Decoding of Motor Imagery Potentials in Driving Using DE-Induced Fuzzy-Neural Classifier

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Abstract— **This paper presents a novel feature selection and fuzzy-neural classification scheme to decode motor imagery signals during driving. To perform this, we would consider the fuzziness involved in sudden left bent, where the driver is supposed to take sudden 90º left turn during acceleration. This requires classification of motor imagery signals during acceleration and steering left control. The fuzzy-recurrent neural network classifier offers better performance using proposed differential evolution-induced feature selection technique, when compared with principal component analysis in such situation and provides the highest classification accuracy of 98.472%. In addition, false classification rate/misclassification rate is also found much higher when using principal component analysis instead of proposed differential evolution-induced feature selection algorithm. The performance of the proposed differential evolution-induced fuzzy recurrent neural network classifier has been compared with a list of standard classifiers including linear support vector machines, k-nearest neighbor and support vector machines with radial basis function kernel, where fuzzy-recurrent neural network classifier outperforms its competitors with an average classification accuracy of 95.472% and 95.647 for steering left and acceleration motor intensions respectively.**

***Keywords*—Electroencephalography, motor imagery, recurrent neural network, differential algorithm, fuzzification, principal component analysis.**

I. INTRODUCTION

Electroencephalography (EEG) is currently gaining importance for its increasing applications in decoding of motor imagination/motor planning using pattern classifiers [1]-[3]. A few interesting applications of motor imagery based problem that deserve special mention includes control of neuro-prosthetic devices for rehabilitative applications [4], [5], thought-controlled driving [6], [7], mind-driven motion control of robots [8-10], wheelchair control [11]-[13], and thought-controlled gaming [14]. Among these, we picked an application where, motor planning plays a vital role. Vehicle-driving is the real-time environment case, where a person needs to plan the correct motor intension when there is a sudden change in driving environment. Decoding of motor imagery signals in driving hence is a complex phenomenon where the person involves in processing various motor intensions, such as braking, acceleration and steering control (here, only acceleration and steering left control). For example, it may appear as a complex situation when a person has to intend correct motor action very fast at a sudden bent on an unknown road map. To deal with the fuzziness appeared in these kinds of situations, we employ a fuzzy neural classifier to correctly decode the motor imagery potential liberated by the person. Both invasive and non-invasive means of motor imagination based control are available in the literature. Although invasive means give better performance in control applications in terms of classification accuracy and precision, we employ non-invasive means of control by placing EEG electrodes over the scalp of the person to record motor imagery potentials for various motor intensions. The well-known motor imagery potential available in EEG literature, known as Event related desynchronization/synchronization (ERD/ERS) [15] has been used in our present study, since ERD/ERS originates during motor planning, imagination and/or execution. ERD is characterized by a decrease in power at the given frequency band at the onset of the imagination/planning/movement and ERS is followed by an increase in power as the intended action is over.

This paper aims at designing a novel scheme of motor imagery detection, where a few significant among a large pool of motor imagery features are first selected and fuzzified, and these fuzzified features then are sent to recurrent neural network classifier. The first novelty of the present research lies in selecting appropriate features using the well-known Differential Evolution (DE) [16] algorithm by jointly satisfying two objective functions. The second novelty lies in reducing the uncertainty in motor planning stage by fuzzification of the selected features so as to ensure correct classification of motor intensions. Last is the selection of a special type of recurrent neural network, where the correct intended classes represent the stable points on the minima of Lyapunov surface designed for the neural network. The choice of the neural network classifier is made because of extensive use in motor imagery classification [17], [18] and of course our background [19], [20].

The rest of the paper is organized as follows. Section II provides the principles and methodology used to design a scheme of motor imagery classification during driving.

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Section III deals with experiments undertaken to study the classification accuracy. The performance of the proposed classifier is studied in section IV. Finally, conclusions are given in section V.

