Methods and Processing Tools for Cognitive States Estimation: A Systematic Review

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Abstract - *Brain Computer Interface is Communication between Computer and Human brain. Nowadays various areas are growing in this domain. One of them is Cognitive research. The mental action of acquiring knowledge through thoughts, experience and Senses is nothing but the Cognitive state. There are many processes and functions that contribute to a cognitive state such as attention, memory, reasoning and problem solving. Recently we have seen, there has been growing research interest using EEG signals to determine the cognitive state of students as they engaged in various learning activities. The cognitive skills of learners in a learning task play a major role in determining how well they perceive the knowledge being presented. It will helps to know about learners Cognitive states during the learning activities. Detecting cognitive states is a crucial step towards the adaptive learning and also to boost the student's mental reasoning process. After knowing this need we motivated to do the study regarding to this. The paper presents the previous work in the field of Brain Computer Interface in relation to estimation* of the *Cognitive States using Electroencephalo - graphy in various fields like as Engineering, Abacus, Medical, Computer Science and also review the various techniques and advanced processing tools available in area ,for the purpose of EEG data preprocessing, feature extraction and Classification of features. As we know cognitive states helps in every person's life for decision making, problem solving and many more. So this study is contribute to know about how much the previous work on cognitive states have been done and also available methods and processing tools are used to study cognitive states.*

Key Words: **Electroencephalography Cognitive States, Processing Tools.**

1. INTRODUCTION

In the field of cognitive neuroscience research recently provides a most widely direction to build more interactive brain computer interfaces (BCI) which can translate human neural responses into control signals for computer-application devices through system's hardware and software. In BCI EEG is a non-invasive technique to analyze human brainwave responses [1].It also be used to describe the power of brain activity concluded from different types of cognitive states of brain or its reaction to exterior interventions. For this external interventions it consists of five brainwave signals such as beta, alpha, theta, Gamma and delta [2] ,[22]. Cognitive neuroscience can be defined as the study of memory, decision making, planning, perception, language learning and conscious awareness [3],[23]. Analysis of cognitive human neural activity through electroencephalography (EEG) is an effective way of applying different cognitive brain computer interface (BCI) applications. Nowadays we see the work on cognitive developmental Robotics able to interact with dynamic environments and have brain like cognitive abilities such as memory, attention and learning [4], [24].

The construct of mental workload can be understood as the level of cognitive engagement which has a direct impact on the effectiveness and quality of a learning process. While an optimal level of mental workload simplifies efficient learning, mental overload could negatively affect task performance and result in more errors [5], [25]. Working memory which is mainly associated with the capability of the human brain to sustain attention to a mental representation of an object or an idea. It is quite obvious that the working memory plays an extremely important role in a number of aspects of every-day life and any damage to this system is troublesome [6], [26].

The properties Concentration or sustained attention is the basic cognitive ability of a person to perform any task or develop a skill. The timely monitoring of this ability is important when his/her performance enhancement is concerned [7],[27].Cognitive neuroscience is an emerging research area in the world. This domain gives us opportunity to analyze our self to improve our mental skill and learning efficiency. So our goal of this paper is to study regarding to previously estimated cognitive states with respect to learning stimuli using Electroencephalography at National and International Level. And as we know after acquisition of EEG signals we need to remove artifacts or noise from these signals after removing the noise it is necessary to extract the features and classify the signals as per our need. So for this Preprocessing, feature extraction and classification of EEG signals of these cognitive activities various processing tools are needed. The third section of this paper contains the tools available for EEG data processing in cognitive states related research.

2. ESTIMATED COGNITIVE STATES USING ELECTROENCEPHALOGRAPHY AT NATIONAL AND INTERNATIONAL LEVEL.

A cognitive state means the mental action of getting the knowledge using thoughts, experience and Senses. There are many processes and functions that contribute to a cognitive state such as attention, memory, reasoning, problem solving. Assessment of cognitive states learning module work as crucial.

