Pattern Recognition Issue (EEG Signals)

AI and Biological Computaion

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1 Introduction

In this project, we aimed to investigate the impact of feature extraction and selection on the performance of multilayer perceptron (MLP) and radial basis function (RBF) neural networks. We utilized time and frequency domain features, normalized and initially selected through Fisher score, and further optimized by a Particle Swarm Optimization (PSO) algorithm. Training both networks with these selected features under 5-fold cross-validation, we compared the outcomes to highlight the PSO algorithm's efficiency in refining feature selection. This approach demonstrated the importance of targeted feature selection in improving neural network accuracy, offering a valuable strategy for future AI applications in complex data analysis scenarios.

2 Methodology

2.a Materials

Our dataset consists of EEG recordings from 59 channels during the exposure to 60 3D VR videos, across 550 experiments involving 10 participants. Each VR video lasts 4 seconds, capturing diverse neural responses. The data is organized into a 59x5000x550 matrix, with 59 representing the EEG channels, 5000 data points per channel reflecting a sampling frequency of 1000 Hz, and 550 denoting the total number of experiments. This setup captures the full 4-second VR experience in high temporal resolution, providing a detailed basis for feature extraction and neural network training. Accompanying this, a label matrix was meticulously constructed, employing a binary classification system where *1* signifies positive valence and *-1* indicates negative valence. This labeling approach facilitated the precise identification of emotional responses, serving as a critical component of our study's focus on feature extraction and neural network training within the nuanced domain of AI and biological computation.

2.b Feature Extraction and Normalization

In the process of feature extraction for our dataset, we meticulously calculated both time domain and frequency domain features to capture the comprehensive dynamics of the EEG signals across all channels. In the time domain, we derived four key features: variance, form factor, correlation between every pair of the 59 channels, and amplitude histograms with 10 bins for each channel. This resulted in a total of 2419 time domain features. For the frequency domain, we focused on extracting features that highlight the spectral properties of the EEG signals. This included calculating the maximum, mean, and median frequency, along with the power spectrum ratio for four sub-frequency bands: theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–49 Hz). The frequency domain analysis yielded a total of 413 features. Following the comprehensive feature extraction, we employed Min-Max normalization to scale both sets of features, ensuring that all values were adjusted to fall within a defined range. The same meticulous process of feature extraction and normalization was applied to both the training and test datasets, guaranteeing that the models would be trained and evaluated on consistently preprocessed data. This meticulous feature extraction process forms the backbone of our study, enabling the effective training of neural network models and the accurate classification of emotional valence based on EEG signals.

2.c Feature Selection

One Dimensional Fisher Score

We improved our dataset by selecting the most informative features using the Fisher score for feature selection, a method renowned for its efficiency in identifying features that offer the most significant separation between classes. The Fisher score for each feature was calculated using the following formula:

$$Fisher = \frac{(\mu_{pos} - \mu)^2 + (\mu_{neg} - \mu)^2}{\sigma_{pos}^2 + \sigma_{neg}^2}$$

where μ_{pos} and μ_{neg} represent the average of the feature values for the positive and negative classes respectively, μ is the overall mean of the feature across all classes, and σ_{pos}^2 and σ_{neg}^2 denote the variance of the feature within the positive and negative classes. We ranked the features based on their scores and chose the top 70 features with the highest scores. To test the robustness of our model, we randomly selected two sets of 50 features from the top 70 and used them to train our neural networks. This allowed us to evaluate how different feature sets affected the network's performance and generalization capabilities.

Particle Swarm Optimization (PSO) Algorithm

We designed a PSO algorithm to pick the best features from a pool of 1000, chosen from a larger set of 2832 features based on their Fisher scores. This PSO algorithm not only found the most valuable features but also figured out the ideal number of features for our model. To avoid selecting too many features, we added a penalty term. We assessed the fitness of each particle using a Random Forest classifier. We used a sigmoid function to convert velocities into probabilities and updated particle positions accordingly. After running the PSO algorithm, we identified the top feature subset and the optimal number of features. This process significantly improved the performance of our neural network models.

2.d Neural Network Models

MLP Network

We used TensorFlow for our neural network and applied a 5-fold cross-validation technique to ensure reliable performance assessment. After experimenting with various architecture, the most effective model featured 3 hidden layers: one with 128 neurons, another with 64 neurons, and a third with 32 neurons. These layers used the ReLU activation function. The output layer employed the sigmoid activation function to produce probability outputs ranging from 0 to 1.

RBF Network

We also explored the RBF (Radial Basis Function) network in our project. To find the best setup, we tried different numbers of centers, ranging from 10 to 1000. In each trial, we used 5-fold cross-validation to rigorously assess the performance. The RBF network was trained using an SVM (Support Vector Machine) classifier with an RBF kernel. We looked for the configuration that achieved the highest average accuracy across all folds, and it turned out that 128 hidden neurons worked best. This helped us compare how well the RBF network could handle complex patterns compared to the MLP network.

