ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org https://doi.org/10.5281/zenodo.2588239

A Filtering Approach to Clean EEG Signal Based on EMD-DF to Improve Classification Accuracy during Hands Movement

Sanjoy Kumar Saha[1], Sujan Ali[2], Jannatul Ferdous[3], Somlal Das[4] and Sumon Kumar Debnath[5]

[1] Department of Computer Science & Engineering, Begum Rokeya University Rangpur, 5400, Bangladesh

[2, 3] Department of Computer Science & Engineering, Jatiya Kabi Kazi Nazrul Islam University Trishal, Mymensingh, Bangladesh

[4] Department of Computer Science & Engineering, Rajshahi University Rajshahi, 6205, Bangladesh

[5] Department of Electrical & Electronics Engineering, Begum Rokeya University Rangpur, 5400, Bangladesh

Abstract

In this research, we present a filtering method for cleaning the EEG signal based on empirical mode decomposition (EMD) to enhance classification accuracy associated with upper limb real movement. In our method, we decompose each channel of EEG signals into a set of IMFs using EMD. We select or reject IMFs based on a calculation of dominant frequency of every IMF. In this procedure, we reject some IMFs whose dominant frequency greater than 30Hz. After reconstruction of the signal, we apply common spatial patterns to reduce the dimension as well as find out features of the signal and then we use support vector machines to classify left hand and right hand movement. Our paper demonstrates that the proposed method successfully extract features from row EEG signal that carries more information by filter out irrelative information. Our method tested on a publicly available dataset and obtained a significantly better performance.
Keywords: *Brain computer interface, Empirical mode decomposition, Dominant frequency analysis, Common spatial pattern and Support vector machines.*

1. Introduction

The Brain computer interface (BCI) is an area of research where communication occurs between the human and computer through bio-signal from the brain without using any muscular channel. In BCI, a subject is required to perform a specific task and EEG signal corresponding to the task is classified in order to generate control signals for driving a machine [1]. The EEG signals are non-invasive in nature and it can be recorded with a transportable recording system with reasonable cost. In BCI different electrophysiological signals e.g. visual evoked potentials (VEP) [2], slow cortical potentials (SCP) [3], evoked potentials P300 [4], event related de-synchronization (ERD) or event-related synchronization (ERS) [5] are used. ERD or ERS phenomena are time-locked to the event and they are highly frequency-band specific [6]. Among them, ERD/ERS based BCI has drawn a lot an interest in terms of motor rehabilitation and it's assisting for the motor function impaired patients by classifying user action e.g. hand movement, legs movement or eye movement [7-9].

A major problem in ERD/ERS based BCI system is the cleaning of EEG signal from the raw EEG signal that contains information uncorrelated to movement. In this paper, we have proposed a new filtering method with empirical mode decomposition (EMD) for improvement of EEG signal earlier than extracting features for classification [5]. The EMD is a data driven method and highly suitable for analysis of non-linear, non-stationary data as like EEG. EMD decompose a composite signal into a set of intrinsic mode functions (IMFs). We have selected and rejected some IMFs using spatial properties called the dominant frequency, which carries the maximum energy among all frequencies found in the spectrum [10].

Feature extraction plays important roles in the performance of classification of a BCI system. There are various methods have been proposed to EEG based BCI system such as laplacian method [11], autoregressive special analysis [12] and common spatial pattern (CSP) [13]. Among them, CSP one of the most well-known feature extraction method for ERD/ERS based BCI. The main aim of CSP is to find optimal spatial filters, which maximize the variance of one class in the meantime minimizing the variance of the other class [13].

In this work, we propose a noble use of dominant frequency to identify those IMFs to obtain enhanced EEG signal, which is responsible for hand movement. In this process, we select IMFs based on dominant frequency with no greater than 30 Hz.

2. Materials and Methods

2.1 Data description

In this research, we used publicly available data available at [14]. The data was recorded from a right handed 21 years old healthy male. The data was taken with eye closing. The data has contained EEG signal of random actual movement of right and left hand. EEG signal was recorded using Neurofax EEG System with 500Hz sampling frequency. The order of the electrodes is "FP1," "FP2," "F3," "F4," "C3," "C4," "P3," "P4," "O1," "O2," "F7," "F8," "T3," "T4," "T5," "T6," "FZ," "CZ" and "PZ" according to 10-20 system.

