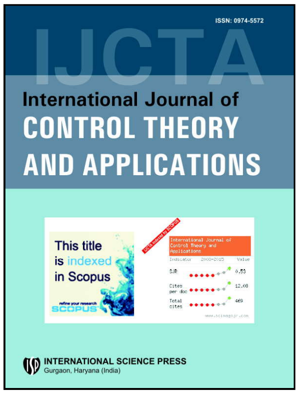

International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 14 • 2017

Dimensionality Reduction for Motor Imagery Signal Classification using Wavelet Analysis

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Abstract: Motor Imagery is a mental practice to recapture network between the mind and the spinal cord, lost due to stoke or any harm in spinal line, which brings about perpetual harm of neural exercises or loss of motion. As indicated by study it is found that there are almost around 1 in 50 individuals living with loss of motion roughly 5.4 million individuals. For this sort of inability Electroencephalography signal based on Brain Computer Interface (BCI) for Motor Imagery of right hand and feet movement imagination is acquired and classified. Haar Wavelet features are extracted comprises of detailed coefficients and approximate coefficient which reduces the dimension of the acquired signal that are then acquainted with number of classifiers. The reduced dimension and classification result have demonstrated the adequacy of proposed technique.

Keywords: Motor Imagery, EEG, DWT, Haar Wavelet

1. INTRODUCTION

Motor Imagery is imagination of movement called motor action without any neuromuscular activity. Thought of movement in brain is intimately linked with action. Different parts of brain are responsible for different movement hence for imagination of particular movement makes that part of brain active [1-2]. Mental rehearsal is done to regain the connectivity lost due to any injury occurred at spinal cord. If damage to spinal cord is less, then simply by mental practice connectivity can be regained but if the patients experiencing more elevated amount harm of spinal cord and are not ready to deliver specific muscle development for which spinal line is influenced. In such illnesses negligible influenced part is sensory area of brain and cognitive function that means sensory part of brain is active but is not able to produce any action. Communication based on Brain Computer Interface (BCI) does not require neuromuscular control hence BCI become medium for communication for disabled people. Due to neuromuscular disorder action can't be performed by patients hence EEG recording during right hand and feet motor imagery can be used as control signals for BCI applications like wheelchair navigation, prosthesis control, control of cursor, etc.

BCI is the interface between brain and the computer, Brain Computer Interface recording there are lots of techniques that can monitor activity of brain like (1) Magneto-encephalography (MEG) (2) Functional magnetic resonance imaging (fMRI) (3) Electro-corticography (ECoG) (4) Electroencephalography (EEG) etc. fMRI, MEG and EEG are non-invasive method where as ECoG is invasive method that means installation of device is done inside the scalp of brain hence it becomes risky. MEG is more accurate as it records the tiny signal generated from brain, for recording MEG requires magnetic shield room hence becomes costly to install MEG for brain signal recording [4-5]. fMRI is not portable device due to the huge size of device [6]. EEG, on other hand non-invasive, portable, cost efficient, and accurate, so for interfacing with brain we are using Electroencephalograph.

When subject performs or imagines movement, motor cortex area of brain and specific frequency components of EEG changes. Mu and beta rhythms 8-12 Hz and 18-25 Hz respectively in EEG recorded from sensorimotor cortex of brain are used as control signal for BCI. Frequency change due to Event-related desynchronization (ERD) and Event-related synchronization (ERS) as both occurs simultaneously as both phenomena are time locked and are responsible for the signals obtained from EEG [3][7].

Quantitative changes in EEG due to imagination of movement are extracted from different electrodes placed at different position on scalp of brain. Recorded signals are large in size because of recording of all the signals which may not be useful for particular movement imagination, huge measure of data may influence the execution precision subsequently just helpful elements are extracted which brings about better exactness and also takes care of the issue of capacity and treatment of expansive data by decreasing the dimension of data. Extracted features are then classified to train the system [8].

