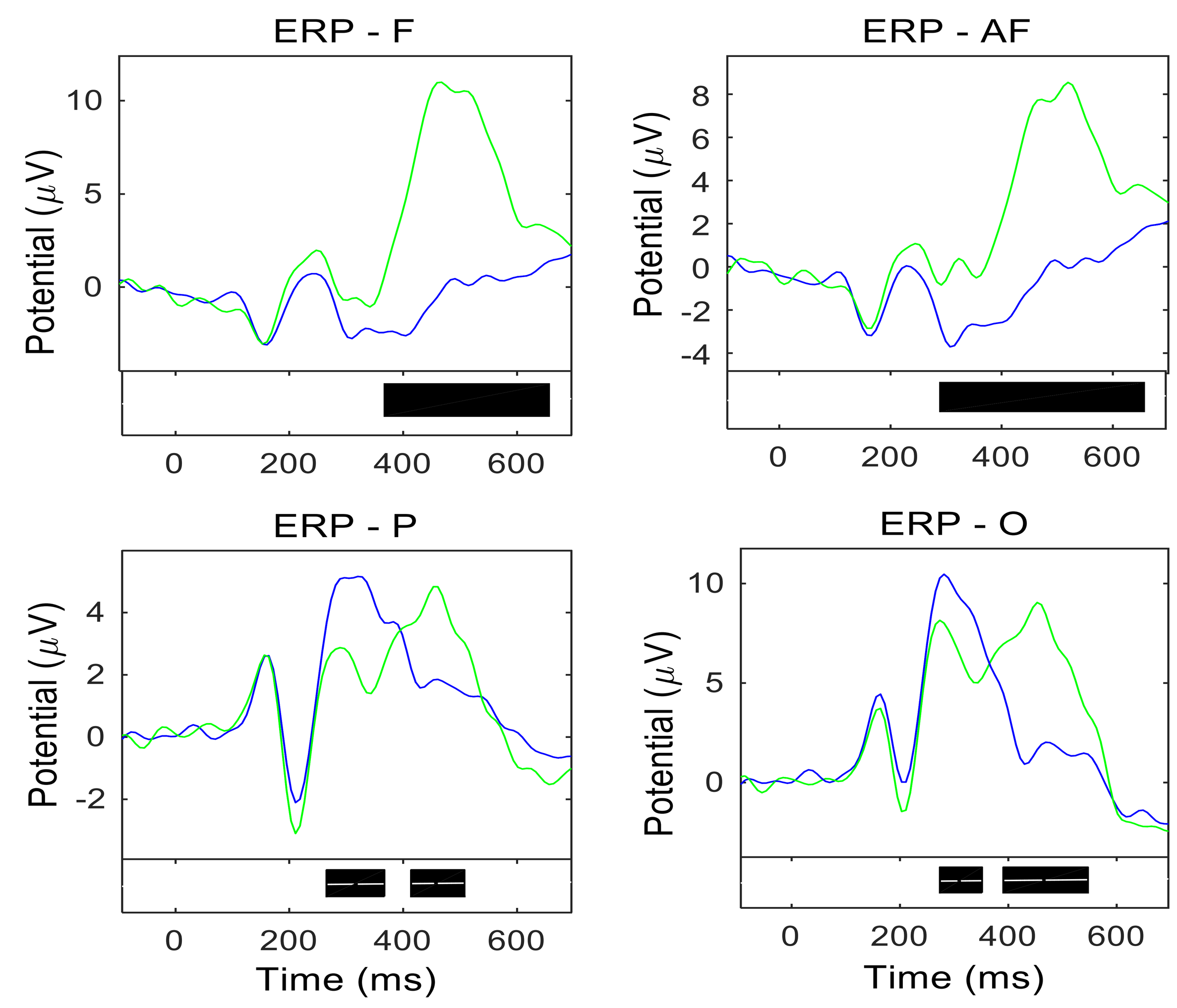
Feature Extraction & Classification

- We use principal component analysis (PCA)[12] and partial least-squares (PLS)[13] for dimensionality reduction of EPR data
- Linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), naïve Bayes (NB), decision tree (DT), k nearest neighbor (k-NN), logistic regression (LR), support vector machine (SVM), and deep neural network (DNN)[14]



