Motor imagery BCI classification based on novel two-dimensional modelling in empirical wavelet transform

Muhammad Tariq Sadiq[✉], Xiaojun Yu, Zhaohui Yuan and Muhammad Zulkifal Aziz

Brain complexity and non-stationary nature of electroencephalography (EEG) signal make considerable challenges for the accurate identification of different motor-imagery (MI) tasks in brain–computer interface (BCI). In the proposed Letter, a novel framework is proposed for the automated accurate classification of MI tasks. First, raw EEG signals are denoised with multiscale principal component analysis. Secondly, denoised signals are decomposed by empirical wavelet transform into different modes. Thirdly, the two-dimensional (2D) modelling of modes is introduced to identify the variations of different signals. Fourthly, a single geometrical feature name as, a summation of distance from each point relative to a coordinate centre is extracted from 2D modelling of modes. Finally, the extracted feature vectors are provided to the feedforward neural network and cascade forward neural networks for classification check. The proposed study achieved 95.3% of total classification accuracy with 100% outcome for subject with very small training samples, which is outperforming existing methods on the same database.

Introduction: Brain–computer interface (BCI) platform has many functions, and it can allow individuals with disabilities to integrate with the physical world by imagination simply. It picks up the brain impulses generated from the cognitive processes and afterwards transforms them through non-muscular channels to produce an output for specific purposes [1]. Motor imagery (MI) is the major neurological audition used for the BCI systems, in which attendees are oriented to envision executing a complex motor initiative, including the trying to move a foot or hand, but with no muscle strength. BCIs focusing on user MI have received intensive significant attention over the past few years, and MI-based electroencephalography (EEG) signal analysis has become the most extensively used technology because of its relatively inexpensive configuration, ease of use, and fairly innocuous essence [2].

To capture the MI information and categorisation is a crucial stage in the formation of BCI so accurate categorisation of MI task is a key challenge. An EEG-based computer-aided MI BCI system consists of pre-processing of raw EEG signals, feature extraction and identification of respective tasks. In the literature [3], numerous linear extraction techniques for features are designs that lack the inherent complexities of EEG signals present due to dynamic characteristics, and so many other methods [4–6] executed many experiments to take the best features which are time consuming and hinder their feasibility for real-world applications.

To resolve these deficits, we introduced a novel feature extraction scheme focused on two-dimensional (2D) modelling of modes acquired with the empirical wavelet transform (EWT). The concept of proposed 2D modelling is the transformation of the characteristics of a time series into the topology of a geometric object enclosed in a space wherein chaotic behaviour and dynamics of the system are represented. With the emergence of event-related desynchronisation (ERD) and event-related synchronisation (ERS), the path of EEG attractors changes so the extracted features in 2D modelling contain more information related to the MI instead of raw EEG signal. With this motivation, we extracted a geometrical feature known as a summation of distance from each point relative to the coordinate centre (SDTC) and input to two neural networks for the classification. In compliance with our best understanding, this is the first research that developed a new 2D modelling of modes with the aid of the EWT. The suggested approach is built to achieve higher accuracy by using a single feature and reduce computational cost rather than taking into account a wide number of features.

Methodology: The proposed framework consists of several sub-blocks such as noise removal and channel selection, modes extraction, 2D modelling of modes, geometrical feature extraction, and classification, as shown in Fig. 1. The detail of sub-blocks are given as follows.

Noise removal and channel selection: For experimentation, we utilised public available data set IVa from BCI competition III available at (http://www.bbci.de/competition/iii/http://www.bbci.de/competition/iii/). In this data set, five participants 'AA', 'AL', 'AV', 'AW' and 'AY' contain different training and testing samples, and data is recorded with 118 electrodes placed according to the 10–20 standard placement on the scalp of each participant. There are a total of 280 trials for the right hand (RH, class 1) and right foot (RF, class 2) movements, and each trial was recorded for 3.5 s with a sampling frequency of 100 Hz [7].

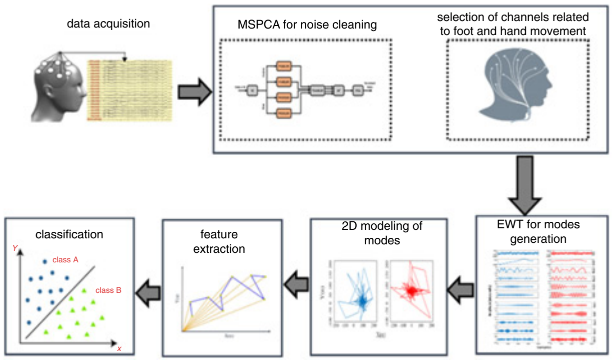

Fig. 1 *Proposed methodology for the classification of MI EEG signals*

We considered labelled data only and each signal length was taken as 400 samples. We utilised C_3, C_Z, and C_4 channels out of a total of 118 channels as these three channels acquired maximum information related to the hand and foot movements. The multiscale principal component analysis (MSPCA) was implemented for the noise removal, where wavelet levels were chosen empirically as 5, and Kaiser rule was employed for the selection of principal components [1].