For extraction of features number of methods are there (1) Fast Fourier Transform (FFT), Fourier transform is done at infinite time and as EEG signals are non stationary so FFT will not able to give better result. And also in FFT frequency and time information cannot be seen at a same time it only uses frequency information of signal hence not suitable for EEG signals. (2) Time-frequency analysis, TF is useful for oscillatory EEG component during Motor Imagery but only oscillatory information of EEG component is not sufficient for better classification. (3) Short Time Fourier Transform (STFT), for analysis of only small section at a time a technique known as "windowing of signal" is used, in this particular segment of signal is assumed to be stationary. The unchanged size of window and dilemma of resolution, like for narrow, window frequency resolution will be poor and for wide window, time resolution will be poor become drawback in using STFT for EEG feature extraction. (4) Wavelet analysis, wavelet analysis is the advanced form of STFT to overcome the resolution problem. EEG signals are non stationary so by use of Fourier Transform, small changes may not be notice. So for spectral analysis, Wavelet Transform is more suitable than Fourier Transform. And also wavelet gives 3D representation of signal as amplitude, frequency and time [9-11].

Wavelet transform provides different levels of decomposition. The basic principle of wavelet transform is described in the third part of proposed algorithm. Section II explains the methodology, the dataset used and the feature extraction technique. Experiment results in Section III and concluding remarks are in section IV.

2. MATERIAL AND METHODS

2.1. Methodology

For signal acquisition from EEG we have taken data from BNCI 2020 Horizon. Preprocessed with a 8^{th} order Butterworth Band-pass-filters to remove noises generated with signal [12]. The obtained data is of very large size of approx 5 to 6 GB. Processing with large data slow down the processor hence speed reduces, and existence of un useful data affects accuracy.

The acquired data consist of 14 participant data out of which in our experiment we are considering 4 subjects data. Each subject is considered as one session and each session divided into training and testing set. In

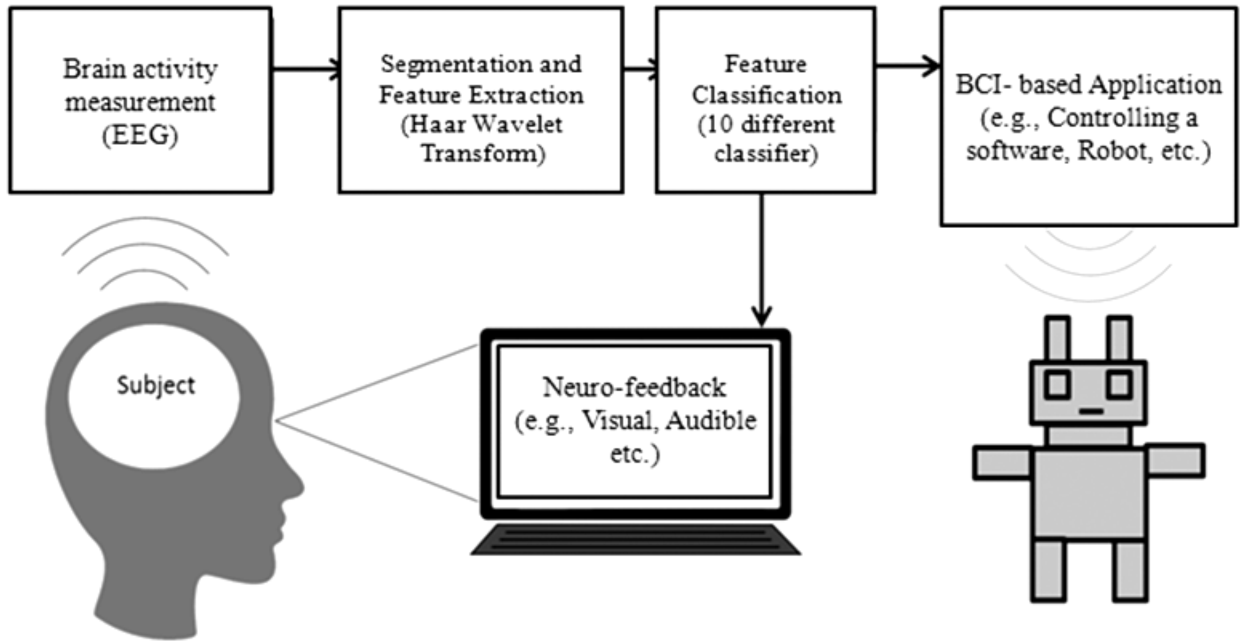

Figure 1: Work flow diagram for EEG based BCI for Motor Imagery

each session 8 runs of 20 trials each is considered so 5 runs for training and 3 for testing. There are two classes, one for right hand movement and other for feet. Class label is given to each trial based on task performed.

