Investigating the Impact of Calibration Time on Classifier Accuracy in c-VEP BCI Systems

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Introduction

In c-VEP BCI systems, different visual stimuli flash according to distinct sequences, and subjects' EEG signals are recorded as they focus on each stimulus [1]. These signals are then classified to identify the specific stimulus the subject is looking at. There are two main classification strategies in c-VEP BCI: the circular approach and the ensemble approach. In the circular approach, an EEG template is created by having the subject repeatedly focus on one stimulus. Since other stimuli sequences are shifted versions of this reference sequence, their EEG templates are generated by circularly shifting the reference template. In contrast, the ensemble approach involves creating separate EEG templates for each stimulus based on individual recordings [2]. This study investigates the relationship between the amount of EEG training data collected during classification calibration accuracy across various classifiers for c-VEP BCI systems.

Methods

We implemented several classifiers in this study, including Template Matching (TM), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), XGBoost, Deep Neural Network (DeepNN), and Convolutional Neural Network (CNN). For both the ensemble and circular approaches, we calculated the classification accuracies of these classifiers under varying calibration session durations.

Results

The results indicate that for both the ensemble and circular classification accuracy improves as the number of training data increases across all classifiers. Notably, in the ensemble approach, DeepNN shows a greater improvement in accuracy compared to other classifiers and outperforms the reference classifier, TM. In the circular approach, the accuracy improvement is consistent across all classifiers, with DeepNN demonstrating the largest gain.

Conclusions

This study demonstrates a strong dependency between the amount of training data and classification accuracy for both the circular and ensemble approaches. Among the classifiers, DeepNN shows the greatest sensitivity to increased training data, resulting in better performance compared to the other classifiers.

References

[1] Mohammadreza Behboodi et al 2020 IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 12, pp. 2762–2772

[2] Víctor Martínez-Cagigal et al 2021 J. Neural Eng. 18 061002

Figures

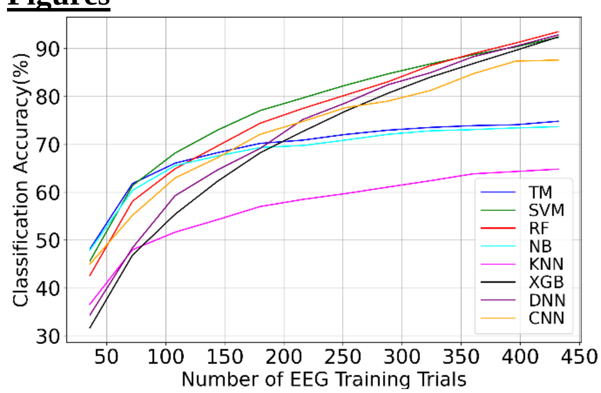

Figure 1. The classification accuracies of the Ensemble approach in different calibration time.

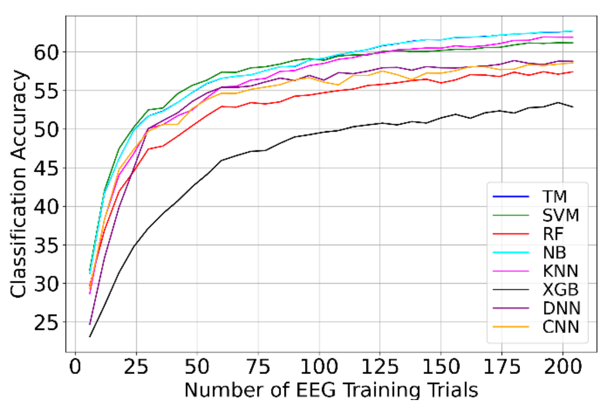

Figure 2. The classification accuracies of the Circular approach in different calibration time.