2.2 Empirical mode decompose

The Empirical mode decomposition (EMD) technique decomposes any time-domain signal into a set of AM-FM components without prior assumption of stationary and linearity of the signal for obtaining highly localized time-frequency estimation. It should be noted that the conventional signal processing techniques for EEG signal analysis based on the Fourier and wavelet transforms use predefined set of basis functions, which result into poor time-frequency localization [10]. It is based on the concept that the signal under analysis is a superposition of intrinsic mode functions (IMFs) which are extracted using the sifting process in the EMD method [10]. The fixed linear basis functions designed basis functions are useful only for stationary signals and can be sub-optimal for analysis of non-stationary signals like EEG [15-16]. In biological systems like a human brain, the frequency of oscillations may not be fixed and drift takes place in EEG rhythms within different frequency bands, and it thus makes the conventional methods like fourier and wavelet analysis, which use predefined fixed basis functions, inappropriate for EEG signal analysis [17]. The EMD method automatically decomposes a signal *x(t)* into a finite set of IMFs $c_i(t)$, which can be considered band-limited and symmetric functions [16]. Symmetric nature of IMFs has been explored for classification of different clinical related EEG signals [11]. Each extracted IMF must satisfy two basic conditions: (a) the number of extrema and the number of zero crossings must differ by at most one, (b) the mean of the envelops connecting respectively the local maxima and local minima are approximately zero [10]. The EMD algorithm [10] for a signal *x(t)* can be outlined

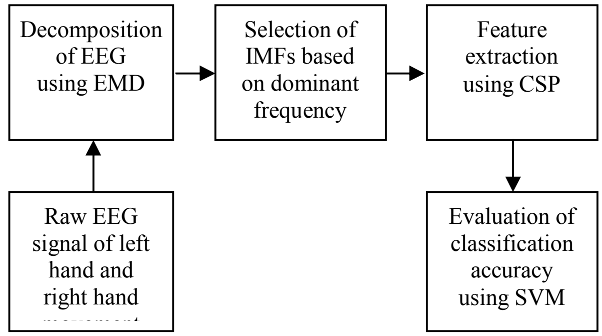

Fig.1. Block diagram for the proposed method

by the following sifting process:

(i) Assume $x'(t) = x(t)$.

(ii) Determine all local maxima and minima of $x'(t)$.

(iii) Calculate lower "envelope," $e_l(t)$ and upper "envelope," $e_u(t)$ by interpolating all minima and maxima respectively with cubic spline interpolation.

(iv) Compute the local mean, $m'(t) = (e_l(t) + e_u(t))/2$.

(v) Subtract the local mean from the original signal $x'(t)$, $c_i(t) = x'(t) - m'(t)$. (*i* is an order of IMF)

(vi) Let $x'(t) = m'(t)$ and repeat step from (ii) to (vi) until $c_i(t)$ becomes an IMF.

The first IMF is subtracted from the original data, $r(t) = x(t) - c_1(t)$and the procedure is applied receptively to the residue, $r(t)$, until it becomes constant or contains no more oscillations as stopping criterion [5]. The signal $x(t)$ is then

$$x(t) = \sum_{i=1}^{M} c_i(t) + r(t)$$

In order to make clear the operation of the EMD, we have used two single trail EEG signal of Cz channel to obtain IMFs from left hand and right hand movement EEG data (Fig. 2). In Fig. 2 x-axis shows the sample number of EEG and y-axis shows the amplitude of EEG signal in microvolt.

IJCSI International Journal of Computer Science Issues, Volume 16, Issue 1, January 2019
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org https://doi.org/10.5281/zenodo.2588239