Taking 1st run of 1st session of training set of subject one, there are approx 1,12,000 instances and 15 attributes from 15 electrode positioned according to 10/20 system of EEG. From 15 attributes as mentioned in figure 2 only center electrode C3, Cz and C4 are responsible for Motor Imagery so only 5, 8 and 11 coloum are taken then each electrode coloum instances is segmented into 20 parts and labeled as per class is defined. 5 level Haar Wavelet technique we are using for extracting the feature. The extracted feature are then applied to 20 different classifiers to check the classification accuracy and true positive (TP) and false positive (FP).

2.2. Dataset

Data of EEG signal has been taken from BNCI 2020 Horizon. The cue-guided Graz-BCI training based paradigm used [1]. Hence within single session recording, training, and feedback was performed. Each session compromises

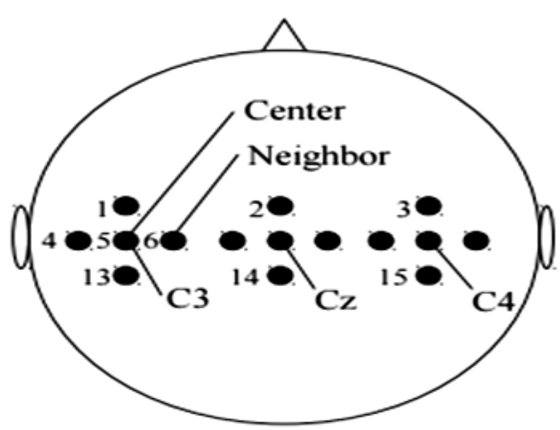

Figure 2: EEG positioning of 15 electrode in 10/20 system

of eight runs, out of which five for training and three with feedback for validation. Each run composed of 20 trials. So together, recorded 50 trials per class for training and 30 trials per class for validation. As instructed by the cue, participants had the task of performing sustained 5 second kinesthetic motor imagery. EEG signal was measured with a bio signal amplifier and active Ag/AgCl electrodes at 512 Hz of sampling rate. C3, Cz, C4 and four additional electrodes around each center electrode at distance 2.5 cm positioned at center, 15 electrodes total taken. On left mastoid reference electrode mounted and on right mastoid ground electrode mounted. The 14 participants were aged between 20 and 30 years, 8 naïve to the task, and no medical or neurological diseases [13]. The arrangement of 10/20 system electrode positioning is shown in figure [25].

2.3. Feature Extraction

There are many techniques for feature extraction [24] we are using wavelet analysis because of the drawback found in other methods mentioned above at introduction. For time-frequency analysis of signal, local information is required and this is major drawback of Fourier Transform. Fourier Transform of a signal does not contain any local information. To overcome this drawback windowed-Fourier transform, i.e. STFT used but this also limit with window size. Hence we are using Wavelet analysis for extracting features. Mathematical expression for Fourier Transform [20] is given as

$$X(F) = \int_{-\infty}^{\infty} x(t) e^{-j2\Pi Ft} dt \tag{1}$$

Where, X(F) = Fourier transform of signal x(t)

x(t) = Signal in time domain

Here x(t) defines the original signal. Original signal gets multiplied with each and every point of other signal and added at last to get new result. Where as in wavelet transform original signal x(t) get convolved with mother wavelet. Mathematical expression for wavelet transform is given as

$$X(a,b) = \int_{-\infty}^{\infty} x(t) \quad \varphi_{a,b}^{*}(t) dt \tag{2}$$

Where, a = Scaling factor

b = Shifting factor

φ(a, b) = Scaling and shifting respectively of mother wavelet

Mother wavelet performs two functions

(1) Scaling that is shrinking or expansion with factor s.