Modes extraction with EWT: To capture the MI information from non-stationary nature of EEG signals, we used EWT by implementing the following steps [6]:

- Each signal frequency spectra (0 to π) was obtained by using a fast Fourier transform.
- The boundary detection method was implemented to acquire segments of the Fourier spectrum.
- Empirical wavelets were introduced as band-pass filters to all spectrum segmentations. The concept of Meyer's wavelets and Littlewood–Paley theory was used for such purpose in this Letter.

By using the aforementioned procedure, we extracted ten modes from each EEG signal as we found in our earlier work [6] that these modes attain sufficient MI information.

2D modelling of modes: For the illustration of the proposed 2D modelling, consider $s(n)$ represents an EEG signal with n samples such as $s(n) = \{s_1, s_2, \ldots, s_n\}$. The square of the $s(n)$ is computed as $s^2(n) = \{s_1^2, s_2^2, \ldots, s_n^2\}$. A 2D illustration $S(n)$ for $s^2(n)$ can be define as

$$S(n) = \left[s^2(n) - M, (-M)^n\right] = \left[S_n^x, S_n^y\right] \tag{1}$$

where M represents the mean value of $s^2(n)$, S_n^x and S_n^y indicate the x and y coordinates of the n_{th} point of $S(n)$, respectively. As an example, the 2D plot of a mode is shown in Fig. 2. Let $A(n)$ is a sequence for consequence angles between three successive points of $S(n)$ and formulated as

$$A(n) = \frac{\left(S_{n+1}^x - S_n^x\right)\left(S_{n+2}^x - S_{n+1}^x\right) + \left(S_{n+1}^y - S_n^y\right)\left(S_{n+2}^y - S_{n+1}^y\right)}{\sqrt{\left(S_{n+1}^x - S_n^x\right)^2 + \left(S_{n+1}^y - S_n^y\right)^2} + \sqrt{\left(S_{n+2}^x - S_{n+1}^x\right)^2 + \left(S_{n+2}^y - S_{n+1}^y\right)^2}} \tag{2}$$

The quantification of variation of the input signal is measured as follows:

$$D(n) = diff\left(s^2(n)\right) = \left[s_{n+1}^2 - s_n^2\right] \tag{3}$$

Finally, the input signal $s(n)$ in 2D is plotted by using the following formulation:

$$2D(n) = [X(n), Y(n)] \tag{4}$$

where $X(n)$ and $Y(n)$ can be defined by angles $A(n)$ and distances $D(n)$ as follows:

$$X(n) = D(n) \times \cos(A(n)) \tag{5}$$

$$Y(n) = D(n) \times \sin(A(n)) \tag{6}$$

Feature extraction: Fig. 2 represents a typical pattern of 2D plot of single mode for RH (blue colour) and RF (red colour) classes. It is notice that the distance of each point to coordinate centre shows a significant difference among both classes. Considering this motivation in mind, we computed the summation of distance from each point relative to the coordinate centre (SDTC) as a feature. Fig. 3 displays the SDTC as a feature, which is defined as follows:

$$\text{SDTC} = \sum_{n=1}^{m} \sqrt{X(n)^2 + Y(n)^2} \tag{7}$$

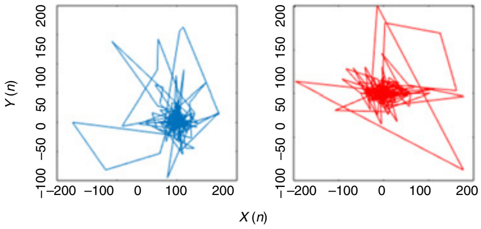

Fig. 2 *2D plot of mode, the blue colour represents the RH class where RF class is denoted with red colour*

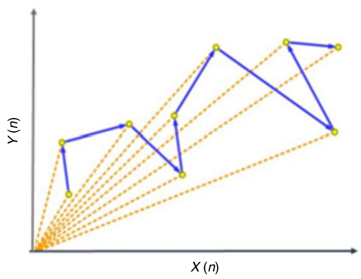

Fig. 3 *Graphical representation of SDTC feature*

Classification: For the classification of RH and RF class features, we implemented cascade forward neural network (CFNN) and feedforward neural network (FFNN) as classifiers. In this Letter, we use the tan-sigmoid transfer function, single hidden layer with empirically chosen ten neurons and Levenberg–Marquardt algorithm for fast training.

Performance evaluation: The efficacy of the proposed methodology is measured with many performance evaluation parameters like accuracy, sensitivity, specificity, precision, recall, F1 score and kappa value.

