Analysis of Signals in EEG with Cross Validation Method.

Suhas .S. Patil1, B.V. Barbadekar[2], D.S. Aldar1, Y.K. Kanse[1]

1: Department of Electronics Engineering, K.B.P. College of Engineering & Polytechnique, Satara 415001, email: suhas20patil@rediffmail.com

2: Department of Electronics Engineering, V.I.T. College of Engineering, Pune.

Abstract

The consistent operation of brain-computer interfaces (BCI's) based on impulsive electro electroencephalogram (EEG) signals requires precise classification of multichannel EEG. The design of EEG versions and classifiers for BCI are unfastened research subject whose obscurity shoots from the requirement to dig out intricate spatial and temporal patterns from piercing multidimensional time series obtained from EEG measurements. The conventional techniques comprise of translating intentional variations in the EEG into a set of specific commands in order to control a real world machine. However, the applicability of such an interface is strongly limited by number of limiting factors such as low bit-transfer rates, slow response times, signal or image acquisition and artifacts removing. Moreover, few other challenges such as averaging, threshold, image enhancement and edge detection constitutes the core operations in the course of preprocessing. In view of the above mentioned challenges, the present communication reports a 'Cross Validation' method for EEG signal analysis that offers a means for checking the accuracy and reliability of results obtained by an exploratory analysis of the data.

Keywords

Brain Computer Interface, Electroencephalogram, Cross Validation, Standard deviation, mean, variance, Electrooculography.

1. Introduction

A Brain Computer Interface (BCI) is a communication channel from a human's brain to a computer which does not resort to the usual human output pathways such as muscles. This approach enhances the capability of human brain beyond the physical limitations of the body abilities. It is more useful to develop prosthesis equipment especially for person with disabilities. Literature survey reveals a good number of examples depicting its usefulness. As reported by Atry et. al. a paralyzed persons can communicate by new communication channel that is EEG signals to real time machines [1]. Researchers have explored different approaches to transform brain signals into control signals. As revealed by the research group of Neuper et. al. [2-4], invasive BCI systems make use of implanted electrode arrays which measure local field potentials. The non-invasive approach typically uses surface EEG. In the motion based BCI systems, the variation in the EEG signal due to the movement or the imagination of the movement in a particular body organ like hands or feet is used for this purpose of control. However as reported by Bayliss and Suttar [5,6], the EEG consist of very sensitive signals that varies even with as action or thought. So it becomes mandatory to take the help of classifier to distinguish between different situations in accordance with change in EEG signal. But classifier should not make confusion to distinguish between different tasks. It should be sensitive and specific. One of the most promising approach in this regard is the 'Cross Validation' a statistical method for identifying pattern and checking consistency. The same is adapted in the present paper for the classification of EEG data and to check its validity. The results are verified by taking up five different subjects with five trials each on five different tasks.

The paper is organized in various sections. Section 2 covers the background and prior art. Section 3 covers the existing methods of analysis and the approach adopted in this work. This follows with the elaboration of the approach in Section 4. Finally the block schematic of the setup and results are presented in depth.

2. Background and Prior Art

It is worthwhile at the outset to mention the notable research work done in this field. Researchers have explored different methodologies for the classification of the EEg data for the formation of BCI. Anderson et.al. [8] Have explored the use of scalar and multivariate autoregressive (AR) models to extract features from the human (EEG) with which mental tasks can be discriminated. While Ramoser et. al. have demonstrated the use of spatial filters for the classification of the EEG data [9]. G. Pfurtscheller et. al. have reported a research approach to develop a brain–computer interface (BCI) based on recognition of subject-specific EEG patterns. EEG signals recorded in their work [10] from sensorimotor areas during mental imagination of specific movements are classified on-line and used for cursor control. Guler et. al. have obtained reliable results of EEG classification that demonstrates usefulness of RNNs employing the Lyapunov exponents in analyzing long-term EEG signals for early detection of the electroencephalographic changes [11]. A recent paper by Blankertz et. al. reports Berlin Brain-Computer Interface using advanced signal processing and machine learning techniques [12]. Similar work is reported in other recent papers in [13-18]. A VLSI approach is also seems to be emerging for custom hardware design for these applications [22].