φ(t/s); s>0

(2) Translation or shifting of mother wavelet with factor k.

φ(t-k); k is any integer or fraction

2.4. Wavelet Analysis

2.4.1. Mother Wavelet

Wavelet is oscillation wave in which amplitude that begins at zero, increases and then back to zero. This finite signal is known as mother wavelet [22]. Mother wavelet can be combined, using a shift, multiply and reverse

Figure 3: Stretched and compressed versions of mother wavelet

Figure 4: EEG time domain signal convolved with mother wavelet

technique called convolution. Mother wavelet get convolved with original signal and decompose into described 5 level decomposition Wavelet Transform are a type of multi-resolution analysis that provide better resolution at lower frequency range, this makes it applicable for EEG signals. Mother wavelet can be of different types like Daubechie (Db5), Gaussian, Haar etc. we are using Haar Wavelet decomposition.

2.4.2. Haar Wavelet Decomposition

Haar Wavelet is an arrangement of rescaled square-shaped functions. It is the type of mother wavelet used to convolve with the original signal to get the scaled and shifted output of the input signal. Result obtained using Haar wavelet analysis is simpler and more precise than other mother wavelet-like Gaussian, Db5 and so on because oscillating signal may or may not convolve with all the essential signal whereas the Haar wavelets is a unit step work henceforth less demanding convolved with more effective outcome. The mathematical expression for Haar wavelet function φ(t) can be described as

$$\varphi(t) = \begin{cases} 1 & 0 \le t < 1/2 \\ -1 & 1/2 \le t < 1 \\ 0 & otherwise \end{cases} \tag{3}$$

Haar wavelet [19] is a simple and efficient algorithm to calculate wavelet transform. As there is no need of multiplications, it requires only additions and there are many elements with zero value in the Haar matrix, so the computation time will be short [15-16] .

In figure 5 D1, D2,…. Dn represent the detail coefficient of Haar wavelet transform and and last one approximate coefficient is obtained. This procedure is carried out for each trial of each session. Scaling factor of Haar Wavelet can be done as (1) Low-frequency scale that is High scale, in this expansion occures hence length

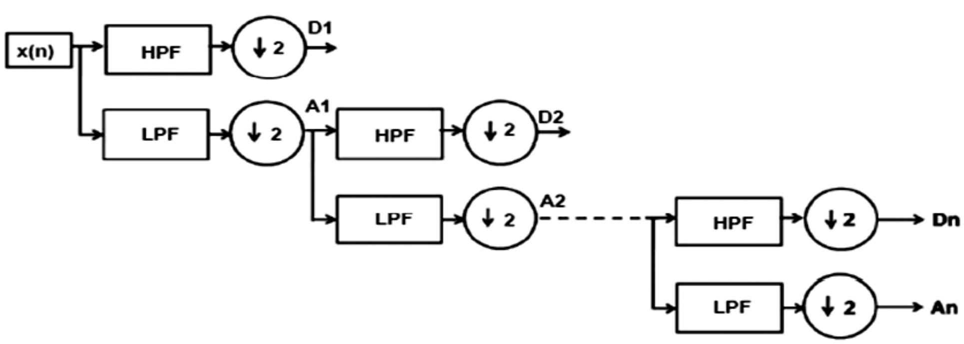

Figure 5: n level Haar Wavelet decomposition

of wavelet increses so becomes less accurate to determine time at particular low frequency curve and some of the coefficient higher then prescribes frequency may not be taken under consideration. Second (2) High-frequency scale that is Low scale, in this compression of signal occures results in better localization in time because they are shorter hence mother wavelet convolved very accurately. In our experiment we are using 5 level signal decomposition because EEG signals do not have any useful frequency components above 30 Hz, the number of level chosen accordingly. Thus we decomposed into D1 to D5 detailed coefficient and one final approximation, A5. The obtained coeffecients are used for further process. Hence the high dimension data has been reduced to very small size of data giving complete information required for post processing that is for classification [23].