ERP Statistics

- Statistical significance of event-related potential (ERP) in card counting (P-300 component)



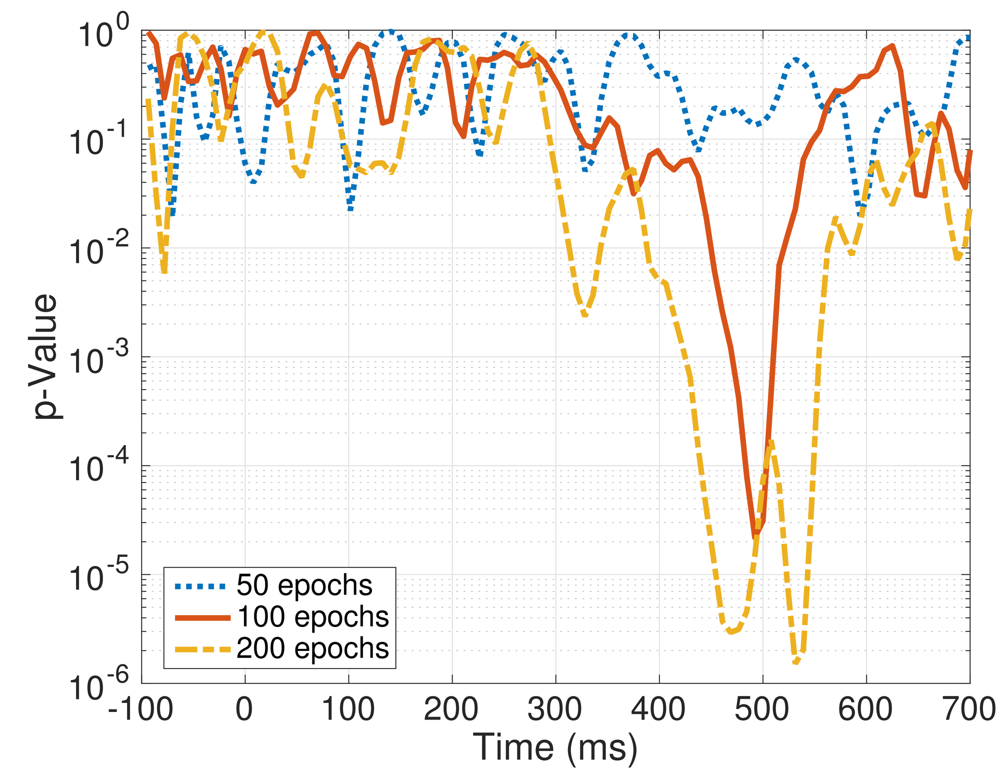
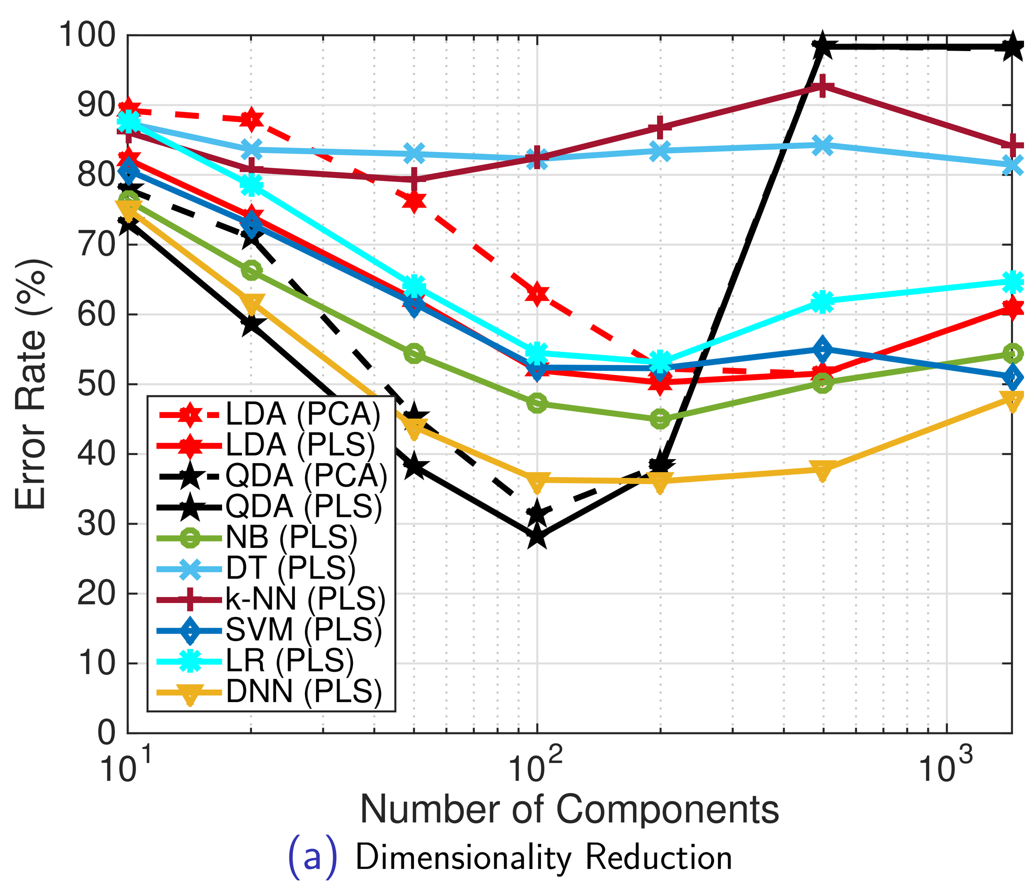


