Recruiting Neural Field Theory for Motor Imagery Data Augmentation

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Abstract—**Brain-computer interfaces accuracy is often limited due to a lack of diverse training data. In this study, we face this problem by using a computational model of neural dynamics, specifically Neural Field Theory, to generate artificial electroencephalogram time series as additional training data. We fitted this model to common spatial patterns of each motor imagery class, jittered the fitted parameters, and augmented the training data by generating time series from the model. We then applied a linear discriminant analysis to classify motor imagery states based on total-power features and tested the accuracy improvement on the ‘2a’ data set from brain-computer interfaces competition IV. Our findings show that data augmentation using Neural Field Theory can significantly improve the accuracy of brain-computer interface classifiers when the number of training samples is limited, providing a biophysically meaningful signal.**

Keywords: brain-computer interface, neural field theory, data augmentation, motor imagery, EEG.

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) allow for controlling computer and robotic applications directly with brain activity. A common problem in BCI systems is poor classification accuracy due to a lack of diverse training data, which is typically collected during tedious calibration sessions. Training data augmentation is a possible solution to this problem. Previous studies have explored various techniques, such as Ensemble Empirical Mode Decomposition (EEMD) [1] and spectral noising [2], to augment Motor Imagery (MI) electroencephalogram (EEG) signals.

Here we harness Neural Field Theory (NFT), a computational model of neural dynamics, to augment MI training data. NFT is a powerful method for constructing models of large-scale brain activity based on physiological principles. These models can be fitted to experimental EEG spectra and generate artificial time series accordingly [3], [4].

The rest of the paper is structured as follows. Section II presents the materials and methods used in this study. In Section III, we present the results obtained from our research. Section IV analyzes these results and compares them to other works in the field. Finally, in Section V, we draw conclusions based on our findings and provide directions for future research.

II. MATERIALS AND METHODS

We applied Common Spatial Patterns (CSP) to the MI EEG epochs and computed the Total Power (TP) and Higuchi Fractal Dimension (HFD) of the CSPs. NFT models were fitted to each CSP time series of each MI class. The fitted parameters were jittered and artificial CSP signals were generated from the models. Linear Discriminant Analysis (LDA) was used to classify MI states based on TP and HFD features. To compare the effectiveness of our augmentation method, we also performed a naive augmentation by adding Gaussian noise to feature values.

We evaluated the accuracy improvement of our augmentation method on the ‘2a’ data set from BCI competition IV, which consisted of 18 subjects performing right and left hand MI [5]. To imitate a small training set, we randomly divided each subject’s data into three equal folds and used the first fold for training and NFT augmentation, and the other two folds for validation (as shown in Fig. 1).

III. RESULTS

Our goal was to reach the classification accuracy of the full training set, by augmenting the small training set. In the case of TP-based classification, our data augmentation method increased the accuracy of the small training set from κ=0.79 (Cohen’s Kappa [6]) to κ=0.83, surpassing the accuracy of the full training set (κ=0.82). In comparison, an augmentation that was done by noising the features decreased the accuracy to κ=0.76. For HFD-based classification, our augmentation method did not result in any improvement in accuracy. Please refer to TABLE I for complete results.

TABLE I. VALIDATION CLASSIFICATION ACCURACY κ [a]

	Full training set	***Small training set***	***Small training set + NFT augmentation***	***Small training set + noise augmentation***
TP feature	0.82	0.79	0.83	0.76
HFD feature	0.89	0.86	0.84	0.84

a. Inter-subject average

IV. DISCUSSION

Our results demonstrate that the NFT-based data augmentation technique effectively improved the

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classification accuracy to the level of a full training set, enabling the use of shorter MI training sessions. The improvement was evident for TP-based classification but not for HFD-based, suggesting that NFT generates EEG signals that better preserve spectrum-based features compared to time-domain-based features.

This augmentation technique outperformed the noise-based augmentation method. This may be attributed to the physiological realism of the NFT-generated signals, which resemble real EEG signals and are distributed in a biophysical manner in a physiologically valid range.

Its performance was at similar levels to the state-of-the-art augmentation methods mentioned before. EEMD-based augmentation increased the accuracy from κ=0.66 to κ=0.82, while spectral noising increased in from κ=0.65 to κ=0.68, both on the '2a' data set [1], [2]. A direct comparison is not feasible due to varying initial accuracy levels and evaluation methods in the studies.

V. Conclusion and Future Work

In this study, we addressed the challenge of limited training data in BCIs by proposing a novel augmentation approach. We used NFT to fit a physiological model to MI EEG signals and generated diverse artificial data for training. Our approach improved the accuracy of MI-based BCI classifiers and provided biophysical meaning to the generated signals. Overall, our findings suggest that data augmentation using NFT can be an effective solution for improving BCI performance when the number of training samples is limited. To assess the generalizability of our method, the next step would be to evaluate its performance on other BCI paradigms, such as Steady State Visual Evoked Potentials (SSVEP) and P300. This would help determine if our results can be extended to other BCI applications.

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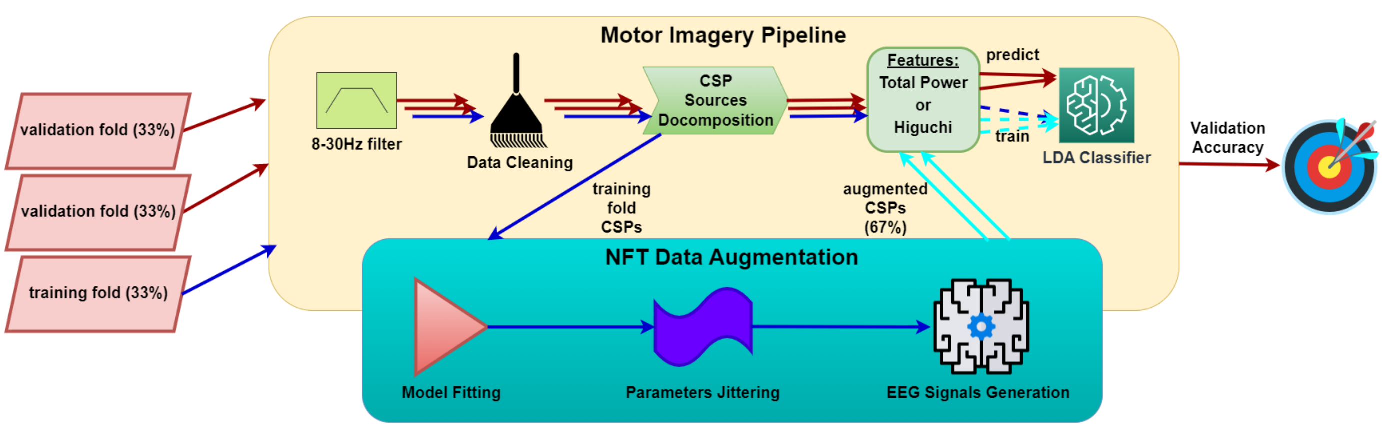

Figure 1. MI data augmentation performance evaluation procedure flow.