3. EXPERIMENT AND RESULT

For evaluation of EEG signal for Motor Imagery, raw data from BNCI Horizon 2020 has been taken. Data consist of signal acquired from 14 subjects from 15 electrodes, situated at better place as indicated by 10/20

	C3						CLASS
	Ea	Ed1	Ed2	Ed3	Ed4	Ed5	1 or 2
S01E.1.P1	71.7482	5.7505	5.7673	4.1098	5.676	6.9482	1
S01E.1.P2	78.525	4.7383	4.6699	3.1257	3.807	5.134	1
S01E.1.P3	76.9142	4.8396	5.2181	3.3337	3.6993	5.995	2
S01E.1.P4	73.867	6.4397	5.7729	3.8522	4.6089	5.4594	1
S01E.1.P5	80.7456	4.1347	4.3376	2.6781	3.0228	5.0813	1
S01E.1.P6	75.3473	5.7417	5.3033	3.4044	4.5442	5.6592	2
S01E.1.P7	75.977	5.4749	5.077	3.363	4.2827	5.8254	1
S01E.1.P8	75.0597	5.4619	5.3825	3.4536	4.7501	5.8921	1
S01E.1.P9	80.8796	3.4061	3.5585	2.4345	3.6433	6.0779	1
S01E.1.P10	79.704	4.1364	4.1158	2.7925	3.8229	5.4285	1
S01E.1.P11	82.4398	3.3806	3.0983	2.6432	3.5186	4.9196	2
S01E.1.P12	81.7574	3.3114	3.602	2.745	3.4058	5.1784	2
S01E.1.P13	75.6752	3.9784	4.3725	3.3143	4.5083	8.1513	2
S01E.1.P14	74.3771	3.8778	4.112	3.8949	5.3896	8.3486	2
S01E.1.P15	74.5728	6.0519	5.986	3.8535	4.7317	4.804	2
S01E.1.P16	77.7236	3.1606	3.1566	3.0069	5.6211	7.3312	1
S01E.1.P17	76.6357	3.4928	3.8437	3.2654	5.3446	7.4179	2
S01E.1.P18	82.2982	3.4948	3.2608	2.2329	3.1569	5.5563	2
S01E.1.P19	72.8785	5.3559	5.2061	3.2056	5.0013	8.3526	1
S01E.1.P20	74.0427	4.5545	4.7036	3.1738	5.0807	8.4447	2

(a)

framework in external scalp of brain of every subject. In our experiment we are managing qualities obtained from three capable channels that is C3, Cz and C4 of 4 distinct subjects. C3 and C4 are the central lobes and responsible for signal for left hemisphere and right hemisphere respectively. The acquired signals from 4 subjects are in terms of volt. The span of occurrences acquired from previously mentioned directs are vast in size approx 112640x15. In this, row shows the number of instances of one channel of one subject and column shows number of electrode, from where signals have been procured. As acquired information is huge so data segmentation has been done. For data segmentation we have break the instances into 20 trials and each trials comprises of approx size of 5632x15 and accordingly class labels has been defined. Matlab R2014a software platform is used for data segmentation as well as for extracting feature using Haar Discrete Wavelet Transform method. 5 level detail coefficients Ed1, Ed2, Ed3, Ed4 and Ed5 and one approximate coefficient Ea for each trial of each run has been obtained after that extracted features are introduced to different classifiers. For classification Weka software platform is used.

The experiment has been performed on four subjects of BNCI Horizon 2020 hence classification results are also obtained from four subjects. 60% training set and 40% testing set for classification.