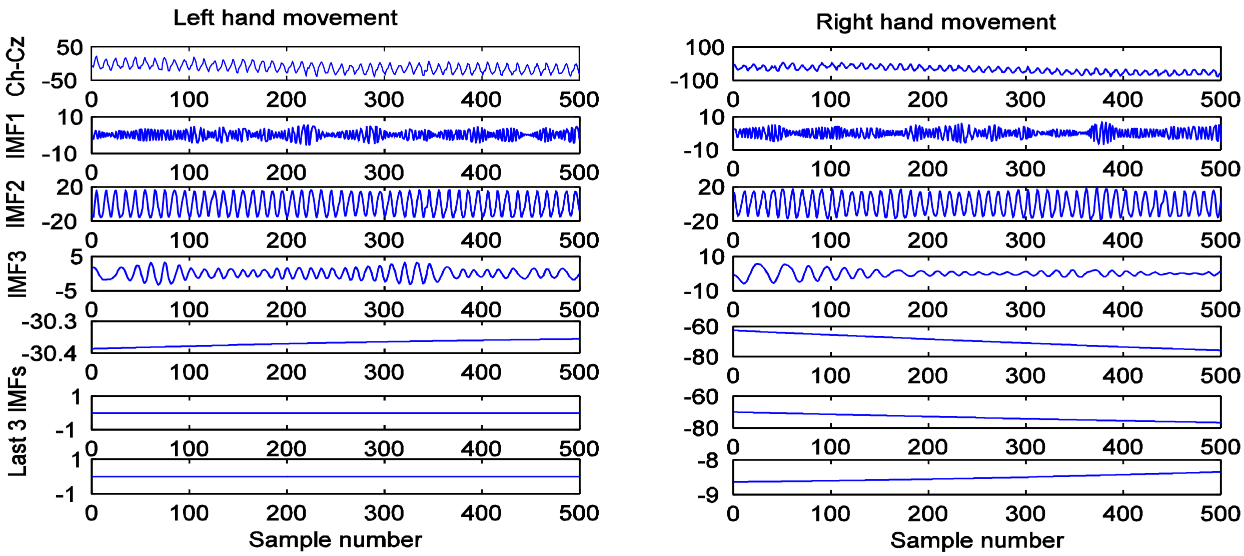

Fig. 2 The EEG signal of Cz channel with the first and last three IMFs generated from left hand and right hand movement.

2.3 Selection of IMFs using dominant frequency estimation

We apply EMD to decompose each channel of EEG signal into a set of intrinsic mode functions (IMFs). We selected some IMFs based on the estimation of power carry by frequency. In this research, we selected some IMFs based on dominant frequency (DF) analysis. Dominant frequency is on the magnitude spectrum as the frequency with the highest peak. We computed power spectra of all IMFs and select some IMFs with dominant frequency no greater than 30 Hz and other IMFs with dominant frequency greater than 30 Hz is rejected. To determine the dominant frequency, we first translate time domain signal into the frequency domain using fourier transformation. The frequency spectrum shows the strength of each frequency component in IMFs. Fig. 3 and Fig. 4 demonstrate the corresponding power spectrum of an IMF during left-hand and right-hand movement that makes up with different frequency. In the frequency spectrum, sinusoid frequencies with 100 HZ and 150 Hz have the largest power and this two IMFs are rejected. In this method, we ignore that IMFs which dominant frequency greater than 30Hz. To find a specific range of dominant frequency we run a grid search to discover which range carry maximum information related with hand movement.

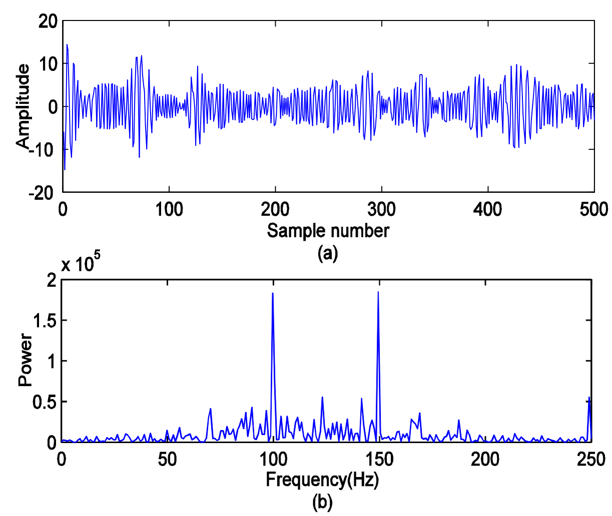

Fig. 3 Dominant frequency analysis of IMF during left hand movement (a) an IMF obtained from a random trail from Cz channel (b) power

2.4 Common spatial pattern

The common spatial pattern (CSP) method is the basis for most of the currently developed EEG based BCI. This algorithm is a feature extraction approach, which attempts is to discriminate between two classes of EEG data based on simultaneous diagonalization of two covariance matrices. A brief description of CSP is given below which is adapted from [18]. Let X signal of EEG data with size N×T denote a matrix that represents the EEG of a single