II. PRINCIPLES AND METHODOLOGY

This section provides the principle and methodology for motor imagery classification, which highlights the proposed feature selection, fuzzification and classification algorithms. The other standard steps for decoding motor intensions during driving are Pre-Processing, Feature Extraction (FE) and Class-representative selection (CS). Raw EEG signal during driving is first pre-processed to remove noise and artifacts due to eye-blinking. The next step is to extract the feature from the raw signal obtained during experiment. This is known as feature extraction (FE). The detail of the features used for this classification problem is described in the next section. The extracted features are sent to feature selection (FS). During feature selection (FS), a set of optimal features is selected by neglecting the redundant features using a proposed objective function as dealing with such high dimensional feature vector may cause over-fitting. The last step for any classification problem is to design a classifier. The main intention is to design a fuzzy-neural classifier, so instead of using these set of optimal features, fuzzified values of them are used as inputs to the Recurrent Neural Network (RNN). Recurrent neural topologies have inherent power to map noisy data points into stable classes, represented by the optima on the energy surface constructed for a given dynamics. This dynamics too satisfies the condition of asymptotic stability, which ensures finding of accurate basin of attractions and the system will never be in utter ambiguity to determine the nature of the input patterns. One intermediate step, class-representative selection (CS) by using Principal component analysis (PCA) [21] has been applied to select one unique data-point/trial for each motor imagery class, which represent the stable minimum on the Lyapunov surface of the recurrent neural network classifier. The novelties of the present study are discussed below.

A. Feature Selection

Let $\mathbf{X}_{N\times D} = \{\vec{X}_1, \vec{X}_2, \ldots \vec{X}_N\}$ be a set of N patterns or data points, each having D features. Given such $\mathbf{X}_{N\times D}$ matrix, a partitioned clustering algorithm tries to find out a centroid matrix $C = \{C_1, C_2, \ldots C_K\}$ of K class with dimensions, such that the sum of the components of the patterns vectors along the direction of the corresponding cluster centroid is maximum whereas the sum of components of a centroid of a class along the direction of centroids of other clusters is minimum.

Mathematically, we can compute two functions say L_1 and L_2 corresponding to the first and second part of the above mentioned verbal statement as,

$$L_1 = \frac{1}{K}\sum_{k=1}^{K}\left(\frac{1}{N_K}\sum_{i=1}^{N_K}\sum_{j=1}^{d} x_{ij}^{k}.x_{c_k j}^{k}\right), \tag{1}$$

$$L_2 = \frac{1}{K}\sum_{\substack{k=1,\\ k\neq l}}^{K}\left(\frac{1}{K-1}\sum_{l=1}^{K}\sum_{j=1}^{d} x_{c_l j}^{l}.x_{c_k j}^{k}\right). \tag{2}$$

The cost function to be minimized is,

$$J = \frac{L_2}{L_1}. \tag{3}$$

It is also to be mentioned that $E[\mathbf{X}_{N\times d}] = \vec{\mathbf{0}}_{1\times d}$, since, the set of entire feature vectors is mean-adjusted. For optimization, Differential Evolution (DE) algorithm is used. DE returns a string consist of 0's (false) and 1's (truth). The optimal feature vectors can be obtained directly using the indices of the truth values.

B. Fuzzification of Feature Vectors

After FS, we obtain a d dimensional feature vector. Next step is fuzzification of these feature values. Idea is to define fuzzy membership function of each feature of each class so that the number of fuzzy membership function is dK where K = no. of classes and d is the dimension. Next step is to calculate the fuzzy membership function of each individual feature value for K different classes and store them consecutively in a row vector. We can construct a matrix having N-number of rows and dK number of columns for d number of features with total N number of feature points in feature space.