3. Common Spatial Pattern Analysis Approaches

The well-known theory of cross-validation was pioneered by Seymour Geisser. Cross-validation, sometimes called rotation estimation, is the statistical practice of dividing a sample of data into subsets such that the analysis is initially performed on a single subset, while the other subset(s) are retained for the subsequent use in confirming and validating the initial analysis [19]. There are three main methods namely Holdout, K-fold cross validation, Leave-one-out cross validation. In depth coverage regarding these methods is covered in literature [14-19].

The present paper builds on the benchmarking data obtained previously by Keirn and Aunon [20-21]. In our work, each individual cell array is made up of a subject string, task string, trial string, and data array. Each data array is 7 rows by 2500 columns. The 7 rows correspond to channels c3, c4, p3, p4, o1, o2, and EOG. Across columns are samples taken at 250 Hz for 10 seconds, for 2500 samples. For example, the first cell array looks like 'subject 1' 'baseline' 'trial 1' [7x2500 single]. Recordings were made with reference to electrically linked mastoids A1 and A2. EOG was recorded between the forehead above the left brow line and another on the left cheekbone for extracting features from the preprocessed data.

4. Technical Approach Adopted in the Present Work

EEG signal were obtained from the patient with the help of electrodes placed on the scalp. However, the obtained signal were not in pure form, because of the inherent noise sources such as line noise from power grid, eye blink, eye movement etc. In order to purify the above mentioned signal, preprocessing was utmost important. The noise alleviation was done by using the filters Parameters such as mean sample value, Standard Variation and variance were obtained with regard to these signals. Peak and valley points in the feature vectors were stored. The feature extraction process was comprised of autocorrelation of the data samples. Thus the formation of the data base was commenced, which was normal without any corruption of noise. In the same manner data base of EEG signals of five tasks viz. ‘Baseline’, ‘Letter Composing’, ‘Rotation’, ‘Multiplication’ and ‘Counting’ was formulated.

In order to accomplish the testing, the unknown EEG data was preprocessed, and feature vectors were calculated for the same. These feature vectors were cross validated with the normal data base, and the results of cross validation were validated on the basis of threshold. The block schematic of the setup is shown in figure 1.

5. Numerical Computation of the Parameters:

This section covers the necessary formulae used in this paper. The Parameters such as mean, standard deviation and variance were found out from unknown EEG to generate feature vector. These features were cross validated with features of known EEG signals. It gives output in terms of tasks which was performed by subject. The necessary formulae needed for calculating EEG features are as given below.

$$mean = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad \text{(I)}$$

$$\text{variance} = \sum_{i=1}^{n} (x_i - mean)^2 / n \qquad \text{(II)}$$

$$SD = \sqrt{\text{variance}} \qquad \ldots \text{(III)}$$

Where, X=input signals. SD= Standard Deviation.