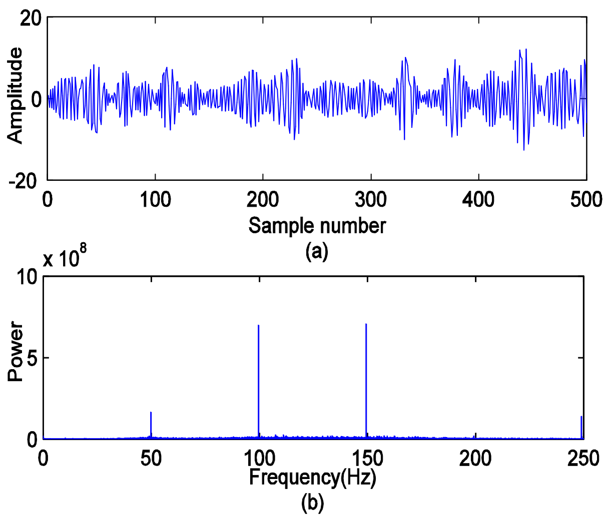

Fig. 4 Dominant frequency analysis of IMF during right hand movement (a) an IMF obtained from a random trail from Cz channel (b) power spectrum of (a).

trial, where N and T are the number of channels and number of measured samples, respectively. The normalized covariance matrix calculated from

$$C = \frac{XX^T}{trace(EE^T)}$$

Where T denotes the transpose operator and $trace(X)$ gives the sum of diagonal elements of X. In this way covariance, matrix C_1 and C_2 of each data trial that belongs to two separate classes of the training set are obtained from normalized covariance matrix.

$$C_c = C_1 + C_2 = F_c \psi F_c^T$$

The matrix P transforms the average covariance based on the simultaneous diagonalization of whitened covariance matrices

$$C_1' = PC_1P^T \text{ and } C_2' = PC_2P^T$$

The eigenvalue decomposition is performed on C_1' and C_2'. The resulting decomposition maximizes the discrimination between two set of data by calculating orthogonal matrix U and diagonal matrix λ, and the sum of corresponding eigenvalues of the two matrices forms an identity matrix I.

$$C_1' = U\lambda_1U^T, C_2' = U\lambda_2U^T \text{ and } \lambda_1 + \lambda_2 = I$$

Now CSP projection matrix will be defines as $W = U^TP$ and we project the EEG signals X as

$$Z = W^TX$$

Every column vector $w_j (j = 1, \dots, N)$ is called a spatial filter. In this study to discernment between two tasks, we only use the row vectors z_1 as the feature vector.

2.5 Support vector machines

Support vector machines (SVMs) were first invented by Vapnik [19] and become a modern machine-learning tool to solve a binary classification problem. The main objective of SVM is to build an optimal separating hyperplane to find a way that the margin of separation between two classes is maximized [20].To build up the SVM based classifiers for linearly separable patterns consider a training set represented by

$$\{(f_i, d_i)\}_{i=1}^N$$

Where f_i is the n dimensional input feature vector and d_i correspond to the target class. The input patterns represented by the target class $d_i = 1$ represent the positive group and the target class $d_i = -1$ represent the negative group. Among so many hyperplanes to separate there will be one optimal separating hyperplane.

The equation of decision surface in the form of the hyperplane is write down as $w \cdot f + b = 0$, where w is the regulating weight vector and b is the bias. A separating hyperplane can be set up for two classes such that $w \cdot f + b \geq +1$ for a positive group of data and $w \cdot f + b \leq -1$for negative group of data. These two equations can be combined [20] as

$$d_i(w \cdot f + b) - 1 \geq 0$$

The distance from starting point to the optimal hyper plane is $(\| b \|)/(\| w \|)$ and $(\| w \|)$ is the Euclidean norm of w. Thus the optimized problem can be stated as [21] for given training samples to be solved to find w and b as follows

$$\text{Min J(w, b, e)} = \frac{1}{2}w^Tw + \frac{1}{2}C\sum_{i=1}^{l} e_i^2$$

subject to the constraints:

$$d_i(w^T\,\phi(f_i) + b) \geq 1 - e_i, \quad e_i \geq 0 \text{ for } i = 1, \dots, l$$

IJCSI International Journal of Computer Science Issues, Volume 16, Issue 1, January 2019
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org https://doi.org/10.5281/zenodo.2588239

