Sampling Rate and Task Selection in EEG-Authentication

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Abstract

EEG-based authentication is a promising security alternative, measuring unique neural patterns, but variability in sampling rate (f_s) across datasets can distort performance metrics. This study evaluates how f_s normalisation impacts authentication accuracy by analysing multiple EEG datasets with differing f_s. Using machine learning classification pipeline, we show that optimal f_s selection depends critically on task-specific neural dynamics: high-frequency gamma tasks require ≥500 Hz, while alpha-dominated paradigms perform well at 128 Hz, and auditory potentials remain stable even at 98 Hz. Notably, prefrontal tasks show inherent limitations unaffected by f_s. Findings emphasise the need for standardised paradigm-specific f_s in EEG authentication to improve reproducibility and robustness. This work provides practical insights for optimising biometric systems and advancing EEG-based authentication. Code available upon request.

Keywords: Electroencephalography (EEG); XGBoost; Sampling Rate (f_s)

Introduction

Authentication is a confirmation of a user's claimed identity, typically through passwords, tokens, or biometrics. Unlike passwords (forgettable) or tokens (physical), biometrics offer inherent security. Among biometrics, EEG-based authentication stands out due to its resistance to spoofing and ability to capture unique neural patterns. Unlike fingerprints or facial recognition, EEG signals are difficult to forge, however adversarial attacks using generative deep models remain an emerging threat. Despite promising results, EEG-based research suffers from inconsistent datasets and limited transparency, affecting reproducibility. Studies (e.g. Kong et al. (2018) and Ben Salem et al. (2020)) reported high accuracy but lacked sample size clarity, complicating chance level evaluation. Binary classification approaches (e.g., Wu et al., 2018) improve verification but underperform for out-of-sample data. This study addresses these gaps by investigating sampling rate (f_s) impact and optimising task selection for classification. We evaluate multiple datasets, demonstrating f_s's influence on performance metrics.

Methods

Dataset analysis. The datasets used in this study vary in sampling rate, electrode placement, and dataset size, – factors which influence authentication performance. The COG-BCI dataset (Dehais & Roy, 2022), with a high sampling rate and 62 electrodes, offers detailed spatiotemporal resolution. In contrast, datasets like STEW (Lim, Sourina & Wang, 2018) and AEP (Abo Alzahab et al, 2021) have lower resolution. Electrode placement also varies, with SignEEGv1.0 (Mishra, 2023) using only 5 electrodes for minimal frontal and parietal coverage, while COG-BCI captures broader cortical activity. Subject and session counts differ widely: SignEEGv1.0 includes 70 subjects over 15 sessions, whereas AEP has just 20 subjects across 3 sessions. The Keirn and Aunon dataset (Keirn and Aunon, 1989), with 7 subjects and variable sessions, uses 6 electrodes.

This discrepancy necessitates standardized pipelines for reliable cross-dataset comparison.

Preprocessing and feature extraction. Raw EEG signals were transformed to a common space using a uniform f_s=128sps and compared against both the native and f_s=98sps sampling rates. Then, bandpass filtering (1-45 Hz) was applied to remove noise and isolate relevant brain activity frequencies. The filtered signal was then transformed using Short Term Fourier Transform, to generate spectrograms. From these, Gray-Level Co-occurrence Matrix features captured spatial patterns. Frequency-band features were also extracted using Welch's method to compute the power spectral density across delta to gamma bands. The extracted features were then combined into a single feature vector.

Machine learning pipeline. ML pipeline for EEG-based authentication starts by selecting the optimal combination of tasks and parameters to maximize classification performance. The data then undergoes normalisation to ensure comparability across different datasets, considering the variability between subjects. Our setup involved 7 subjects and 1 session, with 4-fold cross-validation to tune for the best parameters. Given the verification nature of the task, binary classification generally yields higher accuracy but may suffer from label overlaps across subjects and high chance level (50%), which complicates selection of consistent features for best accuracy. For this reason, a multiclass classification was chosen for its lower chance level, allowing better identification of users while reducing the issue of varying feature selection per user. A grid-based hyper-parameter optimization was used to evaluate all possible task combinations (up to 3) on metrics like accuracy, F1-score, and AUC. XGBoost was selected as the classifier for its efficiency, training faster than baseline models, and producing interpretable results. The best task combination and parameters were selected based on the highest accuracy.

Results

The experiments showed a fundamental relationship between f_s and the spectral characteristics of neural activity. High-frequency cognitive tasks such as PVT demonstrate strict dependence on incremented f_s, as their reliance on transient gamma oscillations makes them particularly vulnerable to aliasing artifacts at lower sampling rates. In contrast, resting-state paradigms maintain robust performance across a wider f_s range (see Table 1) due to their utilisation of lower frequency-bands that remains well-resolved even at moderate sampling rates. Auditory evoked potentials show particular resilience to f_s, as their characteristic under 30 Hz components are inherently less susceptible to undersampling effects. However, certain paradigms like prefrontal cognitive tasks exhibit consistent performance limitations regardless of f_s, suggesting these constraints stem from fundamental properties of the underlying neural signals rather than technical sampling parameters.

Table 1. Key trends for top-performing tasks

Paradigm type	SF sensitivity	Performance (Acc)	Dominant F-band
High-F cognitive tasks (COG-BCI)	High (≥500 Hz)	0.9827 (500 Hz) to 0.9962 (128 Hz)	Gamma
Resting state (COG-BCI)	Moderate (~128 Hz)	0.9977 (128 Hz) to 0.9838 (98 Hz)	Alpha
AEP	Low (resilient for 98 Hz)	0.8333	ERP
Prefrontal tasks (STEW)	Insensitive (poor)	0.5708-0.6127	Diffuse

Conclusion

These findings collectively establish that optimal f_s selection must be tailored to each paradigm's specific neural dynamics.

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