The membership function chosen is a triangular membership function defined as,

$$f(x:a,b,c) = \begin{cases} 0, x \le a \\ \dfrac{x-a}{b-a}, a \le x < b \\ \dfrac{c-x}{c-b}, b \le x < c \\ 0, c \le x \end{cases} \tag{4}$$

where,

$$a = mean(x_j^k) - \frac{\max(x_j^k) - \min(x_j^k)}{2},$$
$$b = mean(x_j^k),$$
$$c = mean(x_j^k) + \frac{\max(x_j^k) - \min(x_j^k)}{2}.$$
$$j = 1,2,\ldots,d$$
$$k = 1,2,\ldots,K.$$

The i^{th} row of the matrix with the fuzzy values is

$$[f_{1,1}^{i} \quad f_{1,2}^{i} \cdots f_{1,K}^{i} \quad f_{2,1}^{i} \cdots f_{d,K}^{i}]$$

These fuzzified feature vectors are used for pattern classification using recurrent neural network. Initially a class representative $\vec{\theta}_k$, k=1 to K is selected using Principle component analysis. The unit vector corresponds to the maximum Eigen value is used as class representative $\vec{\theta}_k$, k=1 to K since this direction signifies the direction of maximum variance. Since the classifier is designed to work on offline data, the data and corresponding features are considered to be stationary in nature. Thus selecting class representative using standard PCA will retain the feature fidelity.

C. Recurrent Neural Network and Lyapunov Stability

Recurrent neural network is used for pattern classification and storage. Conventionally, the network design starts with a dynamics and then designer verifies whether the dynamics is stable by predicting appropriate Lyapunov function. In this paper we approach in a different manner by first, choosing a Lyapunov function with multiple well-defined minima (basins of attraction) for pattern storage and then the dynamics is derived by accumulating the conditions for Lyapunov stability.

An Ackley-type function is used as Lyapunov function. This modified Ackley function is positive definite, has multiple well-defined minima which is ideal for pattern classification problems. The function is as follows,

$$V(\vec{\theta_k}) = \left(20 + e - 20 \times \exp\left(\frac{0.2 \times \vec{\theta}_k^T . \vec{\theta}_k}{d} \right) - \exp\left(\frac{\sum_{j=1}^{d} 2\pi \cos(\theta_{kj} . w_j)}{d} \right) \right), \tag{5}$$

where,

$\vec{\theta}_k$ = Class representative of k^{th} class,

$\vec{w}$ = weight-vector.

Now,

$$\dot{V}(\vec{\theta}_k) = \frac{dV(\vec{\theta}_k)}{dt} = \sum_{j=1}^{d} \frac{\partial V(\theta_{kj})}{\partial \theta_{kj}} \frac{d\theta_{kj}}{dt}$$

$$= \left(\frac{1}{d} \times \sum_{j=1}^{d} \left(8.\theta_{kj} \exp\left(-\frac{0.2 \times \vec{\theta}_k^T . \vec{\theta}_k}{d} \right) + 2\pi \sin(\theta_{kj} w_j).w_j . \exp\left(\frac{\sum_{j=1}^{d} 2\pi \cos(\theta_{kj} . w_j)}{d} \right) \right) \right) \frac{d\theta_{kj}}{dt}. \tag{6}$$

For asymptotic stable system,

$$\frac{d\theta_{kj}}{dt} = -\frac{\partial V(\theta_{kj})}{\partial \theta_{kj}}$$

$$= -\left(\frac{1}{d} \times \left(8.\theta_{kj} \exp\left(-\frac{0.2 \times \vec{\theta}_k^T . \vec{\theta}_k}{d} \right) + 2\pi \sin(\theta_{kj} w_j).w_j . \exp\left(\frac{\sum_{j=1}^{d} 2\pi \cos(\theta_{kj} . w_j)}{d} \right) \right) \right), \forall k, j. \tag{7}$$

Equation (7) defines the stable dynamics of the network.

Classification using a neural network includes two steps – encoding and recall. Encoding means adaptation of weight vectors such that the network converges to a stable state starting from an arbitrary initial state. Recall means determining a stable basin of attraction on the Lyapunov surface for an unknown input pattern.

Encoding: Let us consider class representative of k^{th} class be $\vec{\theta}_k$ for k=1 to K. The main objective of encoding cycle is to determine an appropriate weight vector $\vec{W}$ such that for each class representative $\vec{\theta}_k$, k=1 to K we have corresponding minimum on the energy surface $V(\vec{\theta}_k)$. Classical DE is used as an optimization technique to obtain optimal weight vector which minimizes the energy function $V(\vec{\theta}_k)$ for each class representative $\vec{\theta}_k$, k=1 to K.