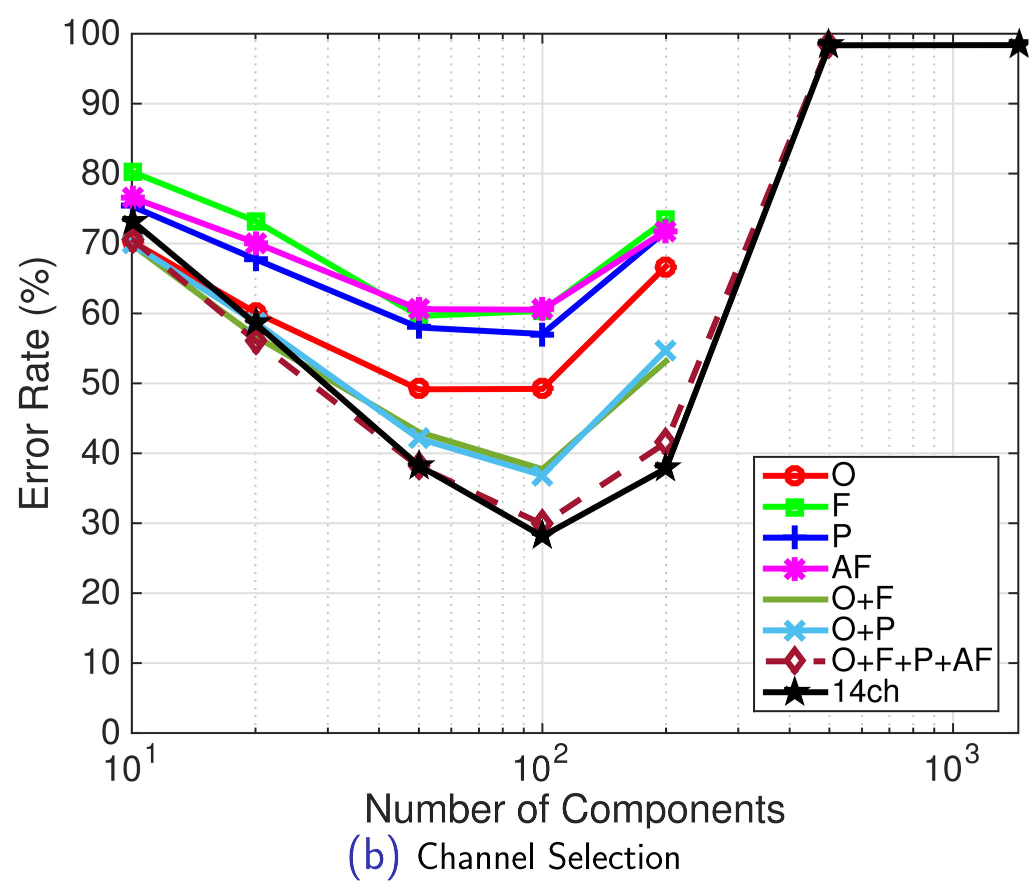
Figure 1: Statistical significance p-value: $p < 10^{-2}$ when 100 seconds for 25 users = 4-second ERP per user

