EEG-Based Virtual Reality Induced Stress Classification

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Introduction

Emotion recognition using human physiological signals remains an active area of research. The development of a robust framework for classifying distinct human emotional states would advance many diverse human-computer interaction applications.

The ability of computer agents to recognize different emotional states is highly advantageous for standardization in the study of emotion theory[1]. Stress is particularly relevant as such objective data would facilitate the systematic monitoring of treatment results over time for various stress-related disorders.

While previous research in this field often relied on multiple types of biosignals[3], this experiment aims to classify varying levels of stress in individuals using only EEG signals.

Experimental Procedure

Experiment: Ten subjects were exposed to a series of eleven virtual reality environments intended to induce varying levels of stress.

Questionnaire: Following the completion of each environment, participants were asked to rank their levels of valence, arousal, stress, and motion sickness on a scale of one to five, from low to high.

Data Classification: All four classifiers were then discretized into the following three categories:

LOW	MEDIUM	HIGH
Rating of 1-2	Rating of 3	Rating of 4-5

Figure 1: Experimental setup showing a subject immersed in a virtual reality environment.

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Classification

Signal Recording: Eight EEG channel locations (FZ, PZ, P3, P4, PO7, PO8, OZ, and CZ) were recorded using the g.Nautilus Dry Electrode Head Cap[2].

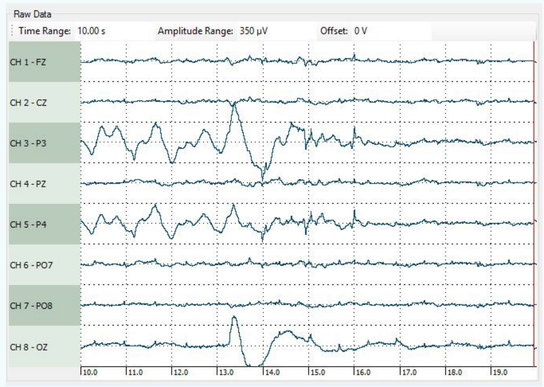

Figure 2: EEG signals recorded for eight channels.

Processing: The original recording was divided into multiple five-second segments each corresponding to a single environment. Each signal was then decomposed based on different frequency bands to yield four new signals: Theta (4 Hz, 8 Hz), Alpha (8 Hz, 13 Hz), Beta (13 Hz, 30 Hz), and Gamma ($>$ 30 Hz). Processing was done using the MATLAB software by Mathworks.

Feature Extraction and Selection: A total of 90 features were extracted per channel to yield a total of 720 features across all eight channels. Minimum redundancy maximum relevance (mRMR) was then applied to identify the most important subset of features, some of which are included below.

- **Selected Features** - Short-Time Fourier Transform minimum and maximum, Power Spectral Density Peaks, Normalized Energy

Classification: Four different models (Bagged Trees, Complex Trees, SVM, and KNN) were tested using both leave one subject out cross validation and five-fold cross validation. The best algorithm was selected based on the accuracies obtained by averaging performance metrics across the validation sets.

References

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3. Healey, J. A., and Picard, R. W. Detecting stress during real-world driving tasks using physiological sensors. *Trans. Intell. Transport. Sys.* 6,2 (2005), 156-166.

Results

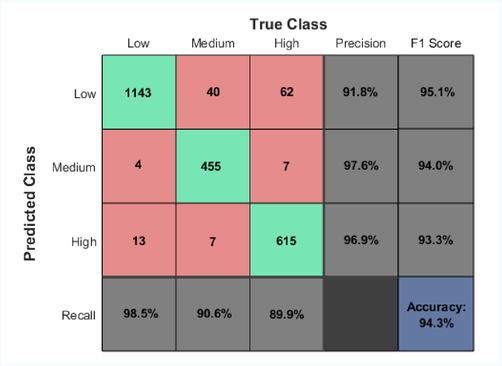

Figure 3: **Confusion Matrix of User-Dependent Stress Level Classification.** Best results were achieved from the Bagged Trees ensemble classifier with an overall accuracy of 94.3%.

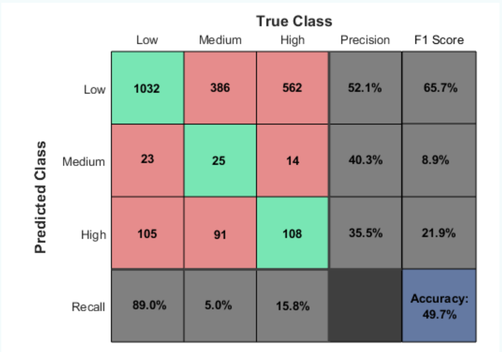

Figure 4: **Confusion Matrix of User-Independent Stress Level Classification.** Best results were achieved using a Support Vector Machine (SVM) with an overall accuracy of 49.7%.

Conclusion

Discussion: Achieved reasonable stress classification using only eight EEG channels. User-independent experiments resulted in much lower accuracies than that of user-dependent experiments, although both were above random classification of 33.3%. Because the latter was exposed to data from the same user prior to current classification, it can be concluded that in order to obtain high accuracy in emotion classification, some initial calibration on the user may be necessary.

Future Work: Prediction accuracy using user-independent experiments may be improved by extracting different features or using a larger number of subjects. Similar classification methods may be pursued to classify additional emotional states in users.