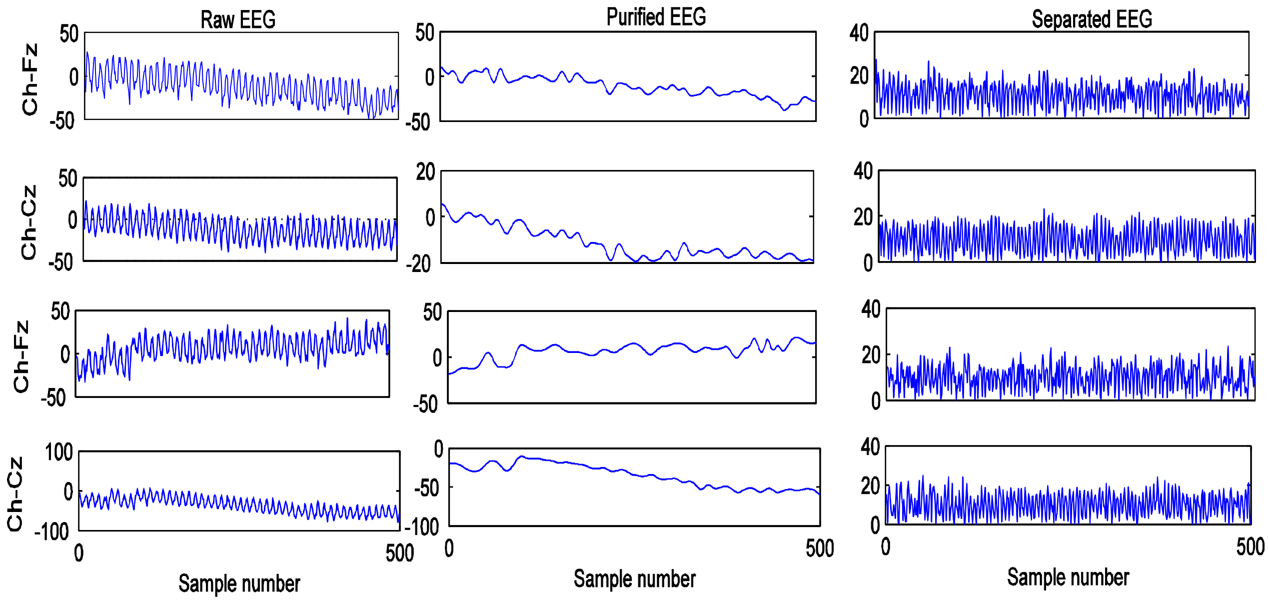

Fig. 5 The separation of pure EEG from raw data using Fz and Cz channel during the left hand and right hand movement. (above two channels for left hand movement and below two channels for right hand movement)

Here C is the regularization parameter, e_i is the classification error variable and J is the cost function. Such a SVM enabled classification using linear decision boundary and is known as a "linear SVM". A nonlinear decision boundary can be created with only a low increase of the classifier's complexity by using the "kernel trick" [22]. In this study we use different kernel named polynomial and radial basis function. These basic kernels are defined as $K(f,f_i) = \phi(f)^T\phi(f_i) = ({f_i}^T f + 1)^n$ (polynomial SVM of degree n); $K(f,f_i) = exp(-\| f - f_i \|^2/2\sigma^2)$ (radial basis function- RBF SVM, where σ is the bandwidth parameter).

3. Results and Discussion

In our study, we have used all trials and account all channels to evaluate the performance of the proposed method. Before applying any method, we make a window with 1s to slice continuously recorded data. To purify the unprocessed EEG we have used EMD to decompose every channel into a set of IMFs. Now dominant frequency was computed for each of the IMFs of the EEG signal corresponding to the left hand and right-hand movement. To obtain enhanced EEG signals corresponding to the left and right-hand task we chose IMFs whose dominant frequency is less than and equal to 30 Hz. It is noted that the cut of frequency with 30Hz is selected using a heuristic search with the different frequency with {10, 15, 20, 25, 30, 35, 40}. Among them, the dominant frequency with 30 Hz shows the best result for this dataset. Now reconstructed signal send to the CSP as a feature extraction method. The extracted features are now used as input features to the SVM classifier for classification of left and right hand movement of the EEG signal. We use a different kernel with SVM to find out which kernel perform better classification exactness. The comparison of classification accuracy using filtered EEG signal and unprocessed EEG signal summarized in Table 1. In this method, k-fold cross validation method is used for evaluation of performance [23]. In k-fold cross-validation, the original sample is randomly divided into k equal sized subsamples. Of the k subsamples, a single subsample is used as the validation data for testing the model, and the remaining $k - 1$ subsamples are used as training data.