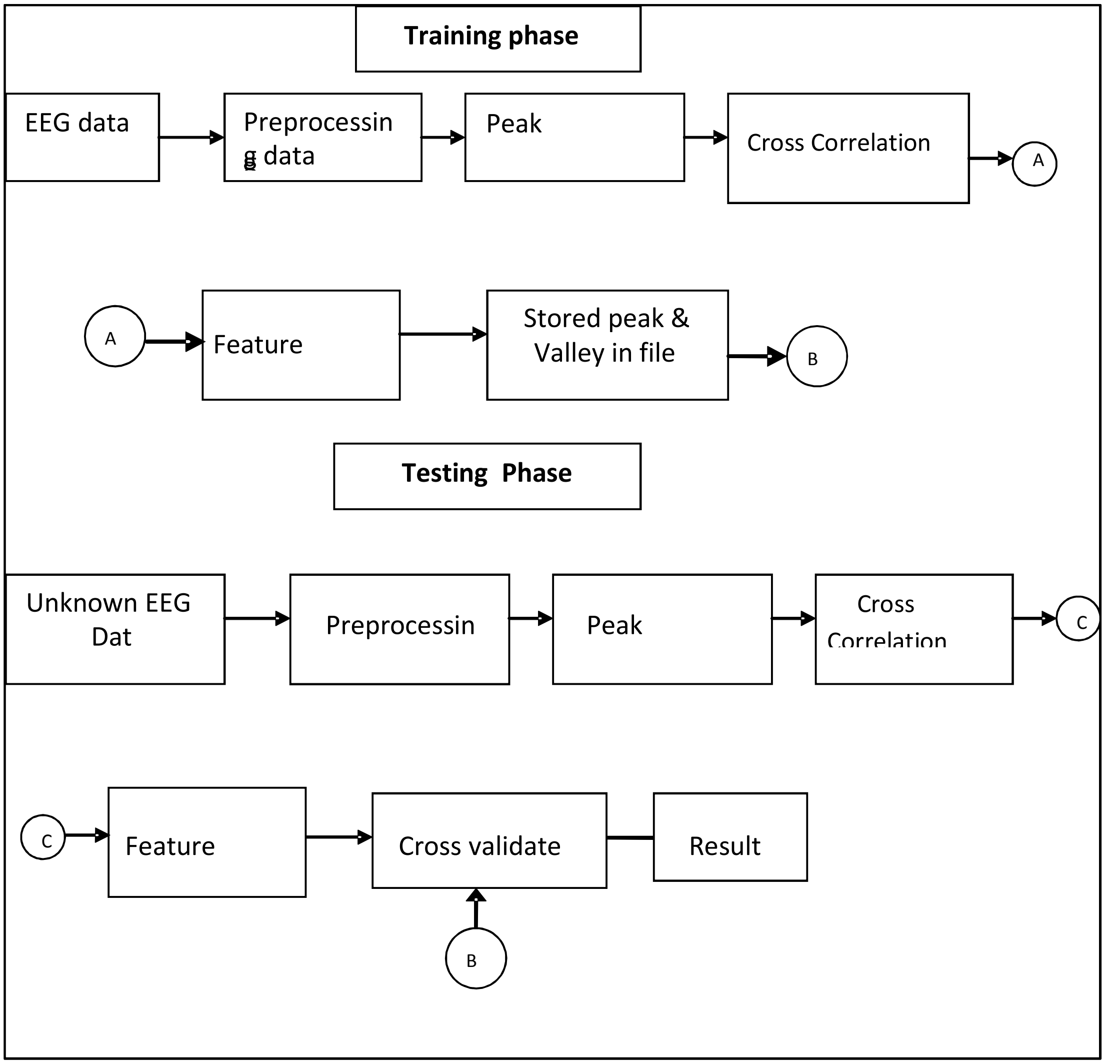

Figure 1: Block schematic of EEG analysis by Cross Validation method.

6. Results and Discussion

The EEG signal acquired in this work were classified in five different classes viz. 'Baseline', 'Letter Composing', 'Rotation', 'Multiplication' and 'Counting'. The classification module was trained to differentiate between different classes based on feature vector values. The basis of the feature was based on mean, standard deviation and variance of the data sets. The matching of mean value among the STD and variance makes sure identification of the task. Our module successfully identified 30 EEG signals from 37 data samples. This indicates accuracy of the system of the order of 81%. The EEG data acquired was comprised of 2500 samples for each channel. Every channel was divided in 9 parts. Mean value for each cannel was calculated and plotted against

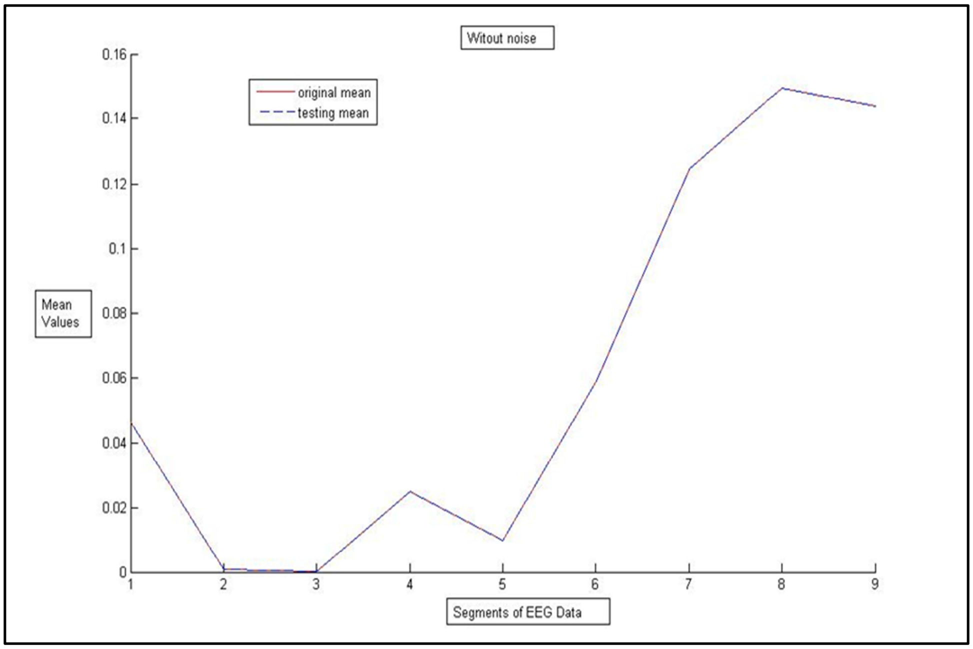

Figure 2: Graph of mean values of EEG signal.

