RNN Classification of Mental Workload EEG

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Introduction: Electroencephalogram (EEG) signals contain correlates for mental workload activities (Berka et al., 2007). Mental workload level predictions using spectral features of individual frequency bands in the EEG signal have yielded high accuracy in MATB-II tasks. (Comstock and Arnegard, 1992; Smith et al., 2001; Chandra et al., 2015; Salaken et al., 2020). Average power present in an EEG frequency band is a prominent feature used for classification in mental workload and motor imagery paradigms (Herman et al., 2008; Lotte et al., 2018). In addition to spectral features, EEG classification frameworks have used temporal (Yang et al., 2019); linear (Das Chakladar et al., 2020), and non-linear signal features (Balli and Palaniappan, 2010) such as approximate entropy (Pincus, 1991; Natarajan et al., 2004).

Long Short-Term Memory (LSTM) cells are modified Recurrent Neural Networks (RNNs) that can learn long temporal dependencies in sequence data. The basic architecture of an LSTM layer is a unit called a memory cell. It has a recurrent connection to itself and several activation gates that regulate the flow of information in and out of the cell. It retains a memory state within the network representing relevant information learned from the input time series. (Hochreiter and Schmidhuber, 1997). LSTM networks are state of the art in many fields, including natural language processing (K. Greff, 2017). The ability to approximate dynamical time-variant systems (Li, X. D., 2005) and learn temporal patterns that span large intervals makes LSTM based architectures a logical choice for classifying EEG signals (Tsiouris, K. M., 2018). There are many variants of this architecture, of which bidirectional LSTM (BiLSTM) cells are of particular interest to classifying EEG data. One can visualize this layer as two standard memory cells parsing the data in opposite directions, enabling the individual cells to update learned representations using either past or future time points. The utilization of future time points to predict the current cell state necessitates that the signal is a complete-time series and not an evolving sequence. (Schuster and Paliwal, 1997).

In this work, we used an RNN network architecture proposed by (Kaushik et al., 2019) and heuristically modified some parameters. We changed the penultimate dense layer of the proposed architecture from 32 to 16 neurons since the number of classes had been halved in the current problem compared to the original implementation. One of the challenges in the cross-session prediction of mental workload levels is the inter-session variability that often limits the network's performance (Yin & Zhang, 2017). To address this problem, we decided to combine data from two sessions under the assumption that intra-sessions variations will enable the network to learn representations generalizable across sessions.

Methods: The whole signal from a 2-second epoch was designated as a single trial instance, and it was filtered with a 1Hz-40Hz bandpass filter. The mean resting-state EEG amplitude of a session was also subtracted from all the trials to eliminate any offset in the data (Chatterjee, B., 2019). All 61 channels of data were chosen for feature extraction. The average power of specific frequency bands in the EEG signal was estimated using Welch's spectral power density estimate. Each value obtained from delta, theta, alpha, beta, and gamma bands for every trial were concatenated in that order, with approximate entropy of the entire trial. The final feature vector had six elements which were then passed into the RNN classifier.

RNN architecture contains one BiLSTM layer and two standard LSTM layers, making up the three operational modules. These individual layers are followed by batch-normalization layers, which helped standardize the variations due to the random initialization of weights and other hyperparameters while training. The flow diagram of our framework is shown in Figure 1.

The EEG data from 1st and 2nd sessions for a single subject were combined and then shuffled before partitioning into training and validation sets by the ratio of 80:20. A 10-fold cross-validation procedure was followed to verify the training for each subject. The trained network was then used to predict the labels of unseen data from the 3rd session.

Results and Conclusion: The average cross-validation accuracy of the proposed classifier is 89.51%, with a standard deviation of 4.7. This work suggests that the BiLSTM classifier can provide a robust framework for EEG mental workload classification when coupled with spectral and non-linear features.

(Link for MATLAB codes : https://github.com/NeuralLabIITGuwahati/RNNClassifier)

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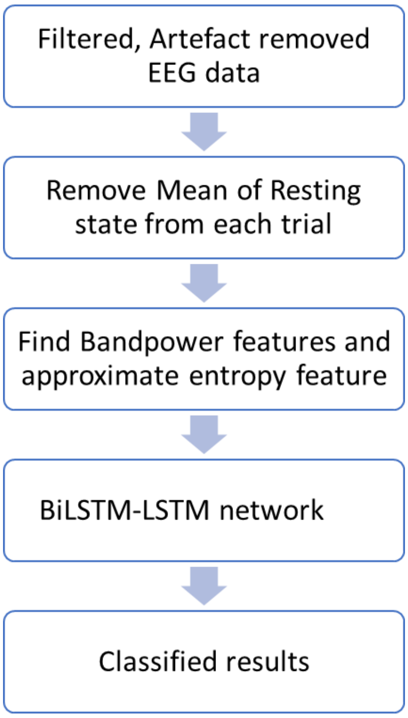

Figure 1. Flow diagram of Mental workload framework

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