Results and discussions: The proposed strategy is experimented on dataset IVa and only trials with class labels were chosen from five subjects. For each subject, experiments were performed individually. From each subject, we selected 400 samples from each EEG trial and only 3 channels out of total 118 to acquire MI information only. The MSPCA applied on each trial samples to obtain clean signals and 2D modelling were implemented on modes acquired with the EWT. The 2D plot of each mode showed significant variation among different classes and represented a geometric pattern thus we extracted one geometric feature define earlier as SDTC. We selected 10 modes of each channel empirically and in total we have 30 modes (10 modes× 3 channels) for each class. Since we extracted only one feature from each mode, so, in total we have 30 feature vectors of every class. Figs. 4*a* and *b* show the probability (p) values of extracted feature vectors (lower p values represent the statistical significance of feature), and mean with standard deviation among different classes, respectively.

Based on the statistical significance of the feature parameters, we fed these features as an input to the CFNN and FFNN, and utilised ten-fold cross-validation method for several performance measures. Figs. 5*a* and *b* show each subject and average results of CFNN and FFNN classifiers, respectively. It is noted in Fig. 5*a*, the average accuracy, sensitivity, and specificity of 95.3, 95.2, and 96% is achieved with the CFNN where subjects 'AA', 'AL', and 'AY' yield 99.4, 98.7, and 100% classification output. Similarly, the sensitivity and specificity results for these subjects are remarkable. These outcomes indicate that the proposed method provides the effective results for subjects ('AA' and 'AL') with sufficient training samples and achieved 100% outcome for subject ('AY') with very small training samples. It is noted that the proposed method is fairly stable in the detection of RH and RF classes as the difference between sensitivity and specificity is very less. Similar behaviour is observed with FFNN and difference of results with CFNN and FFNN is not much different as shown in Fig. 5*b*. The kappa value for CFNN and FFNN is 95.5 and 94.3% representing the un-biased nature of classifiers in detection of both classes.

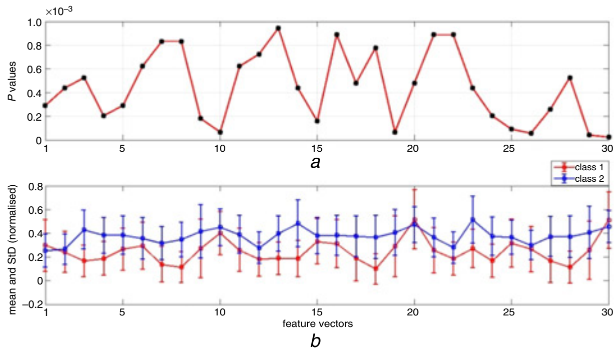

Fig. 4 *Statistical significance of extracted features.*

a P values of features

b Mean and standard deviation among RH and RF class features

Fig. 5 *Classification performance of each and overall subjects with ten-fold cross-validation by employing*

a CFNN

b FFNN

The execution time is an integral part for the design of real-time BCI application, thus we provide the training and testing time of the proposed design. As shown in Fig. 6, the proposed method provide training time (which is collected by considering all trials) in Fig. 6*a* and testing time for single trial is shown in Fig. 6*b*. As notice, the proposed system testing time for single trial is less than 1 s which indicate that the system is perfect candidate for real-time applications.

In the end, we compared the proposed study with other suggested studies experimented on dataset IVa. As shown in Table 1 we mention the classification accuracy of each subject as well as total classification accuracy obtained by all subjects. The highest scores are highlighted in bold font. Furthermore, the amount of channels and features used in each study is also noted. It is shown in Table 1 that the proposed method achieves the highest classification accuracy of 95.3% in comparison with all other studies. In our earlier study [6], we achieved 95.2% classification accuracy but we utilised 18 channels with 10 features for each subject, however, in this study, we utilised only 3 channels and single feature to obtained the highest score. It is also noted that subjects 'AA' and 'AY' ranked at number one in terms of classification accuracy with 99.4 and 100% scores, whereas subject 'AL' rated as second with score of 98.7%. It is concluded that the proposed method can be used to develop a subject-specific BCI platform.