In below table 1. Shows the research work done by various authors at National and International level on various cognitive activities such as attention , working memory ,cognitive load etc., using various EEG headsets and also review different preprocessing ,feature extraction and classification techniques used in cognitive research .

3. EEG PROCESSING TOOLS FOR COGNITIVE RESEARCH.

At the time of collection of EEG signal acquisition some artifacts or noise comes. Our need is to remove that noise and also used processed data for feature extraction and classification purpose. To overcome these steps we required some techniques and tools. There are various different processing tools are available. In this section we investigate some of them tools which are useful for EEG data processing in Cognitive research.

This study focus on various MATLAB and Python Tools used in EEG data processing.

- **EEGLAB.**

In EEGLAB consist of a general offline analysis environment for EEG and other electrophysiological data. [28] (www.sccn.ucsd.edu/eeglab), an interactive menu-based and scripting environment for processing electrophysiological data based under MATLAB. EEGLAB provides command line and interactive graphic user interface (GUI) allowing users to flexibly and interactively process their high-density electrophysiological data (up to several hundred channels) or other dynamic brain data time series. Its functions implement several methods of electroencephalographic data analysis including independent component analysis (ICA) [29, 30] and time/frequency analysis [23]. EEGLAB has become a extensively used platform for processing biophysical time series and sharing new techniques. Here we can says that as a minimum 28 plug-in functions have been implemented by a variety of user groups. Both MatRiver and BCILAB use the EEG dataset structure of EEGLAB. Thus BCI applications written in either environment may make direct use of the many EEGLAB data processing and visualization functions.

- **BCILAB.**

BCILAB is a system for easily constructing new BCI systems with a strong focus on advancing the state of the art. BCI systems constructed using BCILAB can be applied online and/or evaluated offline. Many BCI designs are Permitted, from the simplest signal processing chain to advanced machine learning systems. BCILAB is designed to become (likely in 2010) a freely available toolbox for the creation, evaluation, and application of BCI systems. BCILAB also provides tools to explore and visualize datasets offline for basic research purposes. As there is no clear boundary between data analysis for BCI and for neuroscience, here BCILAB blends into EEGLAB on which it is built. BCILAB system design is based on three concepts:

1)BCI Detectors :- These are the fundamental component of any BCI system, the actual methods mapping continuous EEG data measures to a control signal.

2) Detector components:- BCILAB provides a large collection of components that can be used to construct BCI Detectors.

3) Detection paradigms:-Detection paradigms are prototypes of commonly re-used Detector designs consisting of multiple BCI components , usually from all three categories .

- **M/EEG**

The Magnetoencephalography and electroencephalography (M/EEG) measure the weak Electromagnetic signals generated by neuronal activity in the brain. Using these signals to characterize and locate neural activation in the brain is a challenge that requires expertise in physics, signal processing, statistics, and numerical methods. As part of the MNE software suite, MNE-Python is an open-source software package that addresses this challenge by providing state-of-the art algorithms implemented in Python that cover multiple methods of data preprocessing, source localization, statistical analysis, and estimation off functional connectivity between distributed brain regions. All algorithms and utility functions are implemented in a consistent manner with well documented interfaces, enabling users to create M/EEG data analysis pipelines by writing Python scripts. Moreover, MNE-Python is tightly integrated with the core Python libraries for scientific computation used (NumPy ,SciPy) and for visualization purpose (matplotlib and Mayavi),as well as the greater neuroimaging ecosystem in Python processing via the Nibabel package[5].

