

ASSESSMENT OF NEURAL CORRELATES OF NEUROCEPTION USING MACHINE LEARNING TECHNIQUES



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requirements for the award of the degree of
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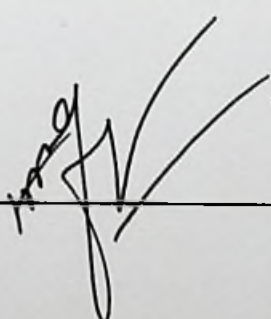
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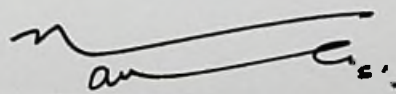
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Dedicated to my parents. My father Muhammad Irtiza Baig (late) and my mother
Kishwer Irtiza whose love and support have always been
source of strength for me

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ABSTRACT

Electroencephalogram (EEG) is amongst the most widely explored biomedical signals used to study and monitor human brain activity. Being considered as quite safe with no possible risk involved, EEG has been gaining significance as valuable and cost effective tool for research purposes in human emotions recognition. The presented thesis is focused towards study of human emotional states using EEG data. Existing literature shows that majority of the relevant work has used single stimulus based paradigm such as pictures, music, videos etc. to elicit emotions. This can lead to low ecological validity of the system. There is a need to explore neural correlates not only independent of subjects but stimuli presentation paradigms as well. EEG signals are usually recorded in a high-dimensional space. Researchers generally ignore the channel selection part while developing an EEG based application. This leads to noisy data, redundancy and longer setup time for the designed system. Furthermore, it is observed that methodologies proposed for electrodes reduction are validated for specific EEG application such as motor imagery classification, emotion recognition. There is a need to develop approaches that perform well in different application domains. Keeping in consideration aforementioned issues, the presented thesis proposed the solutions in two lines of approach. Firstly, EEG domain for emotion recognition has been investigated. The second approach is targeted towards EEG electrodes selection not only for emotion recognition but also for motor imagery classification. A novel paradigm to evoke human emotions has been presented. Moreover, a methodology based on Common Spatial Pattern (CSP), Linear Discriminant Analysis (LDA) and Genetic Algorithm has been proposed and it is found that the classification in gamma spectral band is better than those of others. Having highest mean classification accuracy of 72.74% across subjects reasonably presents evidence for feasibility of reliable classification of fear emotional state induced with two different stimuli. Furthermore, the regularized (R) CSP filters are

learnt on the training set. Log-variances of the filtered data are then used as input features to LDA. We found that Composite CSP and Composite CSP with Kullback-Leibler Divergence regularized techniques have outperformed conventional CSP. In order to identify configuration with lesser number of electrodes two methods have been proposed. One is based on Genetic Algorithm that initializes with random population and works in an iterative manner. The results in all paradigms show improvement in performance with reduced number of channels. Classification accuracy has been increased from 75.07% to 79.47% and 78.95% to 82.14% for emotional imagery and videos induced paradigms respectively with 15 electrodes only. Second method for electrode selection based on CSP filter weights has been proposed and validated for motor imagery EEG data. It is found that instead of using data from 60 electrodes only six can be used without significant degradation in classification performance. The thesis presents results that are promising for future EEG systems ensuring low set up time and cost for conducting EEG studies.

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