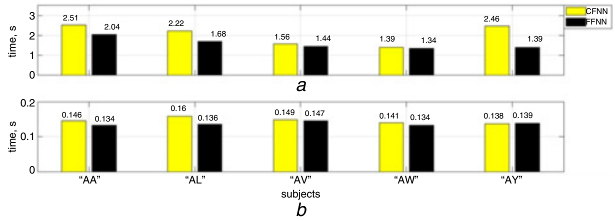

Fig. 6 *Execution time of proposed strategy for the implementation of real-time BCI*

a Training time
b Testing time

Table 1: Comparison with other studies

Article authors	Suggested studies	Classification efficacy, %					
		'AA'	'AL'	'AV'	'AW'	'AY'	Av.
the proposed	MSPCA+2D modelling+STDC +CFNN	**99.4**	98.7	92.2	85.7	**100**	**95.3**
	amount of channels	3	3	3	3	3	—
	amount of features	1	1	1	1	1	—
Sadiq *et al.* [6]	EWT+IA2+tuned LS-SVM	94.5	91.7	**97.2**	95.6	97	95.2
	amount of channels	18	18	18	18	18	—
	amount of features	10	10	10	10	10	—
Kevric and Subasi [8]	MSPCA +WPD +HOS + k-NN	96	92.3	88.9	95.4	91.4	92.8
	amount of channels	3	3	3	3	3	—
	amount of features	6	6	6	6	6	—
Siuly *et al.* [9]	clustering+LS-SVM	92.6	84.9	90.8	86.5	86.7	88.3
	amount of channels	118	118	118	118	118	—
	amount of features	9	9	9	9	9	—
Song and Epps [10]	SSRCSP	87.4	97.4	69.7	96.8	88.6	87.9
	amount of channels	18	18	18	18	18	—
	amount of features	20	20	20	20	20	—
Lu *et al.* [11]	R-CSP through aggregation	76.8	98.2	74.5	92.2	77	83.7
	amount of channels	118	118	118	118	118	—
	amount of features	6	6	6	6	6	—
Zhang *et al.* [12]	Z-LDA	77.70	**100**	68.4	**99.6**	59.9	81.1
	amount of channels	118	118	118	118	118	—
	amount of features	6	6	6	6	6	—

Conclusion: In this Letter, we suggested a new platform for classification of MI EEG signals by 2D modelling of modes acquired with the EWT and extraction of single feature only. The average classification performance of 95.2%, whereas 100% outcome is achieved for subject with very few training samples. The suggested approach is a new contribution in BCI field as 2D modelling help to visualise the changes in different MI signals. This Letter also showed the significance of single feature which outperform other studies. In future, we intend to extend the proposed method for multi-class MI classification.

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One or more of the Figures in this Letter are available in colour online.

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References

1 Sadiq, M.T., Yu, X., Yuan, Z., *et al.*: 'Motor imagery EEG signals decoding by multivariate empirical wavelet transform-based framework for robust brain–computer interfaces', *IEEE Access*, 2019, **7**, pp. 171431–171451
2 Chaudhary, S., Taran, S., Bajaj, V., *et al.*: 'A flexible analytic wavelet transform based approach for motor-imagery tasks classification in BCI applications', *Comput. Methods Programs Biomed.*, 2020, **187**, p. 105325
3 Siuly, S., Wang, H., and Zhang, Y.: 'Detection of motor imagery eeg signals employing Naïve Bayes based learning process', *Measurement*, 2016, **86**, pp. 148–158
4 Siuly, S., Li, Y., and Wen, P.: 'Identification of motor imagery tasks through CC–LR algorithm in brain–computer interface', *Int. J. Bioinf. Res. Appl.*, 2013, **9**, (2), pp. 156–172
5 Siuly, S., Li, Y., and Wen, P.P.: 'Modified cc-lr algorithm with three diverse feature sets for motor imagery tasks classification in EEG based brain-computer interface', *Comput. Methods Programs Biomed.*, 2014, **113**, (3), pp. 767–780
6 Sadiq, M.T., Yu, X., Yuan, Z., *et al.*: 'Motor imagery EEG signals classification based on mode amplitude and frequency components using empirical wavelet transform', *IEEE Access*, 2019, **7**, pp. 127678–127692
7 Blankertz, B., Muller, K.R., Krusienski, D.J., *et al.*: 'The BCI competition III: validating alternative approaches to actual BCI problems', *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2006, **14**, (2), pp. 153–159
8 Kevric, J., and Subasi, A.: 'Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system', *Biomed. Signal Process. Control*, 2017, **31**, pp. 398–406
9 Siuly, S., Li, Y., and Wen, P.P.: 'Clustering technique-based least square support vector machine for EEG signal classification', *Comput. Methods Programs Biomed.*, 2011, **104**, (3), pp. 358–372
10 Song, L., and Epps, J.: 'Classifying EEG for brain-computer interface: learning optimal filters for dynamical system features', *Computational Intelligence and Neuroscience*, 2007, **2007**, article no. 057180
11 Lu, H., Eng, H.L., Guan, C., *et al.*: 'Regularized common spatial pattern with aggregation for eeg classification in small-sample setting', *IEEE Trans. Biomed. Eng.*, 2010, **57**, (12), pp. 2936–2946
12 Zhang, R., Xu, P., Guo, L., *et al.*: 'Z-score linear discriminant analysis for EEG based brain-computer interfaces', *PLOS One*, 2013, **8**, (9), article no. e74433