Table 01: Previous Work on Cognitive States analysis using EEG

Author and Year	Cognitive Activity	Stimuli used	Number of Participants with age	Preprocessing Techniques	Feature Extraction /Classification Techniques	EEG Signal acquisition Devices	Status and Accuracy
Chris Berka, Daniel J. Levendowski 2007	Task engagement and Mental Workload	Grid, forward digit span, Mental arithmetic,Back ward digit span, and trails.	80 participants	-	Power Spectral Density (PSD)	Bi-polar sensor site	International [1]
Andreas Fink , Daniela Schwab, Ilona Papousek 2011	Cognitive and Affective stimulation	One word with 2 answers , sound clip and 15 words	45 Participants :23 males ,22females ,(18 to 32 years)	-	-	-	International [2]
Yongchang Li , Xiaowei Li, Martyn Ratcliffe, 2011	Attention	1) Comprehension. 2) Arithmetic task . 3) A question answering task.	08 Participants : 3 male 5 female (20 to 25 year)	FIR Filtering	k-Nearest-Neighbor (KNN)	EEG Device Nexus-4	International [3] 57.03%
Dan Szafir, Bilge Mutlu, 2012	Attention	Verbal and Non verbal cues	30 Participants :15 male and 15 female	-	ANNOVA	-	International [4]
Kavitha P Thomas, A. P. Vinod,2013	Attention and cognitive skills	Neurofeedack games	08 Participants		ANNOVA	Emotive Apoc	International [5]
Ning-Han Liu , Cheng-Yu Chiang and Hsuan-Chin Chu,2013	Attention	Listening to English phrases and then answering related questions.	24 Participants :12 male 12 female (22 to 27 Years)	Low pass filter	Support Vector Machine	Mindset	International [6] 76.82%
Nanda(D) Nandagopala, Vijayalakshmi R, Bernie Cocks, Nabaraj Dahala 2013	Cognition	1)Eyes open (EOP), 2)Eyes closed (EC), 3)Mild cognitive load (Cog1), 4)Heavy cognitive load (Cog2))	04 males Participants (25-50years)	Band Pass filtering , VEOL threshold	ICA(Independent Component Analysis),Fast Fourier Transform	30 sintered silver/silver chloride (Ag/AgCl) electrodes	International [7]
Geeta U Navalyal and Rahul D Gavas, 2014	Attention	3D all Moving Game	1)13 Abacus students :8-Males, 5-Females (6 -15 years), 2)3 under graduate	-	-	Mind wave Mobile from Neurosky.	National [8]

			students :2-males, 1-Female (20 – 22 Years), 3) 3 professionals :2-Males, 1-Female (40 – 50 years) 4)2 senior citizens :1-Male, 1-Female (Above 60 years)				
Necmettin Firat Ozkan, Emin Kahya, 2015	Cognitive load	1)Typing “ABCDE” on the screen and 2)Typing “ESOGU2014 then used NASA-TLX form	30 Participants :15 female, 15 male (18 - 27 years)		t- test	EEG with P300Amplitude	International[9]
Poulami Ghosh, Ankita Mazumder, Saugat Bhattacharyya,2015	Working memory and Cognition	5 Pictures shown	10 Participants : 6 male 4 female(22-28 years)	High pass filter ,Low pass filter	Discrete Wavelet Transform, Support Vector Machine	EEG Headset	National [10] 85.6%
Bin Hu, Xiaowei Li, Shuting Sun, Martyn Ratcliffe, 2016	Attention	Music, Learning content	10 Participants :03 Females 07 Males	Independent component analysis	Time-domain analysis, Hjorth parameters,Correlation-based feature selection (CFS) and a k-Nearest Neighbor (KNN)	Nexus-32 EEG	International [11] Correct Classification Rate 80.84± 3:0%
Raheel Zafar, Sarat C. Dass, Aamir Saeed Malik, 2017	Cognitive States	260 grayscale photographs of human, animal, building, natural scenes and fruits. were presented in a single session	26 Participants (24 to 34 Years)	Bandpass Filter	Hybrid Algorithm, ConvolutionalNeural Network,t-test ,Likelihood Ratio-based Score Wavelet Transform ,Support Vector Machine	128 channel Electrical Geodesics Incorporated(EGI, Eugene, OR, USA) system	International [12] 79.9%
Winnie K. Y. So, Savio W. H. Wong, Joseph N. Mak, Rosa H. M. Chan ,2017	Cognitive Engagement	Arithmetic operation, Finger tapping, Mental rotation and Lexical decision task	20 Participants : 6 male ,16 Female (22 Years)	Bandpass filter ,ICA	Support Vector Machine	EEG Headset	International [13] 65-% to 75%