	Cz						CLASS
	Ea	Ed1	Ed2	Ed3	Ed4	Ed5	1 or 2
S01E.1.P1	74.232	3.9612	4.2031	3.629	5.6487	8.326	1
S01E.1.P2	78.41	3.9762	3.883	3.4884	4.4084	5.8338	1
S01E.1.P3	78.891	3.4644	4.1626	3.1377	4.1023	6.2416	2
S01E.1.P4	73.287	4.8472	4.7544	4.0954	6.0756	6.94	1
S01E.1.P5	78.078	4.0133	4.4931	3.2599	4.2501	5.9055	1
S01E.1.P6	76.42	4.2521	4.381	3.4055	4.3887	7.1528	2
S01E.1.P7	75.453	4.6426	4.5031	3.5737	5.2398	6.5882	1
S01E.1.P8	75.756	4.2974	4.3859	3.3136	5.1195	7.1278	1
S01E.1.P9	78.255	3.2698	3.523	2.8069	4.2872	7.8577	1
S01E.1.P10	74.66	4.2218	4.5056	3.5704	5.7457	7.296	1
S01E.1.P11	79.454	3.2512	3.3358	3.062	4.9855	5.9116	2
S01E.1.P12	79.7	2.7645	3.1262	3.0232	4.6199	6.7664	2
S01E.1.P13	76.795	2.876	3.5282	3.2911	5.091	8.4184	2
S01E.1.P14	74.958	3.1152	3.379	4.1432	6.1557	8.2488	2
S01E.1.P15	75.088	4.4473	5.1307	3.9249	5.3673	6.0415	2
S01E.1.P16	77.566	2.4083	2.6353	3.1321	5.9886	8.2693	1
S01E.1.P17	76.691	2.8157	3.3488	3.4655	6.4505	7.2283	2
S01E.1.P18	83.087	2.6008	2.6493	2.322	3.5766	5.7645	2
S01E.1.P19	74.85	3.9246	4.243	3.5195	5.5745	7.8886	1
S01E.1.P20	74.229	3.476	4.0698	3.3872	5.7718	9.0667	2

(b)

	C4						CLASS
	Ea	Ed1	Ed2	Ed3	Ed4	Ed5	1 or 2
S01E.1.P1	68.311	5.7248	6.008	4.6221	6.0442	9.2901	1
S01E.1.P2	74.543	5.1264	5.0641	4.0785	5.2301	5.9582	1
S01E.1.P3	73.838	4.9463	5.8083	4.1289	5.1411	6.1373	2
S01E.1.P4	70.742	6.627	6.1161	4.5064	5.4629	6.5459	1
S01E.1.P5	71.411	5.7213	6.4263	4.5703	4.8313	7.0399	1
S01E.1.P6	70.639	5.9185	5.8613	4.2575	5.2309	8.0924	2
S01E.1.P7	72.912	6.0746	5.8218	4.2546	4.6969	6.2398	1
S01E.1.P8	71.697	5.5572	5.4296	4.0165	5.7341	7.5656	1
S01E.1.P9	69.924	5.1719	5.1972	4.0956	5.6223	9.989	1
S01E.1.P10	69.753	5.6679	5.8097	4.6613	6.1048	8.0038	1
S01E.1.P11	73.566	4.9812	4.931	3.9995	5.7062	6.8161	2
S01E.1.P12	75.991	3.6569	4.1451	3.2796	5.3427	7.585	2
S01E.1.P13	74.844	3.9132	4.4945	3.6603	5.1899	7.8977	2
S01E.1.P14	71.477	4.3661	4.5541	4.4844	6.2423	8.8765	2
S01E.1.P15	70.145	5.8244	7.0664	4.268	6.1785	6.5176	2
S01E.1.P16	76.356	3.1227	3.4227	3.2944	6.0126	7.7914	1
S01E.1.P17	72.698	3.7877	4.3376	4.0243	6.7756	8.377	2
S01E.1.P18	82.893	3.1864	3.067	2.3275	3.3773	5.1487	2
S01E.1.P19	74.235	4.949	5.0174	3.3346	5.3998	7.0647	1
S01E.1.P20	72.088	4.3942	4.8574	3.779	5.9789	8.9025	2

(c)

Table 1: 5 level Haar Wavelet feature extraction of channel (a)C3, (b) Cz and (c) C4 of test set 1 of subject 1 for each trial and corresponding class lables

Above indicated table gives the 5 level extracted feature of channel C3, Cz and C4 of trial 1, here S01E.1.P1 indicates part 1 of trial 1 of testing set of subject 1 same for every one of the 20 trials. The class label 1 and 2 indicates right hand movement and feet respectively. For all subjects channel C3,Cz and C4 likewise same wavelet components are extricated and afterward all subjects are independently acquainted with various classifiers. The input to the classifier are reduced as useful data obtained from original data hence response of classifier increased. The classifier which gives best result are shown in below tables.