Recall: In Recall cycle, the unknown instants are allowed to go through Pre-Processing, FE, FS and Fuzzification phases. The obtained representative for this unknown instant acts as initial state for the neural network. When a stable state is achieved, the corresponding class is obtained by measuring Euclidean distance between this stable state and those stable states achieved in Encoding phase. Mathematically, class I for the unknown pattern is given by,

$$i = \arg\min_k \left\| \vec{\theta}_k^{stable} - \vec{\theta}_i^{stable} \right\|, k = 1,2,..., K \tag{8}$$

III. Experiments and Results

This section provides experiments undertaken to examine classifier performance using proposed FS technique as well as classification accuracies of the proposed RNN classifier in comparison to other standard classifiers.

Here, an emulated driving environment based on virtual-reality scene including a realistic steering wheel, accelerator and brake pedals is used to classify the motor imagery signals for steering left control and acceleration of the participants. Each driving session takes approximately 14 minutes for each of 12 healthy subjects aged between 22 and 30 and each subject participates in each session for 10 times. It is important to mention here that each driving session again comprises thirty (2×15=30) independent driving instances of acceleration and steering left control, each comprises of ten seconds of duration. Remaining time duration refers to rest conditions between two consecutive driving instances. All experimental trials are recorded by a stand-alone EEG machine (manufactured by Nihon Kohden) comprising 21 electrodes and 200Hz sampling frequency. EEG signals are captured from P3, P4, Pz, (parietal) and C3, C4 (motor cortex) electrodes for classifying motor imagery responses, since previous literature [22],[23] already reveal that parietal and motor cortex regions are found significantly active during motor planning and motor execution. Fig. 1 shows ERD/ERS response when the driver performs motor planning during sudden left turn.

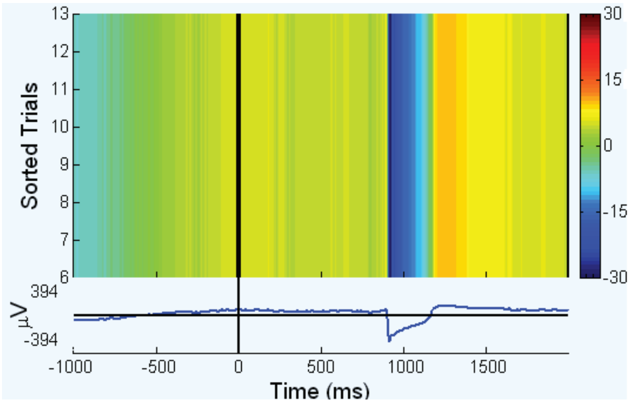

Fig. 1. Fall in signal response (ERD) is identified at around 900 ms during motor imagination, and again rise in signal response (ERS) is prominent after the motor imagination is over.

Pre-processing of raw EEG signal is done by designing a band pass filter having a suitable pass band frequency. Among the well-known infinite impulse response (IIR) filter including Butterworth, Chebyshev and Elliptic, Elliptic filter of order 4 with a pass band frequency of 3-30 Hz has been selected for the present problem. The choice of filter is possible for sharpest roll-off and equi-ripple in pass and stop band that can be varied accordingly. The pass band frequency of the filter is selected due to the presence of motor imagery signals in theta (3-7 Hz), alpha (7-13 Hz) and beta (13-30 Hz) [21] frequency bands.

Literature [22],[23] reveal several time-, frequency- and time-frequency EEG features for motor imagery classification. However, we select a combination of time and frequency domain features to take care of both temporal and spatial information of EEG signals. Power spectral density (PSD), autoregressive (AR) parameters and approximate Entropy (ApEn) features have been used for extracting the basic primitives (features) from motor imagery response during driving. Our experience of working with EEG reveal that PSD and AR parameters give a good indication of motor imagination about movement-related tasks. ApEn is another important parameter that provides better anti-noise property during the evaluation of more complex EEG signal. During EEG recording, we obtain altogether 3600×2000 samples from a specific electrode position for extracting features, from which we obtain 129 PSDs, 11 AR parameters and 1 ApEn features.