Xi Liu, Pang-Ning Tan, Lei Liu, Steven J. Simske 2017	Cognitive state	Reading ,Question answering ,Mind wandering	11 Participants: 7 male 4 female	-	Local model, Global model. Multi-task learning	EEG Headset	International [14] 67%,90%
Richard W Montgomery and Leslie D Montgomery, 2018	Cognitive Performance	Calculating the algebraic sum of four one-digit numbers presented in the center of a computer screen.	11 Participants (20 to 35 years)	-	ERP energy density analysis with the marginal cost benefit analysis of brain resource allocation.	EEG Headset	International [15]
Zainab Mohamed, Mohamed El Halaby, Tamer Said, Doaa Shawky, and Ashraf Badawi,2018	Attention and Working Memory	Test regarding to basic skills and compound skills	86 Participants :72 males 14 females (18-23 years)	Low pass filter	Support Vector Classifier and Neural Network	EEG Headset	International [16] 84% and 81%
Damodar Reddy Edla, Kunal Mangalorekar 1, Gauri Dhavalikar, Shubham Dodia 2018 2018	Concentration ,Meditation	To solve a mathematics problem mentally, Subject allow to meditate by closing their eyes and relaxing their mind	40 Participants :33 male .07 female (18 to 22)	-	Random Forest	Neurosky Mindwahe EEG	National [22] 75%
Muhammad Zeeshan Baig , and Manolya Kavakli, 2019	Rest, Drawing, Manipulation	To draw 3D Table in AutoCAD, Questionnaire	08 Participants (21 to 30 years)	Low pass Filter and High Pass Filter, ICA Decomposition	k-Nearest-Neighbor(k-NN),Linear Discriminant Analysis (LDA),Naïve Bayes(NB) NB, Support Vector Machine (SVM),Tree	EEG Headset	International [17] 90%
Muhammad Zeeshan Baig and Manolya Kavakli, 2019	Cognitive workload	3D table using given input keyboard/mouse and speech/ gesture to draw the 3D object in AutoCAD.	11 Participants (21 to 30 Year age)	Low pass filtering	Power Spectral Density (PSD)	Emotive EEG with 14channel	International [18]

Antoine Gaume, Ge´rard Dreyfus François-Benoıˆt Vialatte, 2019	Visual sustained attention	Motor control of a cursor using a joystick.	14 Participants: 11 males,3 females 23.7(19-32 years)	Zero-phase 3rd-order digital Butterworth filter	Linear Discriminant Analysis	EEG Headset	International [19] 75% for 5 s epochs, and 85% for 30 s epochs.
Mohamed El Kerdawy , Mohamed El Halaby, Afnan Hassan ,2020	Engagement and instantaneous Attention, Focused attention,Planning, Shifting	Facial expressions ,continuous performance task,Psychology Experiment Building Language (PEBL) test battery,cognitive assessment provided by the Cognifit test battery.	109 Participants :6 males 63 females (18 to 26)years	Independent Component Analysis	Time domain features ,Frequency domain features Shallo and Deep models	EEG Headset	International [20] 0.86, 0.82, and 0.63 scores and 0.78 and 0.81 I
Aurelien Appriou, Andrzej Cichocki, Fabien Lotte, 2020	Cognitive and Affective states	DEAP database ,Letter display on screen	22 Participants	-	Riemannian geometry based classifiers (RGC) and Convolutional Neural Networks (CNN),	EEG Headset	International [21]

Table 2. Review on Signal processing, feature extraction, and Machine learning algorithms in the BCILAB/EEGLAB framework[49].