User Identification Performance

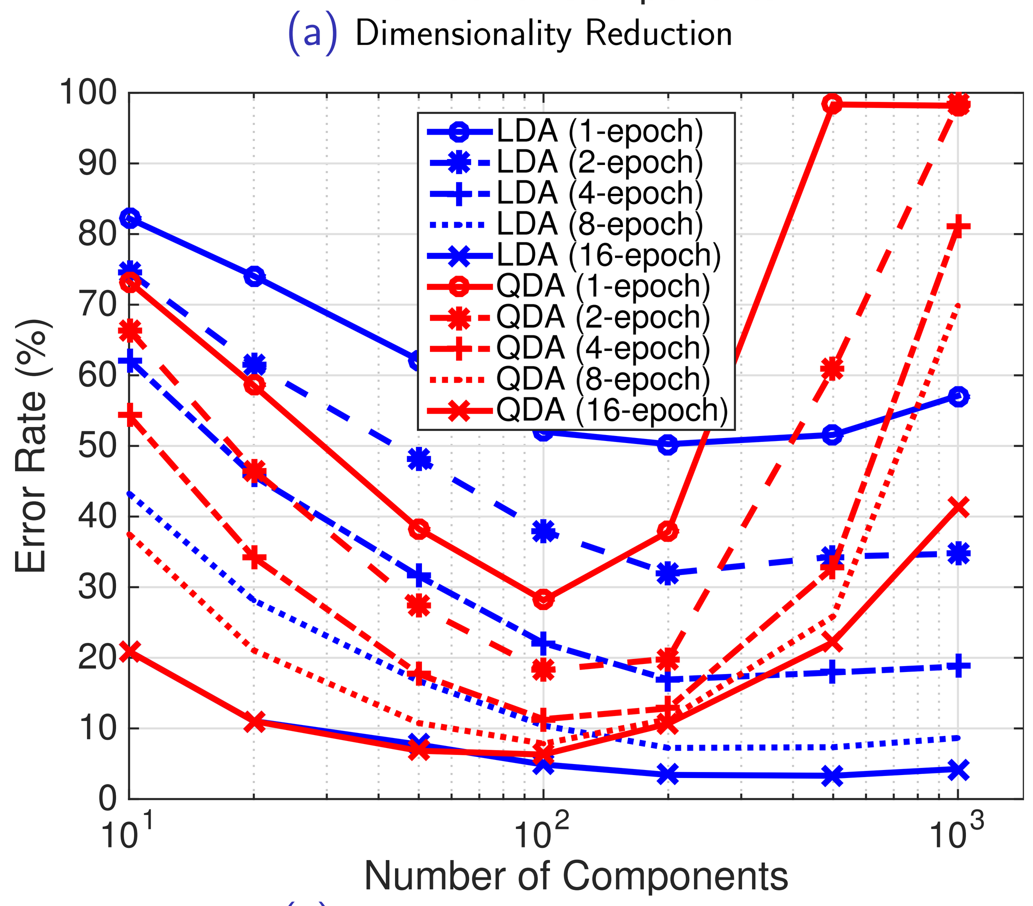
- QDA + PLS achieved 97% accuracy for 25-user identification
- Linearly degrading as the number of users increases
- Exponentially improving as the length of EEG measurement extends



