



INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

A REVIEW ON CLASSIFICATION OF EEG SIGNAL DATA

Pratibha Rana*, Ms. Jyotsna Singh

Under the guidance of Ms. Jyotsna Singh Department of computer science engineering THE NORTHCAP UNIVERSITY, Sector 23A, Gurgaon, Haryana-122017

DOI: 10.5281/zenodo.51018

ABSTRACT

A Brain computing system is a communication channel between the human or animal brain and external environment; it's a collaboration in which brain controls a mechanical device as a natural part of its representation of the body. It is a type of communication which practically uses both software and hardware systems for the communication. It's the type of system which provides a new way of communication between non-muscular channels with the external hardware. Basically Brain computing system is broadly divided into two major categories 1) EEG data signal based pattern recognition approach which actually train the particular brain mental stage and machine observe this pattern, on the behalf on this pattern machine further labels mental state of mind using the classification of pattern. 2) The apparent conditioning approach based on the self-recognition of the EEG signal response. In this paper we review some of the classification techniques for first type of brain computing interface.

KEYWORD: BCI (Brain Computer Interface), Classification, EEG signal data, ERD, Neural Network **INTRODUCTION**

In the field of Brain Computer interface, the first official research meeting held in June 1999 at the Rensselaerville institute near Albany, New York city, brain computer Interface was defined at that time by (JanneLehtonen, 2002) as: "A Brain computer interface is a communication system that does not depend on the brains normal output pathways of peripheral nerves and muscles".Mr. Lehtonen also suggested another name that is Brain Machine interface or often called a Mind-Machine Interface (MMI). It's also called a direct neural interface which actually detects input from the user's wishes and commands while the user remains immobilized or silent. Brain computing interface is also important for the people who are suffering from different types of diseases of the nervous system that gradually cause the body's motor neurons to degenerate. Example of few diseases is Amyotrophic Lateral Sclerosis, Brain stem stroke or spinal cord injury. These diseases eventually cause total or partial paralysis and the affected individual becomes trapped in his own body, basically making him unable to communicate this is where BCI comes in. BCI is a very good and diverse research area as it enables communication under difficult circumstances. It introduces new communication link between the suffering individuals and the external environment. Other than that BCI finds other applications in the fields like Bionics, cybernetics, gaming controls and feedback loop to enhance benefits of certain therauptic methods etc.

BCI machine is actually controlled by the thoughts of the affected individual and this brain activity is monitored. For this various techniques are available in the field such as functional Magnetic resonance imagining (fMRI) that exploits changes in magnetic properties of hemoglobin as it carries oxygen. Activating a part of brain increases oxygen levels thereby increasing the ratio of oxyhemoglobin to deoxyhemoglobin.

From above mentioned techniques, MEG (Mangentoencephelography) and EEG give continuous and instantaneous recording of the brain activity, this is near to real BCI interface. MEG detects the small magnetic fields created as neurons fire within the Brain. However, MEG is not a very practical approach to be used in Brain interface system. As, it requires the electrodes should be inserted inside the skull called as invasive recordings where electrodes are surgically implanted within the brain. Because of reasons like this almost all the systems of Brain computing interface reported till date have been based on the EEG signals where non-invasive techniques can be applied.



SIGNAL ACQUISTION

The acquisition of brain signals is done by using various non-invasive methods like in EEG and functional magnetic resonance imaging signal acquisitions.

A. EEG

EEG was recorded on the animal brain in 1875 by Richard Caton when he laid out the groundwork about the electrical nature of brain. It was first recorded on the human brain by Hans Berger in 1929 (Jonathan R. Wolpaw et. al 2000). EEG is the most common and best method for brain signals acquisition because of its high temporal resolution, safety and ease to use. In general experiment 15-20 standard electrode placement in used to acquire EEG signal. EEG has low spatial resolution and is non-stationary in nature too. EEG signals are very susceptible to artifacts caused by the eye blinks, eye activities, heartbeat, muscular and the power line interferences or simply by moving the electrodes may cause electrode pops.

B. fMRI

The fMRI technology is used in clinical laboratories in general. fMRI makes use of the level of hemoglobin. It measures brain activity basically by detecting the changes in the blood flow. More setup cost is required in the technology. It has high temporal and spatial resolution. Time delay mostly occurs in data acquisition process (Hans Knutson et. al 2012). fMRI is used in research as well as clinical context and can also be combined with other measures like EEG and NIRS.