Signal processing	Feature extraction	Machine Learning Algorithms
• Channel selection • Resampling • Deblinking • Envelope extraction • Epoch extraction • Baseline filtering • Re-referencing • Surface Laplacian • filtering [38] • ICA methods • (Infomax, FastICA, • AMICA) [28, 39] • Spectral filters (FIR,IIR) • Spherical spline interpolation [40]	• Multi-window averaging for detection based on slow cortical potentials [34, 35] • Common Spatial Patterns (CSP) [32] • Spectrally-weighted Common Spatial Patterns [36] • Adaptive Autoregressive Modeling, from BioSig [31]	• Linear Discriminant Analysis (LDA) [29] • Quadratic Discriminant Analysis (QDA) [42] • Regularized LDA and QDA [42] • Linear SVM [41] (implemented using LIBLINEAR) • Kernel SVM [43] (implemented using SVMPerf, with LibSVM fallback) • Gaussian Mixture Models (GMM three methods [44], [45], [46], implemented using GMMBAYES) • Variational Bayesian Logistic Regression [30] (contributed by T.Klister), • Deep Restricted Boltzmann Machines [31] (contributed by F.Bachl) • Relevance Vector Machines (RVM) [47] (implemented using Sparse Bayes).

4. CONCLUSION

Recent progress in neuroscience has given us a deeper understanding of how the brain works and provides us with novel ways to detect and analyze brain activities. One of them is Analysis of Cognitive States at the time of learning activities using Electroencephalography. Because the Cognitive states are very crucial in every person's life for problem solving, decision making. This paper gives the review regarding to various cognitive states like attention, working memory. Various techniques are available for analyzing the states but mostly used method by various authors is Support Vector Machine at National and International Level. This paper also focus on various EEG data Processing tools available for preprocessing, feature extraction and classification of cognitive states during learning stimuli. This will helps to getting information regarding to study of cognitive activities. Estimation of the Student's or Person's Cognitive states during doing any learning activities helpful for improving Cognitive States as well as learning efficiency.

REFERENCES

[1]Chris Berka, Daniel J. Levendowski," EEG Correlates of Task Engagement and Mental Workload in Vigilance, Learning, and Memory Tasks, Aviation, Space, and Environmental Medicine ,Vol. 78, No. 5, Section II ,May 2007

[2] Andreas Fink , Daniela Schwab, Ilona Papousek ," Sensitivity of EEG upper alpha activity to cognitive and affective creativity interventions", International Journal of Psychophysiology ,pp-233–239, 82 (2011).

[3]Yongchang Li , Xiaowei Li, Martyn Ratcliffe," A Real-time EEG-based BCI System for Attention Recognition in Ubiquitous Environment", Research gate 2011

[4] Dan Szafir, Bilge Mutlu," Pay Attention! Designing Adaptive Agents that Monitor and Improve User Engagement",2012.

[5]Kavitha P Thomas, A. P. Vinod," Enhancement of Attention and Cognitive Skills using EEG based Neurofeedback Game, 6th Annual International IEEE EMBS Conference on Neural Engineering San Diego, California, 6 - 8 November, 2013

[6] Ning-Han Liu , Cheng-Yu Chiang and Hsuan-Chin Chu," Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors, Sensors, 13, 1424-8220, pp-10273-10286, 2013

[7] Nanda(D) Nandagopala, Vijayalakshmi Rb, Bernie Cocksa, Nabaraj Dahal ," Computational Techniques for Characterizing Cognition using EEG Data - New Approaches", 17th International Conference in Knowledge Based and Intelligent Information and Engineering Systems - KES2013, Procedia Computer Science 22 ,pp-699 – 708 ,2013

[8] Geeta U Navalyal and Rahul D Gavas," A dynamic attention assessment and enhancement tool using computer graphics", Navalyal and Gavas Human-centric Computing and Information Sciences 2014

[10]Necmettin Firat Ozkan, Emin Kahya, An Experiment in Use of Brain Computer Interfaces for Cognitive Researches", International Journal of Intelligence Science, , 5,pp- 80-88, 2015

[11] Poulami Ghosh, Ankita Mazumder, Saugat Bhattacharyya , An EEG Study on Working Memory and Cognition",2015.