Table 2
Classification result along with true positive and false positive of subject 1 and subject 2 using 10 different classifier

	Subject 1				*Subject 2*			
Classifier	*Accuracy*	*Class*	*TP*	*FP*	*Accuracy*	*Class*	*TP*	*FP*
Naïve Bayes	48.4375	1	0.323	0.364	71.875	1	0.657	0.207
		2	0.636	0.677		2	0.793	0.343
Naïve Bayes Multinomial	45.3125	1	0.452	0.545	71.875	1	0.657	0.207
		2	0.455	0.548		2	0.793	0.343

(*contd...Table 2*)

	Subject 1				*Subject 2*			
Classifier	*Accuracy*	*Class*	*TP*	*FP*	*Accuracy*	*Class*	*TP*	*FP*
Naïve Bayes Updateable	48.4375	1	0.323	0.364	71.875	1	0.657	0.207
		2	0.636	0.677		2	0.793	0.343
Multilayer Perceptron	48.4379	1	0.710	0.727	56.25	1	0.457	0.310
		2	0.273	0.290		2	0.690	0.543
LWL Classifier	56.25	1	0.710	0.576	53.125	1	0.857	0.862
		2	0.424	0.290		2	0.138	0.143
Iterative Classifier Optimizer	42.1879	1	0.710	0.848	62.5	1	0.943	0.759
		2	0.152	0.290		2	0.241	0.057
Randomizable Filtered Classifier	53.125	1	0.452	0.394	50	1	0.400	0.379
		2	0.626	0.548		2	0.621	0.600
Hoeffding Tree	48.4379	1	1.000	1.000	71.875	1	0.657	0.207
		2	0.000	0.000		2	0.793	0.343
LMT Classifier	48.4379	1	1.000	1.000	59.375	1	0.400	0.172
		2	0.000	0.000		2	0.828	0.600
Random Forest	42.1879	1	0.452	0.606	54.6879	1	0.543	0.448
		2	0.394	0.548		2	0.552	0.457

Table 3
Classification result along with true positive and false positive of subject 3 and subject 4 using 10 different classifier

	Subject 3				*Subject 4*			
Classifier	*Accuracy*	*Class*	*TP*	*FP*	*Accuracy*	*Class*	*TP*	*FP*
Naïve Bayes	48.4375	1	0.848	0.903	51.5625	1	0.296	0.324
		2	0.097	0.152		2	0.676	0.704
Naïve Bayes Multinomial	56.25	1	0.758	0.645	46.875	1	0.556	0.595
		2	0.355	0.242		2	0.405	0.444
Naïve Bayes Updateable	48.4375	1	0.848	0.903	51.5625	1	0.296	0.324
		2	0.097	0.152		2	0.676	0.704
Multilayer Perceptron	54.6875	1	0.697	0.613	56.25	1	0.556	0.432
		2	0.387	0.303		2	0.568	0.444
LWL Classifier	48.4379	1	0.212	0.226	37.5	1	0.815	0.946
		2	0.774	0.788		2	0.054	0.185
Iterative Classifier Optimizer	51.5625	1	1.000	1.000	42.1875	1	1.000	1.000
		2	0.000	0.000		2	0.000	0.000
Randomizable Filtered Classifier	50	1	0.545	0.548	46.875	1	0.593	0.622
		2	0.452	0.455		2	0.378	0.407
Hoeffding Tree	48.4375	1	0.848	0.903	51.5625	1	0.296	0.324
		2	0.097	0.152		2	0.676	0.704
LMT Classifier	54.6875	1	0.394	0.290	43.75	1	0.630	0.703
		2	0.710	0.606		2	0.297	0.370
Random Forest	51.5625	1	0.576	0.548	35.9375	1	0.481	0.730
		2	0.452	0.424		2	0.270	0.519

For one run of one subject 112640x15 size of information was there and has been diminished to 20 × 18 size of information and one coloum for class mark. So altogether for one subject there is 8 run of information subsequently approx size of information was 901120 × 15 and is diminished to 160 × 18 and individual class marks. For every single other subject likewise same way information has been lessened and connected to classifier. The better classifiying classifier are appeared in above Table 2 for subject 1 and subject 2 and Table 3 for subject 3 and subject 4.