Table 1: Comparison of classification accuracy using clean EEG and raw EEG signal.

SVM with different kernel	Accuracy with raw EEG (%)	Accuracy with EMD-DF based filtering (%)
Linear	86.0	92.4
Polynomial	70.4	79.0
RBF	82.6	90.0

Table 1 demonstrated the EEG signal with EMD-DF filtering shows better performance compare to raw EEG by 6.4% for the linear kernel, 8.6% using the polynomial kernel and 7.4% using RBF kernel. It is clear that the classification accuracy using SVM with linear kernel shows the highest accuracy in actual hands movement. To calculate the classification accuracy we have performed 5-fold cross-validation in order to obtain the best possible accuracy by the SVM classifier and all parameters remain same during comparison. The separation result from raw signal to purified EEG signal is shown in Fig. 5. This improved classification makes clear that frequency with no greater than 30 Hz carries very important information related to left hand movement and right hand movement and our proposed method effectively find information from unprocessed data through a noble cleaning approach. The results clearly showed the classification accuracy increase significantly, when we used EMD-DF based filtering with the raw EEG signals.

4. Conclusion

In our paper, we presented a noble features extraction algorithm by means of filtering EEG signal based on empirical mode decomposition (EMD) and dominant frequency (DF) to enhance the performance to classify real left hand and right hand movement. In our proposed method, a combination of IMFs has selected whose dominant frequency is less than and equal to 30 Hz. The classification accuracy of the filtered signal using our method is better than the unfiltered signal by 6.4%, 8.6% and 7.4% with linear, polynomial and RBF kernels of SVM classifier. This classification improvement is archived because of features obtained using CSP are more separable. Therefore, it is clear our EMD-DF based filtering method filter out unnecessary information from the raw EEG signal that is irrelevant to upper limbs movement effectively. Thus, dominant frequency analysis is shown to be useful to identify the EEG patterns correlated to upper limb movement.

Acknowledgments

This work is supported in part by “University Research Grant,” Begum Rokeya University, Rangpur, Bangladesh (budget code: 5921).

References

[1] D. J McFarland and J. R. Wolpaw, “Brain-computer interfaces for communication and control,” Commun.ACM, vol.54, no. 5, pp. 60-66, 2011.

[2] Y. Zhang, P. Xu, T.Liu, J. Hu, R. Zhang, and D. Yao, “Multiple frequencies sequential coding for SSVEP-based brain computer interface,” PLos ONE, vol.7, no.3, Article ID e29519, 2012.

[3] N. Birbaumer, N. Ghanayim, T. Hinterberger et al.,“A spelling device for the paralysed,” Nature, vol. 398, no. 6725, pp. 297–298, 1999.

[4] S. Halder, E. M. Hammer, S. C. Kleih et al., “Prediction of auditory and visual p300 brain-computer interface aptitude,” PLoS ONE, vol. 8, Article IDe53513, 2013.

[5] J. R. Wolpaw and D. J. McFarland, “Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans,” Proceedings of the National Academy of Sciences of the United States of America, vol. 101, no. 51, pp. 17849–17854, 2004.

[6] G. Pfurtscheller, “Functional brain imaging based on ERD/ERS”, Vision Research, vol. 41, no. 10, pp. 1257-1260, 2001.

[7] M. Takahashi, K. Takeda, Y. Otaka, “Event related desynchronization modulated functional electrical stimulation system for stroke rehabilitation: a feasibility study,” Journal of Neuro Engineering and Rehabilitation, vol. 9, pp. 56, 2012.

[8] B. Varkuti, C. Guan, Y. Pan et al., “Resting state changes in functional connectivity correlate with movement recovery for BCI and robot-assisted upper-extremity training after stroke,” Neurorehabilitation and Neural Repair, vol. 27, pp. 53–62, 2013.

[9] S. R. Soekadar, M. Witkowski, J. Mellinger, A. Ramos, N. Birbaumer, and L. G. Cohen, “ERD-based online brain-machine interfaces (BMI) in the context of neurorehabilitation: optimizing BMI learning and performance,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 19, no. 5, pp. 542–549, 2011.