their corresponding segment number. These values were again tested with same signal free from noise. The values again indicate perfect matching as shown in figure 2. Figure 3 shows testing of the same signal with another EEG signal corrupted by noise of 50 Hz. In this case the mean values of each segment are seen to be changing. Further to the above analysis, the noise was removed by employing a notch filter. The improvement seen in the results reveals the need of removal of artifacts from the EEG signals which becomes one of the vital requirement. In lieu of the noise removal, the classification module for BCI is seen generating wrong decision based on input EEG signal.

Table1 reveals the comparison of mean and STD values of EEG signals with Noise while Table 2 presents calculation of all the metrics with respect to the datasets. In this table T indicates 'True' when data sample and unknown sample got same response, F indicates 'False' when data sample and unknown sample got different response. Matching of the response of both the parameters indicate success of the model in recognizing EEG signal of the correct task.

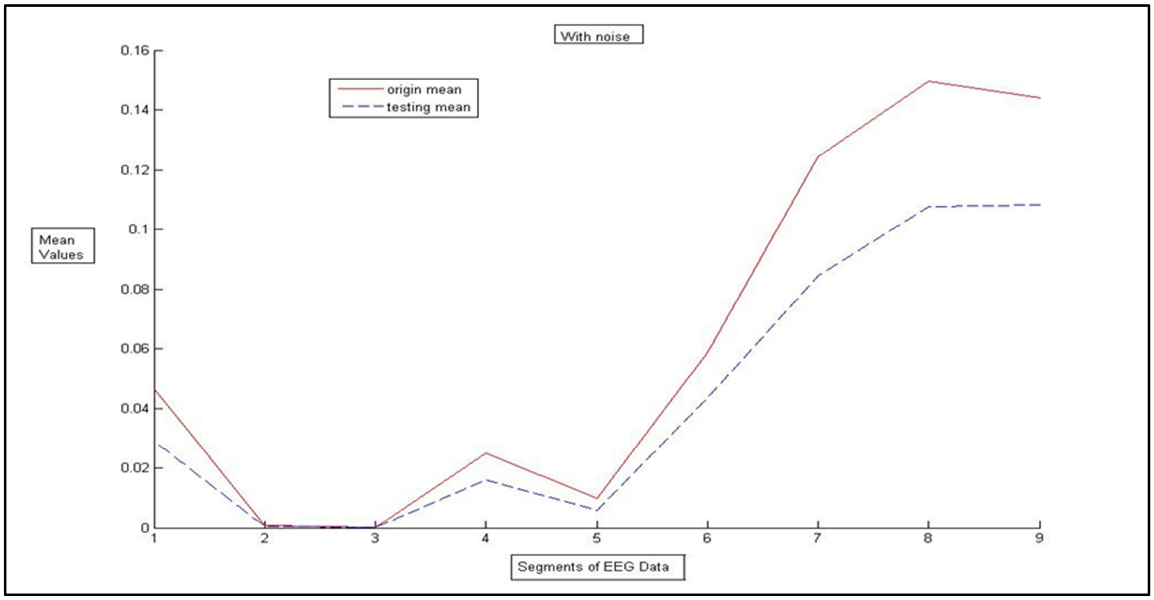

Figure 3: Graph of mean values of EEG signal corrupted by 50 Hz. noises

Table1. Comparison of Mean & STD values of EEG signals with Noise

Data	Noise	Mean (Without noise)	Mean (With noise)	Standard Deviation(Without noise)	Standard deviation(With noise)
Data(1)	50Hz	0.0631	0.0626	0.1732	0.1718
Data(2)	50Hz	0.0849	0.0845	0.1906	0.1895
Data(3)	50Hz	0.0736	0.0731	0.1816	0.1804
Data(4)	50Hz	0.0632	0.0629	0.1654	0.1648
Data(5)	50Hz	0.2119	0.2115	0.2226	0.2222
Data(6)	50Hz	0.0468	0.0467	0.1600	0.1598
Data(7)	50Hz	0.0400	0.0400	0.1438	0.1435
Data(8)	50Hz	0.0264	0.0264	0.1551	0.1550
Data(9)	50Hz	0.1159	0.1159	0.2191	0.2190
Data(10)	50Hz	0.0790	0.0789	0.1571	0.1570
Data(11)	50Hz	0.0201	0.0200	0.1953	0.1950
Data(12)	50Hz	0.0861	0.0860	0.2017	0.2016
Data(13)	50Hz	0.0628	0.0628	0.1107	0.1106
Data(14)	50Hz	0.0761	0.0759	0.1600	0.1597
Data(15)	50Hz	0.0590	0.0588	0.1593	0.1587