SIGNAL PRE-PROCESSING AND FEATURE EXTRACTION

After signal acquisition phase, Signals are to be preprocessed. Signal preprocessing means enhancement of signal by apply some signal processing techniques. In General, the acquired brain signals are contaminated by the noise and artifacts. The artifacts such as eye blinks, eye movement, Heartbeats are the reasons why experience is required to interpret EEGs correctly. In addition to these, muscular movement and power line interference is also involve mingled with brain signal as stated by (**Teplan, 2002**). Artifact removal can be done using some common techniques like Common Average referencing (CSP), Principal Component analysis (PCA), Probability Based principal component analysis (PPCA) and independent component analysis (ICA). After these first step signal is passed for the Normalization, local averaging techniques, Robustkalman filtering, common spatial subspace decomposition (CSSD) etc. which are generally the most common techniques for Filtration



Fig 1.1 a) EEG



ISSN: 2277-9655 Impact Factor: 3.785



Fig 1.2 b) fMRI

Method	Signal Captured	Advantages	Disadvantage
EEG	Electrical signal on brain scalp that are used to capture signals from the brain.	 Very High temporal resolution Safe and easy technique 	 Susceptible to EOG signal, ECG signal, Muscular activities and power line interference Low Spatial resolution Non stationary signal
fMRI	Metabolic Signals using BOLD response techniques.	 High temporal and spatial resolution 	High setup costdelay in data acquisition process

TABLE 1: EEG and fMRI

A. ICA

ICA was first applied to EEG by Makeiget. al 1996. ICA separates the artifacts from the EEG signals into the independent components based on the characteristics of the data which we acquire without relying on the reference channels. The ICA algorithm decomposes the multi-channel EEG data into temporal independent and spatial-fixed components. ICA is performance and computationally efficient. ICA shows very high performance when the size of the data to decompose is large.

B. PPCA

PPCA (Probability based principal component analysis) was invented in 1901 by Kerl Pearson and later developed independently by Harold in 1930. The PPCA transform the correlated vector into linearly unordered vectors. The unordered vectors are called principal components. The PPCA is applied when the dataset size is too large which means we need the probability to calculate the principal components. This is best feature extraction techniques as per records. PCA might not be a better technique when it comes to BCI.



ISSN: 2277-9655 Impact Factor: 3.785

Method	Advantages	Disadvantages
ICA	 Computationally efficient Show High performance for large sized data. Decomposes signal into temporal and spatial fixed components 	 Cannot be applicable for under determined cases Requires more computation s for decompositi on
PPCA	 Helps in reduction of feature dimensions Ranking will be done and best helps for classification 	• Data lose is there sometimes because of dimension reduction.

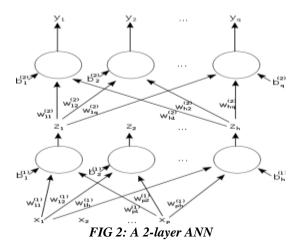
TABLE 2: ICA and PCA

CLASSIFICATION

A. Neural network approach

Neural network algorithm is a powerful technique for machine learning. This algorithm is powerful because of the fact that it has a good classification approach. The algorithm's architecture is basically a replica of our brain's biological neural networks. This approach is used to solve a wide variety of tasks that are usually hard to solve using ordinary methods. In this classification technique we divide the dataset into three major parts: 1) Training data 2) Test data 3) Validation data and a certain amount of hidden layers.

Normally, Training data is 70% of original data after feature extraction, Test data is 15% of original data after feature extraction and Validation data is 70% of original data after feature extraction. For training we have to create a logical matrix for the target.



B. KNN classifier

The KNN classifies an object based on where the majority of the neighbors belong to. The choice of the number of neighbors is discretionary and up to the choice of the users. If k is 1 then it is classified [10] whichever class of neighbor is nearest.

http://www.ijesrt.com



ISSN: 2277-9655 Impact Factor: 3.785

result = knnclassify(*Sample*, *Training*, *Group*, *k*)

In, MATLAB we need above parameter for KNN. This Group can be defined as the number of classes; k is the minimum distance between two neighbors. By default this algorithm works on the Euclidian distance.

C. SVM

SVM classification is a non probabilistic linear binary classifier, which can analyze input data and predict which of two classes it belong to. In order to differentiate between two samples SVM builds a hyper plan for separating the two classes based on which one is of higher dimension.

svmStruct = svmtrain(xdata,group,'ShowPlot',true);

result 2 = svmclassify(SVMStruct, Sample)

In SVM we need to prepare SVMStruct by using the inbuilt MATLAB function that's symtrain. After SVMStruct we pass samples to our main syntax for the prediction.

Method	Advantage	Disadvantage
Neural Network	 Deep pattern recognition techniques and provides best output on the difficult pattern Easy to understand. Logical work 	• Failed with raw dataset
KNN	 Euclidean distance based Finds nearest co-ordinate so, it works on every pattern. 	• Deep pattern is difficult to understand
SVM	• Differentiate data into hyper plan which is the best way to work on raw data	• Deep pattern is difficult to understand.