[10] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shin, Q. Zheng, N. C. Yen, C. C. Tung, and H. H. Liu, “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis,” Proceedings of the Royal Society of London: Mathematical, Physical and Engineering Sciences, vol. 454, pp. 903-995, 1998.

[11] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw, "Spatial filter selection for EEG-based communication," Electroencephalography and Clinical Neurophysiology, vol. 103, no. 3, pp. 386–394, 1997.

[12] D. J. McFarland and J. R. Wolpaw, "Sensorimotor rhythm-based brain-computer interface (BCI): model order selection for autoregressive spectral analysis," Journal of Neural Engineering, vol. 5, no. 2, pp. 155–162, 2008.

[13] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and Klaus-robert Muller, "Optimizing spatial filter for robust EEG single-trail analysis," IEEE Signal Processing Magazine, vol. 25, no. 1, pp. 41-56, 2008.

[14] https://sites.google.com/site/projectbci

[15] C. Park, D. Looney, N. Rehman, A. Ahrabian, and D. P. Mandic, "Classification of motor imagery BCI using multivariate empirical mode decomposition," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 21, no. I, pp. 10-22, Jan. 2013.

[16] J. Saiki, T. Koike, and M. DeBrecht, "Ocular artifacts removal from EEG using EMD," in Advances in Cognitive Neurodynamics, ICCN 2007. Springer Netherlands, 2008, pp. 527 - 530.

[17] S. R. H. Davies and C. J. James. " Novel use of empirical mode decomposition in single –train classification of motor imaginary for use in brain-computer interfaces," in 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2013, pp.5610-5613.

[18] H. Ramoser, J. M. Gerking, and G. Pfurtsscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," IEEE Trans. Rehab.Eng., vol. 8, no.4, pp. 441-446,2000.

[19] V. Vapnik, "The nature of statistical learning theory. Springer-Verlag, 1995.

[20] E. Osuna, R. Freund, & F. Girosi, "Training support vector machines: An application to face detection," Proceedings of computer vision and pattern recognition, pp. 130–136, 1997.

[21] G. M Foody, and A. Mathur, "A relative evaluation of multiclass image classification by support vector machines," IEEE Transactions on Geoscience and Remote Sensing, vol. 6, pp.1335–1343, 2004.

[22] S. Haykin, "Neural networks: A comprehensive foundation", 2nd ed., Pearson Education, 1999.

[23] Kohavi, Ron. "A study of cross-validation and bootstrap for accuracy estimation and model selection." In Ijcai, vol. 14, no. 2, pp. 1137-1145. 1995.

Sanjoy Kumar Saha has received his B.Sc.(Hons.) and M.Sc. degree in Computer Science & Engineering from Rajshahi University, Rajshahi, Bangladesh in 2014 and 2015. Currently he works as a lecturer at the dept. of Computer Science & Engineering in Begum Rokeya University, Rangpur, Bangladesh. His major research focuses on the brain computer interfacing, biomedical engineering and digital signals processing.

Sujan Ali completed his B.Sc. and M.Sc. from the department of Electrical & Electronics Engineering, Islamic University, Kushtia, Bangladesh. Currently he is an associate professor of Jatiya Kabi Kazi Nazrul Islam University, Mymensingh, Bangladesh. He is interested in EEG signal processing & digital image processing.

Jannatul Ferdous obtained her B.Sc. and M.Sc. degree in Electrical & Electronics Engineering from Islamic University, Kushtia, Bangladesh. He is a faculty of computer science & engineering, Jatiya Kabi Kazi Nazrul Islam University, Mymensingh, Bangladesh. Her current research interest includes EEG signal processing and digital signal processing.

Somlal Das has earned his B.Sc.(Hons.) and M.Sc. degree in Applied Physics & Electrical Engineering from Rajshahi University. He also received his PhD degree from Rajshahi University. Now he is a professor of Computer Science & Engineering in Rajshahi University. His research interest is digital signal processing.

Sumon Kumar Debnath completed his B.Sc. and M.Sc. degree in Information & Communication Engineering from Rajshahi University, Bangladesh. He obtained his PhD degree from Okayama University, Japan in distributed system design. Now he is a faculty of dept. Electrical & Electronic Engineering, Begum Rokeya University, Bangladesh. His research interests are ad-hoc networks, MIMO and audio signal processing.