Documentation

AVMIB is a standalone application, hence involves no complexity of extra software installation. The design of AVMIB has been made modular and straightforward. The software architecture is based on the well-known feature extraction algorithm Common Spatial Pattern (CSP) and regularized CSP (RCSP). AVMIB presents data visualization and analysis of 11 RCSP algorithms including classical CSP on total of 17 subjects' MI data from 3 standard BCI competition datasets. Additionally, AVMIB enables subject performance analysis using machine learning, based on several key metrics.

Motivation was to provide this resource (AVMIB) to the inexperienced researchers such as fresh Masters/PhD students to develop an understanding of the multi-stage analysis of motor imagery based BCI datasets. It is a very easy-to-use desktop application and does not require a background with good programming skills to use it. AVMIB uses machine learning (ML) for analyzing BCI data and the parameters required for analysis can be easily selected using Graphical User Interface (GUI). AVMIB runs in all the major OS platforms (such as, Linux, Windows, and OS X). One of the major goals of AVMIB is to help user to develop in-depth understanding of the BCI domain without being concerned on the programming side.

Algorithms used:

AVMIB employs common spatial pattern (CSP) algorithm and its regularized variants for feat ure extraction. CSP is one of the most popular and efficient algorithms in motor imagery (MI) based BCI domain. The aim of CSP is to find the spatial filters which maximizes the variance of one class while minimizing the variance of the other class [1]. Hence maximizes the discri minability between two classes [2, 3]. CSP algorithm is proved to be an efficient algorithm, e specially during BCI competitions [4, 5].

Despite of its efficiency and widespread use, it is very sensitive to noise and prone to overfitt ing with small training set [6, 7]. To overcome this issue the researchers developed regularize d CSP algorithms by adding prior information to the learning process [3, 4, 5, 6]. It has been s hown that the regularized CSP (aka RCSP) outperformed the classical CSP.

CSP can be regularized in many ways. Two major approaches are discussed here [7], i.e., (i) regularizing covariance matrix and (ii) regularizing the objective function of CSP. In the first approach prior knowledge is incorporated into the spatial covariance matrix estimation as the regularization terms. Based on this approach several CSP algorithms have been designed. Composite CSP (CCSP1 ans CCSP2), Regularized CSP with Generic Learning (GLRCSP) and Regularized CSP with Diagonal Loading (DLRCSP) are few names of such regularized CSP algorithms. Here is a brief description of the algorithms. In case of DLRCSP regularization parameter, gamma is used for the regularization of covariance matrix. Based on the methods used for the selection of gamma DLRCSP can be of 3 types, such as, DLCSPauto, DLCSPcv and DLCSPcvdiff. In the second approach i.e. regularizing the objective function, a regularization term is added to the CSP objective function to penalize spatial filter solutions, that do not meet a priori. There are several regularized CSP algorithms based on this principle, such as, CSP with Tikhonov Regularization (TRCSP), CSP with Weighted Tikhonov Regularization (WTRCSP) and Spatially Regularized CSP (SRCSP) etc.

Method:

AVMIB has been developed in MATLAB version 2020a. The front-end was designed using MATLAB appdesigner, the GUI development environment of MATLAB. In the appdesigner, the file extension is .mlapp. There exist two tabs in each .mlapp file, i.e., Design view and Code view. The whole function logic is defined in the Code view tab and the design layout is drawn in Design view tab. In the proposed application four types of functionalities have been included such as plotting of filtered and raw EEG signal, Subject wise accuracy analysis, Subject wise performance metrics analysis and topographical map of best CSP filter which increases discriminability between the two classes under consideration. Each of the four functionalities has been represented by individual module and each module corresponds to a sub-GUI. Each of these sub-GUIs contains the logic behind each process. Effort has been made to access the GUI without the need of MATLAB installation for the users. For the present study a performance comparison between classical CSP and other types of regularized CSP algorithms such as CCSP, GLRCSP, DLRCSP, SRCSP and TRCSP [7] etc. have been presented in the form of a graphical representation. AVMIB takes input EEG data and displays plot after preprocessing(filtering) in GUI which makes it easy to get insight into the data used. AVMIB uses the key performance metrics such as Specificity, Sensitivity, Precision, Recall used in machine learning along with accuracy, for performance evaluation in graphical form that helps user to develop in-depth understanding of the domain. AVMIB also portrays the result in the form of a confusion matrix and AUC-ROC curve for each subject, which are useful to build understanding about the classifier model.

References:

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