For FS, 141 features are sent altogether, from which DE optimally selects 20 features for classification using fuzzy-neural classifier. From each set of 180 trials for a specific motor imagery task, one ideal class-representative has been obtained from the experimental trials having reduced feature dimension. To realize the significance of the proposed FS technique, we compare the classification accuracy of the proposed fuzzy-neural network classifier using it and PCA for feature selection. Table I presents the average classification accuracy of fuzzy-RNN classifier by using PCA and proposed DE feature selection on test data for different motor imagery responses, where proposed DE-fuzzy-RNN classifier gives the highest classification accuracy of 98.472%. In the 4^{th} column of Table I, the statistical significance level (here, '+') of the difference of the means of best two algorithms using paired t-tests is reported. It is here noteworthy that '+' sign indicates the t value of 49 degrees of freedom is significant at a 0.05 level of significance by two-tailed t-test.

Besides classification accuracy, it is also important to examine the misclassification rate of the classifier. For this, we compute confusion matrices including the actual classes and predicted classes for different motor intensions. Here, we present confusion matrices for acceleration and steering left control for sake of understanding the fuzziness involved in these two situations when driver experiences sudden sharp left bend on the road map. The large diagonal entries in Table IIA indicate high classification accuracy using proposed feature selector-classifier for individual class, over ~97%, for all the test stimuli of two different motor intensions. Table IIB, designed to study the performance of the proposed fuzzy-RNN classifier using PCA, and indicates minimum individual classification accuracy over ~89%. Moreover false classification rate / misclassification rate is much higher (over ~ 9%) when using PCA instead of proposed DE feature selection algorithm (over ~2%). This considerable dip in performance using PCA in comparison to the performance using proposed DE feature selection makes sense as DE-induced feature selection provides better (lower) classification (misclassification) rate than using PCA.

Finally, the performance of the proposed classifier has been compared with a list of standard classifiers including linear support vector machine (LSVM) [24], k-nearest neighbor (kNN) [25] classifier and SVM with radial basis function (SVM-RBF) [24] classifier. The classification accuracies are obtained after performing 10-fold classification, where, 9 out of 10 fold is used for training and the remaining old is applied for validation. Table III lists the average classification accuracies for all five classifiers during testing, where the highest average classification accuracy using proposed DE induced fuzzy RNN as the best classifier is marked in bold.

TABLE III: MEAN CLASSIFIER ACCURACY (STANDARD DEVIATION) OF TESTING DATA USING PROPOSED DE-BASED FEATURE SELECTION ALGORITHM

Features	Motor Intensions	Average Classifier Accuracy (in %)				Statistical Significance
		L-SVM	KNN	SVM-RBF	Proposed DE-fuzzy-RNN Classifier	
PSD+ApEn+AR-Coefficients (dimension:141)	Steering Left	80.741 (0.01117)	81.230 (0.01188)	87.147 (0.01288)	**95.472 (0.01341)**	+
	Acceleration	78.288 (0.01039)	80.017 (0.01103)	85.241 (0.01231)	**94.647 (0.01317)**	+

TABLE I: COMPARISON BETWEEN MEAN (STANDARD DEVIATION) OF TESTING DATA OF THE PROPOSED DE-BASED FUZZY RECURRENT NEURAL CLASSIFIER WITH PCA AND PROPOSED DE-BASED FEATURE SELECTION ALGORITHM

Features	Average Classifier Accuracy (in %)		Statistical Significance
	PCA + Fuzzy-RNN Classifier	Proposed DE-fuzzy-RNN Classifier	
PSD+ApEn+AR-Coefficients (dimension: 141)	89.647 (0.01259)	**96.472 (0.01341)**	+

TABLE IIA: CONFUSION MATRIX OF TWO DIFFERENT CLASSES USING PROPOSED FUZZY RECURRENT NEURAL CLASSIFIER WITH PSD, APPROXIMATE ENTROPY AND AR COEFFICIENTS FEATURES AND PROPOSED DE FEATURE SELECTION ALGORITHM