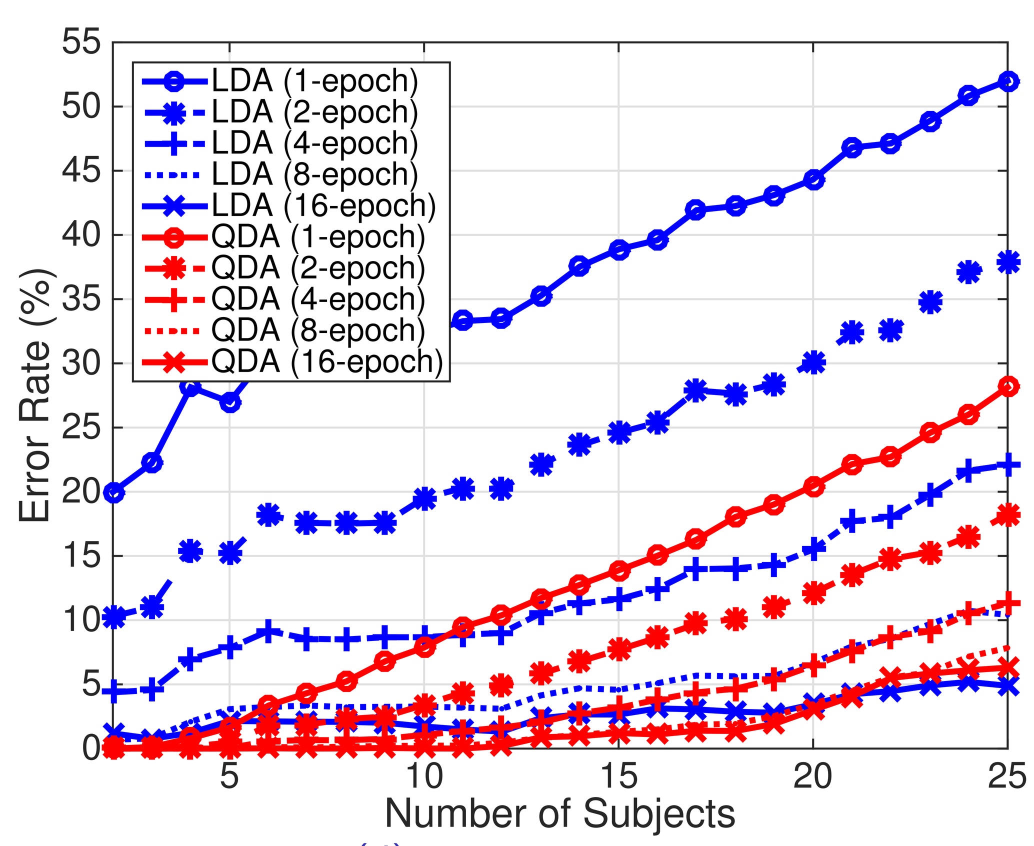
(a) Dimensionality Reduction



(b) Channel Selection



(c) Multi-Epoch Classification



(d) Number of Users

Summary

- Demonstrated the potential for EEG biometrics via consumer-grade sensors
- Analyzed the impact of dimensionality reduction, classification algorithms, channel selection, length of EEG, and the number of users.

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