Above Figure 6 demonstrates the comparison of the 4 subjects as for exactness. Precision demonstrates the right reaction for specific errand given to the members.

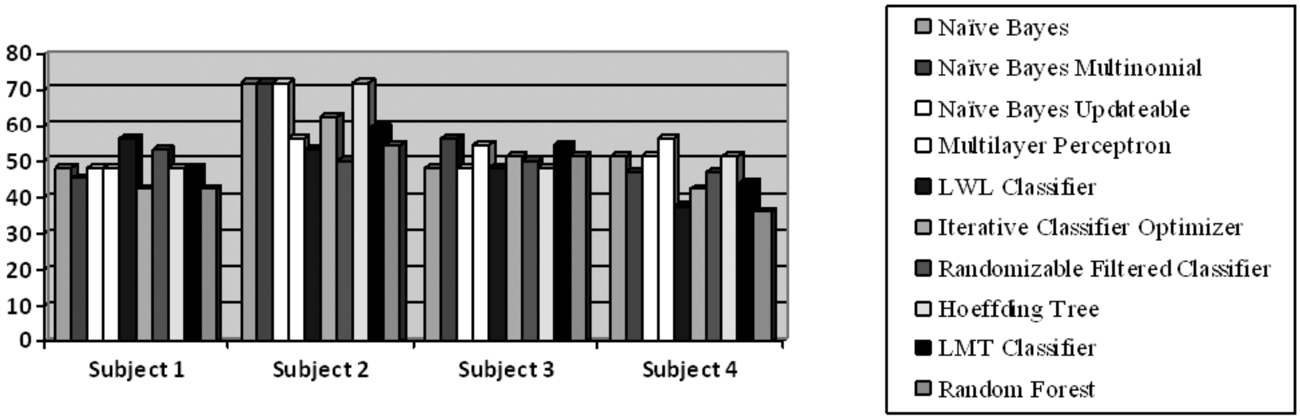

Figure 6: Classification accuracy of 4 different subject with 10 different classifier

Table 4
Experiment Result

Subject	*Classifier*	*Accuracy*
Subject 1	LWL Classifier	56.25
Subject 2	Naïve Bayes	71.875
Subject 3	Naïve Bayes Multinomial	56.25
Subject 4	Multilayer Perceptron	56.25

Table 4 Show the maximum accuracy of all the signals of four different subjects applied at 20 different classifier. The better accuracy is obtained from LWL of lazy classifier for subject 1, Naïve Bayes of Bayes classifier for subject 2, Naïve Bayes Multinomial of Bayes classifier for subject 3, and Multilayer perceptron of function classifier for subject 4. Hence the classification accuracy obtained, using small size of data having complete required information of Motor Imagery signals. Two class data has been used, class label 1 and 2 for right hand and foot movement respectively. The above result table shows the accuracy, that means correctly classified signal according to class label. The problem of dealing with large size of data has been solved by reducing the dimension hence response of system also increased as size of data is reduced.

4. CONCLUSION

Dimensionality lessening with most extreme precision was the goal of research. For achieving this we have gone through various classification techniques and studied various features that can be useful in achieving better accuracy. We obtained better outcome from wavelet decomposition technique of feature extraction and hence the dimension of the signal also has been diminished from approx 5 GB data to very few KB of data with better precision additionally acquired. In future work center will be given for addition of signal accuracy while adding some more features to the signal.

ACKNOWLEDGMENT

This work was supported by a grant from the National Institute of Technology Raipur. The authors acknowledge the Head of Department Information Technology National Institute of Technology Raipur. The authors also acknowledge the constructive criticisms by several anonymous reviewers of an earlier draft of this paper.

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