Data(16)	50Hz	0.0833	0.0832	0.1384	0.1381
Data(17)	50Hz	0.0695	0.0692	0.1231	0.1228
Data(18)	50Hz	0.0376	0.0376	0.1185	0.1183
Data(19)	50Hz	0.0365	0.0364	0.1395	0.1392
Data(20)	50Hz	0.1038	0.1035	0.1458	0.1455

Table 2: Calculation of the Parameters and Identification of the Task

Data Set No.	Task	Mean	Standard Deviation	Variance	True /False	Identification of the task
1	Baseline	T	T	T	T	Baseline
2	Baseline	T	T	T	T	Baseline
3	Baseline	T	T	T	T	Baseline
4	Baseline	T	T	T	T	Baseline
5	Baseline	T	F	F	F	Undefined
6	Baseline	F	T	T	F	Undefined
7	Multiplication	T	T	T	T	Multiplication
8	Multiplication	T	T	T	T	Multiplication
9	Multiplication	F	T	T	F	Undefined
10	Multiplication	T	T	T	T	Multiplication
11	Multiplication	T	T	T	T	Multiplication
12	Multiplication	F	T	T	F	Undefined
13	Multiplication	T	T	T	T	Multiplication
14	Letter Composing	T	T	T	T	Letter Composing
15	Letter Composing	T	F	F	F	Undefined
16	Letter Composing	T	T	T	T	Letter Composing
17	Letter Composing	T	T	T	T	Letter Composing
18	Letter	T	T	T	T	Letter Composing

	Composing					
19	Rotation	T	T	T	T	Rotation
20	Rotation	T	T	T	T	Rotation
21	Rotation	T	T	T	T	Rotation
22	Rotation	T	T	T	T	Rotation
23	Rotation	T	T	T	T	Rotation
24	Rotation	T	T	T	T	Rotation
25	Rotation	T	F	T	T	Rotation
26	Counting	T	T	T	T	Counting
27	Counting	T	T	T	T	Counting
28	Counting	F	F	F	F	Undefined
29	Counting	T	T	F	T	Counting
30	Counting	T	T	F	T	Counting
31	Counting	T	T	F	T	Counting
32	Counting	F	T	F	F	Undefined
33	Counting	T	T	T	T	Counting
34	Counting	T	T	F	T	Counting
35	Counting	T	T	T	T	Counting
36	Counting	T	T	F	T	Counting
37	Counting	T	T	F	T	Counting

7. Conclusion

The paper presents a useful method for the validation of electroencephalographic measurements and evoked potentials (EP) measurements. The results reveals improved reliability of the cross validation method when incorporated in the validation process integrated in the overall processing scheme. A useful methodology for calculation of variance, mean and standard deviation parameters along with per subject application of constant threshold reveals artifact free reference measurements. The study indicates the necessity of EEG validation procedure combined with feature detection so as to derive a reliable BCI.

Acknowledgements

Authors are thankful for the assistance by Sumit, Amod and Supriya during the course of this work. Thanks are also due to Dr. Kapare for medical interpretation of the signals. Mr. A. N. Jadhav deserves special appreciation for his cooperation in the course of research work. My Special thanks are due to Dr. R. K. Kamat for his suggestions in improving the quality of this article.

References

1. F. Atry , A. H. Omidvarnia and S. K. Setarehdan "Model Based EEG signal purification to improve the accuracy of BCI system." Control and Intelligent Processing Centre of Excellence, ECE Dept., University of Tehran.

2. C. Neuper, A. Schlögl, G. Pfurtscheller. "Enhancement of left-right sensorimotor EEG differences during feedbackregulated motor imagery" J Clin Neurophysiol. 16(4):373-82, 1999.