[12] Bin Hu, Xiaowei Li, Shuting Sun, Martyn Ratcliffe," Attention Recognition in EEG-Based Affective Learning Research Using CFS+KNN Algorithm, JOURNAL OF LATEX CLASS FILES, VOL. 11, NO. 4, DECEMBER 2016

[13] Raheel Zafar, Sarat C. Dass, Aamir Saeed Malik ," Electroencephalogram-based decoding cognitive states using convolutional neural network and likelihood ratio based score fusion",PLOS one,2017

[14] Winnie K. Y. So, Savio W. H. Wong, Joseph N. Mak, Rosa H. M. Chan ,"An evaluation of mental workload with frontal EEG", PLos one ,2017

[15] Xi Liu, Pang-Ning Tan, Lei Liu, Steven J. Simske ," Automated Classification of EEG Signals for Predicting Students' Cognitive State during Learning", In Proceedings of WI '17, Leipzig, Germany, August 23-26, 2017

[16] Zainab Mohamed , Mohamed El Halaby , Tamer Said , Doaa Shawky and Ashraf Badawi ," Characterizing Focused Attention and Working Memory Using EEG", Sensors 18, pp-37-43, 2018

[17] Muhammad Zeeshan Baig and Manolya Kavakli," Analyzing Novice and Expert User's Cognitive Load in using a Multi-Modal Interface System",Research gate ,2019

[18] Muhammad Zeeshan Baig , and Manolya Kavakli," Connectivity Analysis Using Functional Brain Networks to Evaluate Cognitive Activity during 3D Modelling",Brain Sciences MDPI ,2019

[19] Antoine Gaume, Ge´rard Dreyfus , François-Benoıt Vialatte,"A cognitive brain–computer interface monitoring

sustained attentional variations during a continuous task",Cognitive Neurodynamics ,13:257–269, (2019)

[20] Mohamed El Kerdawy, Mohamed El Halaby, Afnan Hassan ,"The Automatic Detection of Cognition Using EEG and Facial Expressions",2020.

[21]Aurelien Appriou, Andrzej Cichocki, Fabien Lotte,"Modern machine learning algorithms to classify cognitive and affective states from electroencephalography signals", IEEE,Sensors, 20, 3516, 2020

[22] Damodar Reddy Edla, Kunal Mangalorekar1, Gauri Dhavalikar, Shubham Dodia," Classification of EEG data for human mental state analysis using Random Forest Classifier ",ELSEVIER, International Conference on Computational Intelligence and Data Science (ICCIDS 2018) ,2018

[23] Rashima Mahajan, Dipali Bansal, "Real Time EEG Based Cognitive Brain Computer Interface for Control Applications via Arduino Interfacing ", 7th International Conference on Advances in Computing & Communications, ICACC 2017, August 22-24, 2017

[24]Pratibha R .Bhise ,Sonali B.Kulkarni, Talal A.Aldhaheri ,"Brain Computer Interface Based EEG for Emotion Recognition System :A Systematic Review ",2nd International Conference on Innovative Mechanisms for Industry Applications (IEEE),March 2020.

[25] Talal A.Aldhaheri , Sonali B.Kulkarni , Pratibha R .Bhise ," Brain Computer Interface and Neuro Linguistics : A Short Review ", 2nd International Conference on Sustainable Communication Networks and Application (Springer),August 2020.

[26]Pratibha R.Bhise ,Sonali B.Kulkarni ,Talal A.Aldhaheri," Multidisciplinary Review on Brain Computer Interface Based EEG for Assessment of Emotion Recognition System and Cognitive States during Learning Activities", IOSR Journal of Engineering ,ISSN:2250-3021,Vol.10,Issue 12 ,pp 34-46,Decemer 2020.

[27] Talal A.Aldhaheri , Sonali B.Kulkarni, Pratibha R.Bhise,"Brain Signal Analysis :Methods and Techniques Used in Nanotechnology", IOSR Journal of Computer Engineering,ISSN:2278-0661,Vol.23,Issue 1,pp 01-06,Jan-Feb 2021.