3 Results

3.a Feature Selection, PSO vs Fisher

Our project explored two feature selection methods for classifying EEG signals: selecting the top 70 features using the Fisher score and employing the PSO algorithm. While the Fisher score provided a good starting point, the PSO algorithm significantly improved the accuracy of both MLP and RBF networks. This demonstrates the PSO algorithm's ability to find more effective features for classification. However, an unexpected result was that the PSO algorithm recommended a significantly larger number of features than anticipated (433 features) despite the fact that we managed this case with the penalty term. Additionally, it's important to note that the PSO algorithm required considerably more time to run compared to the Fisher score method. This increased computational time underscores the need for balancing the benefits of improved accuracy against the practical constraints of model training time and complexity.

3.b Neural Network Performance, MLP vs RBF

In this project, MLP networks outperformed RBF networks in terms of accuracy. However, designing and optimizing RBF networks was simpler compared to the more complex MLP architectures. Despite the superior accuracy of MLPs, the simplicity of RBF networks offers a noteworthy advantage in terms of ease of setup and configuration.

3.c Comparison

	MLP	RBF
Details of the Network	3 layers, (128, 64, 16)	32 hidden neurons
Fisher Selected Features	95.09%	79.82%
Details of the Network	2 layers, (64, 16)	64 hidden neurons
PSO Selected Features	96.91%	90.36%

- **Prediction of the best MLP Network trained on Fisher data :**

```
[[0. 0. 1. 1. 1. 0. 1. 0. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 1. 1.
  0. 1. 1. 1. 0. 1. 0. 1. 0. 0. 0. 0. 1. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0. 0.
  1. 1. 0. 0. 1. 1. 0. 0. 1. 0. 1. 0. 0. 1. 1. 1. 0. 1. 0. 1. 0. 0. 1. 0.
  1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 1. 0. 0. 1. 0. 0.
  1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 1. 1. 0. 1. 0. 0. 1. 1. 0. 1.
  1. 0. 0. 1. 1. 1. 0. 1. 0. 0. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 0. 1. 0. 1.
  1. 0. 0. 1. 0. 1. 0. 0. 1. 0. 1. 1. 1. 0. 1.]]
```

- **Prediction of the best RBF Network trained on Fisher data :**

```
[0 0 1 1 1 0 1 0 1 1 0 1 1 1 0 1 1 1 1 0 0 0 1 0 0 1 1 1 0 1 0 1 0 0 0 0 1
 1 1 1 0 1 0 1 1 0 1 1 0 1 1 0 1 1 0 0 1 0 1 1 0 0 1 0 0 1 0 1 1 0 1 0 1 1
 1 1 0 0 1 1 0 1 0 0 1 0 0 0 0 1 1 1 0 0 0 0 1 1 1 0 0 0 0 0 0 0 1 0 1 0 1
 1 0 1 0 0 1 1 0 1 1 0 1 1 1 1 1 1 0 0 1 1 1 1 1 1 0 1 1 0 1 1 0 1 1 0 0 1
 0 1 0 0 1 0 1 1 1 0 1]
```

- **Prediction of the best MLP Network trained on PSO data :**

```
[[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1. 1. 1. 0. 1. 0. 1. 0.
  0. 0. 1. 1. 1. 1. 0. 1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 0. 1. 0. 0. 1. 1.
  1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 0. 0. 1. 0. 1. 1. 0. 1. 0. 0. 1. 0.
  1. 0. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 1. 1. 1. 0. 1. 1. 0. 1.
  0. 1. 1. 1. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 1. 1. 0. 0. 0. 1. 1. 1. 1. 0.
  1. 0. 1. 0. 0. 0. 0. 1. 0. 0. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 0. 1.
  1. 0. 0. 1. 1. 1. 1. 0. 1. 0. 1. 0. 0. 0. 1.]]
```

- **Prediction of the best RBF Network trained on PSO data :**

```
[0 0 1 1 1 0 1 0 1 1 0 1 0 0 0 1 1 1 0 0 0 0 1 0 0 0 1 1 0 1 0 1 0 0 1 0 1
 1 1 1 0 1 0 1 0 0 0 1 1 1 1 0 1 1 0 0 1 1 1 1 0 0 1 1 0 1 0 1 0 0 1 0 1 1
 0 0 0 1 1 1 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 1 1 1 0 0 1 0 1 0 0 1 0 1 0 1
 0 0 1 0 1 1 0 1 0 1 0 1 0 0 0 0 1 0 0 0 0 1 1 1 1 0 1 1 1 1 1 0 1 1 0 0 1
 0 1 1 0 0 0 1 0 1 0 1]
```

In the end, the predictions generated by the models, along with the lists of features selected by both the Particle Swarm Optimization (PSO) algorithm and the Fisher score method, have been meticulously compiled and saved. These artifacts are provided as CSV files for comprehensive analysis and future reference.

4 Refrences

EEG-based emotion recognition in an immersive virtual reality environment