3. G. Pfurtscheller, C. Neuper, A. Schlögl, K. Lugger "Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters", IEEE Trans Rehabil Eng. 6(3):316-25, 1998.

4. G. Pfurtscheller, C. Neuper. "Motor Imagery and Direct Brain–Computer Communication", Proceedings of the IEEE, VOL. 89, NO. 7, JULY 2001.

5. J. Bayliss, A Flexible Brain-Computer Interface. Ph.D. Thesis, Computer Science Dept., U. Rochester, August 2001.

6. E.E. Sutter, "The brain response interface: communication through visually-induced electrical brain responses", Journal of Microcomputer Applications, v. 15, pp. 31—45, 1992.

7. Information about EEG processing, Zak Keirn at Purdue University, Retrieved from http://www.cs.colostate.edu/eeg

8. Charles W. Anderson, Erik A. Stolz and Erik A. Stolz, Multivariate Autoregressive Models for Classification of Spontaneous Electroencephalogram during Mental Tasks, preprint of the article in Scientific Programming retrieved from Google Scholar

9. H.Ramoser,J.Muler-Gerking,G.Pfurtscheler, Optimal spatial Filtering of single Trial EEG imagined Hand Movement, IEEE TRANSACTIONS ON REHABILITATION ENGINEERING,VOL.XX,NO.Y,AUG.1998, pp. 100- 120

10. G. Pfurtscheller, C. Neuper, C. Guger, W. Harkam, H. Ramoser, A. Schlögl, B. Obermaier, and M. Pregenzer, Current Trends in Graz Brain–Computer Interface

(BCI)Research, IEEE TRANSACTIONS ON REHABILITATION ENGINEERING, VOL. 8, NO. 2, JUNE 2000, pp. 216-218.

11. Nihal Fatma Gu¨lera, Elif Derya beylib and I˙nan Gu¨lera, Recurrent neural networks employing Lyapunov exponents for EEG signals classification, Elsevier, Expert Systems with Applications 29 (2005) 506–514

12. Alois Schlögl, Julien Kronegg, Jane Huggins, and Steve G. Mason.Evaluation Criteria for BCI Research. In Guido Dornhege, Jose del R. Millán, Thilo Hinterberger, Dennis McFarland, and Klaus-Robert Müller, editors, Towards Brain-Computer Interfacing, pages 297–312., MIT press, Cambridge, MA, 2007.

13. A. Schnitzler, S. Salenius, R. Salmelin, V. Jousmäki, and R. Hari. Involvement of primary motor cortex in motor imagery: a neuromagnetic study. NeuroImage, 6:201–8, 1997.

14. Stephen H. Scott. Converting thoughts into action. Nature, 442:141–142, 2006.

15. Pradeep Shenoy, Matthias Krauledat, Benjamin Blankertz, Rajesh P. N. Rao, and Klaus-Robert Müller. Towards adaptive classification for BCI. J. Neural Eng., 3:R13–R23, 2006.

16.Ryota Tomioka and Kazuyuki Aihara. Classifying Matrices with a Spectral Regularization. In ICML '07: Proceedings of the 24th international conference on Machine learning, pages 895–902. ACM Press, 2007.

17.Ryota Tomioka, Kazuyuki Aihara, and Klaus-Robert Müller. Logistic regression for single trial EEG classification. In B. Schölkopf, J. Platt, and T. Hoffman, editors, Advances in Neural Information Processing, Systems 19, pages 1377–1384. MIT Press, Cambridge, MA, 2007.

18.Ryota Tomioka, Guido Dornhege, Kazuyuki Aihara, and Klaus-Robert Müller. An iterative algorithm for spatio-temporal filter optimization. In Proceedings of the 3rd International Brain-Computer Interface Workshop and Training Course 2006, pages 22–23. Verlag der Technischen Universität Graz, 2006.

19.R. Kohavi. A study of cross-validation and bootstrap for accuracy estimation and model selection.In Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence, pages 1137–1143, 1995.

20.Z. A. Keirn. Alternative modes of communication between man and machine. Master's thesis, Purdue University, 1988.

21.Z. A. Keirn and Jorge I. Aunon. A new mode of Communication Between man and his surroundings. IEEE Transactions on Biomedical Engineering, 37(12):1209– 1214, December 1990

22. Gaikwad P.K., Shinde S.A., Kamat R.K., Design and Realization of Soft IP Core for Pulse Oximetery Applications, International Journal of Applied Engineering Research, Year: 2008, Volume: 3, Issue: 11