Predicted Class Actual Class	Steering Left Control	Acceleration
Steering Left Control	97.542.	2.458
Acceleration	4.598	95.402

TABLE IIB: CONFUSION MATRIX OF TWO DIFFERENT CLASSES USING PROPOSED FUZZY RECURRENT NEURAL CLASSIFIER WITH PSD, APPROXIMATE ENTROPY AND AR COEFFICIENTS FEATURES AND PCA AS FEATURE SELECTION ALGORITHM

Predicted Class Actual Class	Steering Left Control	Acceleration
Steering Left Control	90.067	9.933
Acceleration	10.772	89.228

IV. CLASSIFIER PERFORMANCE

McNemar's Test [26] has been applied to determine the performance of two classification algorithms for correct classification of the feature vectors. Here, we define a null hypothesis suggesting that the two algorithms A and B should have same error rate, i.e., $n_{01=}\ n_{10,}$ where n_{01} be the number of examples misclassified by A but not by B and n_{10} be the number of examples misclassified by B but not by A (vide Table IV). Let f_A and f_B are classifiers' output obtained by algorithms A and B respectively when both the algorithms run on a common training dataset. We now define a statistic as χ^2 with 1 degree of freedom, called Z scores, which is given by (9).

$$Z = \frac{(|\,n_{01} - n_{10}\,| - 1)^2}{n_{01} + n_{10}} \tag{9}$$

At the end of the test, the Z scores will indicate whether the null hypothesis is accepted and the alternative hypothesis is rejected or vice-versa.

TABLE IV
STATISTICAL COMPARISON OF CLASSIFIERS USING MCNEMAR'S TEST

Reference Algorithm: DE - Recurrent Neural Net				
Classifier algorithm used for comparison using desired featureds d=50	**Parameters used for McNemar Test**		**Z**	**Comments on acceptance / rejection of hypothesis**
	n_{01}	**n_{10}**		
PCA-LSVM	35	11	11.5	Rejected
PCA-KNN	27	8	9.2571	Rejected
PCA-SVM-RBF	21	10	3.2258	Accepted

We evaluate Z which denotes the comparator statistic of misclassification between the DE-hybridized recurrent network-based classification algorithm (Algorithm: A) and any one of the competitor algorithms (Algorithm: B) for the Indian dataset for desired number of features equal to 20. The hypothesis is rejected if $Z > \chi^2_{1,\,0.95} = 3.841459$, which indicates that the probability of the null hypothesis is correct only to a level of 5% of error for two-tailed chi-square test and so, we reject it. It is apparent from Table IV that the proposed classifier outperforms all its competitors excluding SVM-RBF. This confirms the fact that SVM-RBF nearly similar to that of the proposed classifier.

V. CONCLUSIONS

This paper presents a novel feature selection and fuzzy-neural classification scheme to decode motor imagery signals during driving. The fuzzy-RNN classifier offers better performance using proposed DE feature selection technique, when compared with PCA and provides the highest classification accuracy of 95.472% and 95.647 for steering left and acceleration motor intensions respectively. In addition, false classification rate/misclassification rate is also found much higher when using PCA instead of proposed DE feature selection algorithm. The proposed DE induced fuzzy RNN classifier outperforms the standard classifiers including LSVM, kNN and SVM-RBF in terms of average classification accuracy.

Here, we consider experienced drivers as subjects for experiments, while the fuzzified feature vectors show clear difference between an experienced driver and a novice car-driver. It can be shown that the fuzzified feature vector for an experienced driver will be more prone to an ideal one than the naive driver. Moreover, since the constructed lyapunov surface has so many well-defined minima, the classifier can be used for all type of drivers from novice to experienced; only we need to train the classifier for different experience levels. In case of experienced driver, the basins will be well separated, whereas in case of a novice driver, the basins will be comparatively closer to each other. Experimental tables in support of this theory cannot be produced due to space complexity.

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