CONCLUSION

The BCI holds several potential applications for rehabilitation and better performances like for treating emotional disorders (like stress, depression etc.) and overcoming the different disabilities. In this paper a clear representation of various signal processing techniques is compare in each level of BCI application system is presented. The result of this survey gives a way to select the appropriate method or a good algorithm for the BCI research. As per our survey neural network is best classification technique if the dataset is filtered and SVM is best classification if the data is not filtered. ICA is best feature extraction techniques if the dataset is not too high and if dataset is too large then PPCA is the best feature extraction technique.

REFERENCES

- [1] Ozkan, I. (2004, July). Entropy assessment for type-2 fuzziness. In *Fuzzy Systems*, 2004. Proceedings. 2004 IEEE International Conference on (Vol. 2, pp. 1111-1115). IEEE.
- [2] Zeng, J., & Liu, Z. Q. (2004, August). Type-2 fuzzy hidden Markov models to phoneme recognition. In *Pattern Recognition*, 2004. ICPR 2004. Proceedings of the 17th International Conference on (Vol. 1, pp. 192-195). IEEE.
- [3] Zeng, J., & Liu, Z. Q. (2004, August). Type-2 fuzzy hidden Markov models to phoneme recognition. In *Pattern Recognition*, 2004. ICPR 2004. Proceedings of the 17th International Conference on (Vol. 1, pp. 192-195). IEEE.
- [4] Rhee, F. C. H., & Choi, B. I. (2007, July). Interval type-2 fuzzy membership function design and its application to radial basis function neural networks. In*Fuzzy Systems Conference*, 2007. FUZZ-IEEE 2007. IEEE International (pp. 1-6). IEEE.
- [5] Park, K. J., Oh, S. K., &Pedrycz, W. (2009, August). Design of interval type-2 fuzzy neural networks and their optimization using real-coded genetic algorithms. In *Fuzzy Systems*, 2009. FUZZ-IEEE 2009. IEEE International Conference on (pp. 2013-2018). IEEE.



[Rana*, 5(5): May, 2016]

ISSN: 2277-9655

Impact Factor: 3.785

- [6] Own, C. M. On the switch between Type-2 fuzzy sets and intuitionistic fuzzy sets. In *12 th conference on Artificial intelligence & applications (TAAI 2007)*.
- [7] Mendoza, O., Melín, P., & Castillo, O. (2009). Interval type-2 fuzzy logic and modular neural networks for face recognition applications. *Applied Soft Computing*, 9(4), 1377-1387.
- [8] Own, C. M. (2009). Switching between type-2 fuzzy sets and intuitionistic fuzzy sets: an application in medical diagnosis. *Applied Intelligence*, 31(3), 283-291.
- [9] Bandyopadhyay, S., Murthy, C. A., & Pal, S. K. (1998). Pattern classification using genetic algorithms: Determination of H. *Pattern Recognition Letters*, *19*(13), 1171-1181.
- [10] Melin, P. (2010, August). Interval type-2 fuzzy logic applications in image processing and pattern recognition. In 2010 IEEE International Conference on Granular Computing (pp. 728-731). IEEE.
- [11] Zhenjiang, M., &Baozong, Y. (1993). A new analytical method for AM neural networks and its application to pattern recognition. In *Neural Networks*, 1993., *IEEE International Conference on* (pp. 1570-1575). IEEE.
- [12] Lin, C. J., Wang, J. G., & Lee, C. Y. (2009). Pattern recognition using neural-fuzzy networks based on improved particle swam optimization. *Expert Systems with Applications*, *36*(3), 5402-5410.
- [13] Zhao, W., Chellappa, R., Phillips, P. J., & Rosenfeld, A. (2003). Face recognition: A literature survey. ACM computing surveys (CSUR), 35(4), 399-458.
- [14] Darwish, S. M., & Mohammed, A. H. (2014). Interval Type-2 Fuzzy Logic to the Treatment of Uncertainty in 2D Face Recognition Systems. *International Journal of Machine Learning and Computing*, 4(1), 24-30.
- [15] Begum, S. A., & Devi, O. M. (2011). Fuzzy algorithms for pattern recognition in medical diagnosis. *Assam University Journal of Science and Technology*, 7(2), 1-12.
- [16] Al-Allaf, O. N. (2014). Review of face detection systems based artificial neural networks algorithms. *arXiv* preprint arXiv:1404.1292.
- [17] Kwan, H. K., &Cai, Y. (1994). A fuzzy neural network and its application to pattern recognition. *Fuzzy Systems, IEEE Transactions on*, 2(3), 185-193.