Abstract

Cognitive load is the amount of mental activity imposed on the working memory of a user performing a cognitive task. The human cognitive system has a limited capacity. Cognitive activity beyond that limits results in a performance crash. Thus cognitive load estimation is important for cognitive monitoring of users to maintain users efficiency. Three methods are available to measure cognitive load namely subjective ratings, performance-based, and physiological methods. Subjective ratings and performance-based methods are not reliable. The more accurate physiological methods are based on the notion that the change in users cognitive state reflects in physiological parameters such as heart rate, pupil size, brain activity. Cognitive load estimation through the brain signals is more accurate as the human brain is the origin of its cognitive activities. Electroencephalography (EEG) is the most suitable Brain-Computer Interface (BCI) device to capture brain signals due to its non-invasive nature and low-cost set-up. Therefore, there is a need for research on the EEG-based estimation of cognitive load. This thesis aims to address this research area.

EEGs are employed with a larger number of channels. All the channels may not be relevant for cognitive load estimation. Further, there may be redundancy among all the relevant channels. Therefore, there is a need for selecting the optimum number of EEG channels. There are two approaches known for EEG channel selection namely filter and wrapper approach. They have their own advantages and limitations. This thesis proposes a hybrid approach by combining those two approaches to make it more accurate and faster. In this study, Pearson's correlation has been used as a filter approach and Prediction shuffling has been used as a wrapper approach. An experimental study proves the usefulness of the proposed method.

Measuring cognitive load using EEG signals requires feature extraction from raw signals. The selection of significant features is a pivotal task for any efficient BCI system. In literature, the majority of feature selection methods select only the relevant features. Few of them also remove the redundant ones. But all of them are supervised techniques. This thesis proposes an unsupervised feature optimization technique that can deal with both relevancy and redundancy without any class information. It evaluates feature relevancy based on two statistical measures namely Index of Dispersion and ratio of Interquartile Range/Range and uses clustering technique to remove the redundant ones. An experimental study proves the efficacy of the proposed method.

As per the literature of BCI, in most of the studies related to EEG signals classification, deep learning techniques outperformed the traditional machine learning algorithms. While in deep learning techniques, the deep network itself extracts features from the given signals, machine learning algorithms use the handcrafted features based on some statistical measures. To investigate the contribution of these two feature sets on the performance of the learning techniques, this thesis performs an analysis of them using clustering methods.

In the field of BCI, machine learning and deep learning techniques are mostly used for the brain signals classification. The traditional machine learning algorithms are specifically designed for classification whereas deep learning networks rely on the single layer softmax function for classification. Machine learning algorithms work on the handcrafted features where deep learning networks are efficient to extract high-level features through its non-linear hidden layers. To grab their superiority while overcoming their limitations, this thesis proposes a hybrid learning method to classify cognitive load EEG signals. This hybrid learning method proves to be more accurate and efficient than existing learning techniques.

Keywords: *Brain-computer interface, electroencephalogram, cognitive load, channel optimization, feature optimization, machine learning, deep learning.*