[28]Pratibha R.Bhise ,Sonali B.Kulkarni ,Talal A.Aldhaheri," Survey on Assessment of Cognitive States during Learning Activities using Brain Computer Interface based EEG",International Journal of Computer Applications,ISSN:0975-8887,Vol.174 ,Issue 15 ,pp 08-12,January 2021.

[29] Delorme, A. and S. Makeig," EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis",J Neurosci Methods,**134**(1): p. 9-21, 2004

[30]Makeig, S., et al.," Independent component analysis of electroencephalographic data", in Advances in Neural Information Processing Systems, p. 145-151, 1996.

[31] Makeig, S., et al., "Dynamic brain sources of visual evoked responses",Science, **295**(5555): p. 690-4, 2002.

[32] Schlögl, A.,"The electroencephalogram and the adaptive autoregressive model: theory and applications", ISBN3-8265-7640-3,2000

[33] Ramoser, H., J. Müller-Gerking, and G. Pfurtscheller," Optimal spatial filtering of single trial EEG during imagined hand movement" IEEE Trans. Rehab. Eng, p. 441-446, 1998(8):

[34] Schölkopf, B. and A. Smola, Learning with Kernels, Cambridge, MA: MIT Press,2002

[35] Blankertz, B., G. Curio, and K. Müller," Classifying single trial EEG: Towards brain computer interfacing", in Advances in Neural Inf. Proc. Systems (NIPS 01), T. Diettrich, S. Becker, and Z. Ghahramani, Editors, p. 157-164, 2002

[36] Blankertz, B., et al. ,"Single trial detection of EEG error potentials: A tool for increasing BCI transmission rates",. in Artificial Neural Networks -ICANN ,2002.

[37] Fisher, R., "The Use of Multiple Measurements in Taxonomic Problems",Annals of Eugenics, **7**: p. 179-188, 1936

[38] Tomioka, R., et al.," An Iterative Algorithm for Spatio-Temporal Filter Optimization",. in 3rd International BCI Workshop and Training Course,2006.

[39] Friedman, J., "Regularized Discriminant Analysis", Journal of the American Statistical Association, 84(405): p. 165-175, 1989.

[40]Babiloni, F., et al.," Performances of surface Laplacian estimators: a study of simulated and real scalp potential distributions", Brain Topogr, **8**(1): p. 35-45, 1995.

[41] Palmer, J.A., et al,"Modeling and Estimation of Dependent Subspaces with Non-radially Symmetric

and Skewed Densities",in 7th International Conference on Independent Component Analysis and Signal Separation, London, UK, 2007

[42] Perrin, F., et al., "Mapping of scalp potentials by surface spline interpolation", Electroencephalogram Neurophysiology, **66**(1): p. 75-81, 1987

[43] Bilmes, J., "Gentle Tutorial of the EM Algorithm and its Application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models", International Computer Science Institute, 1998.

[44] Vlassis, N. and A. Likas," A Greedy EM Algorithm for Gaussian Mixture Learning", Neural Processing Letters, Kluwer Academic Publishers. 15. Vol. 15. 2002

[45] Figueiredo, M. and A. Jain, "Unsupervised Learning on Finite Mixture Models", IEEE transactions of pattern analysis and machine intelligence, 24(3), 2002.

[46]Jaakkola, T. and M. Jordan," A variational approach to bayesian logistic regression models and their extensions", in Sixth International Workshop on Artificial Intelligence and Statistics, 1997.

[47] Hinton, G., S. Osindero, and Y. Teh, "A fast learning algorithm for deep belief nets", Neural Computation,. 18: p. 1527-1554, 2006.

[48]Tipping, M., "Sparse Bayesian learning and the relevance vector machine", Journal of Machine Learning Research,1: p. 211-244, 2001.

[49] Arnaud Delorme , Christian Kothe et.al," MATLAB-Based Tools for BCI Research", The Human

in Brain-Computer Interfaces and the Brain in Human-Computer Interaction,2010

[50] Alexandre Gramfort, Martin Luessi ,et.al," MEG and EEG data analysis with MNE-Python",Frontiers in Neuroscience,Vol.7,2013