Fusion of Motif and EEG Spectrum Related Features for Improved Automated Emotion Recognition

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Abstract

Objectives: Emotion recognition is a burgeoning field allowing for more natural human-machine interactions and interfaces. Electroencephalography (EEG) has shown to be a useful modality with which to measure and monitor user emotional states, particularly primitives such as valence and arousal. However, EEG is highly sensitive to artefacts which could be caused by electrode movement, muscle activity etc. This abstract shows the usefulness of noise-robust ordinal patterns analysis [1], also called motifs, for improved EEG-based emotion recognition. Furthermore, various feature selection and fusion methods were used to further improve the valence and arousal predictions.

Feature Description: The data analyzed in this study was from the publicly available DEAP (Dataset for Emotion Analysis using EEG and physiological signals) database. It consists of physiological recordings from thirty-two healthy participants (50% females, average age = 26.9 years). EEG signals were collected from 32 channel electrodes (10-20 electrode placement) with sampling frequency of 512 Hz while the participants watched 40 one-minute long music videos with varying emotional content. Following this, they were asked to rate their emotional response on the valence-arousal scale. The valence-arousal space is a two dimensional scale used to characterize emotions [2]. Valence refers to the (un)pleasantness of an event, whereas arousal refers to the intensity of the event, ranging from very calming to highly exciting. We used the pre-processed EEG data available for public download, which includes common referencing, down-sampling to 128 Hz, bandpass filtering between 4-45 Hz, and eye blink artifact removal via independent component analysis. The EEG signals were band decomposed into theta ($4 < \theta < 8$ Hz), alpha ($8 < \alpha < 13$ Hz), beta ($13 < \beta <30$ Hz), and gamma ($30 < \gamma < 45$ Hz) bands. The power spectral features for each of the bands were then calculated along with inter-hemispheric asymmetry index features as benchmark. Furthermore, various power band ratios were also used as benchmarks. For the proposed set, motif based features were calculated which include permutation entropy [1] and ordinal distance dissimilarity [3] (similar to asymmetry index). Further, functional connectivity graphs were calculated using motif synchronization [4]. Graph-theoretic features were then calculated from the graphs, including degree of connectivity, clustering coefficient, transitivity, characteristic path length, global efficiency and small world characteristics.

Feature Selection and Fusion: Several feature selection and fusion methods have been explored to improve the performance of the feature sets. For feature selection, three methods were utilized, ANOVA based feature selection, minimum redundancy maximum relevance (mRMR) and recursive feature elimination (RFE). Following selection of the best algorithm, various feature fusion methods were tested. These include, i) feature level fusion, which concatenates the feature vectors together, ii) output associative fusion, which tries to learn the correlations in the valence and arousal outputs and iii) score level fusion, which fuses the outputs of the decisions from the two feature sets by giving weights to them.

Classification Analysis: SVM classifiers (with a radial basis function – RBF – kernel) were trained on two different binary classification problems, namely, discriminating between low and high valence states, as well as low and high arousal states. The classifiers were implemented using the open-source scikit-learn library for python [5]. Prediction was done on the subject-wise binarized

arousal and valence ratings. Subject-wise binarization helps remove any subject biases in the ratings while ensuring a more balanced dataset. Balanced accuracy (BACC) was used as the performance metric as it takes into account class unbalances. For evaluation, feature selection and training was performed on 90% of the randomly shuffled data. In order to have a more generalized performance of the classifier, once the feature selection step was performed, classifier training and testing was performed 100 times with different train/test partitionings. This setup provides a more generalized performance of the features and their invariance to the training set used.

Results/Discussion: RFE selection typically resulted in the highest accuracy with the best $BACC$ vs. number of features tradeoff. This is expected as RFE considers the interaction of features among themselves and the final outcome. Overall, the best accuracy was achieved with the combined set, followed closely by the models trained on the proposed motif features. These findings corroborate the complementarity of the two different feature types and show the importance of motif features for affective state recognition. For the various fusion strategies, feature-level fusion showed to be the best strategy for valence and was observed to be significantly better than score-level and output associative fusion, whereas score-level fusion for arousal being significantly better than both feature and output associative fusion. Comparing with previous work, the fused models can provide up to 9% improvement relative to benchmark features alone and up to 16% to non-motif based graph theoretic features.

Keywords— EEG, Affect Recognition, Emotion, Motifs, Ordinal Analysis

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