Journal of Basic and Applied Engineering Research
p-ISSN: 2350-0077; e-ISSN: 2350-0255; Volume 4, Issue 7; October-December, 2017, pp. 537-541

http://www.krishisanskriti.org/Publication.html

A New Discriminant Feature Fusion Technique for Classification of EEG Signals

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Abstract—*Feature fusion is promising signal processing technique to incorporate large volume information. In recent time it gains attention in machine learning algorithms. In this article, we propose a discriminate correlation analysis (DCA) based fusion method to classify electroencephalogram (EEG) signals. First a set of multi-dimensional features are generated from input signals. The feature vectors are then segmented uniformly to create a set of sub-multi-view feature followed by DCA projection. Finally the low order DCA features are fused to derive discriminate representations for classification. Statistical test analysis of variance (ANOVA) shows that the method is significant ($p < 0{:}05$). Results show that the proposed feature fusion based method is superior to many prior methods.*

Index Terms*: Discriminate correlation analysis and feature fusion.*

1. INTRODUCTION

Feature fusion (FF) is most widely used feature concatenation technique in pattern recognition applications [1]–[4]. It provides an effective representations of input information or data to improve performance of decision model [5]. The objective of FF is to utilize the relevant information from multiple sources or signals for possible characterization of objects [6].

Availability of multiple responses or signals in medical domain is inherent [7]. Efficient use of information from these signals is prerequisite for effective decision outputs [8]. As a result multi-view feature fusion based learning models have made remarkable success [9]. Usually support models employ principal components analysis (PCA) [10], [11], linear discriminant analysis (LDA) [12], unsupervised LDA, and selforganizing feature map [13] to reduce he dimensionality of input feature space. The low dimensional features are applied for classification. However, these techniques do not provide feature fusion strategy for discriminate representation input vector for classification. In recent time discriminate correlation analysis (DCA) based fusion schemes have more attention in pattern recognition [5]. Similar to canonical correlation analysis (CCA) [5], it finds two sets of linear transformations. Further it incorporate class related information to analysis.

In this article, we propose a feature fusion based discriminate model for classification of electroencephalogram (EEG) signals. The rest of the article is organized as: Section II gives Literature review, section III describes methodology. Results and discussion and Conclusion are presented in section IV and V respectively.

2. LITERATURE REVIEW

EEGs recordings are used to assess the brain abnormalities activities. In recent past, a huge number of quantitative analysis techniques are developed to overcome the limitations of traditional visual assessment. For instant, in [21] the authors developed time-frequency feature based model to detect seizure activities. In [22], discreet wavelet transformation (DWT) based method was reported. Hassan et al. [23] employed a linear programming boosting. EEG signals were first decomposed by using ensemble empirical mode decomposition method and estimated spectral moments were used for classification of EEG patterns. Besides, Bootstrap aggregating [24] and tunable-Q factor wavelet transform [25] were also adopted. Orhan et al. [26] developed DWT-neural network model for epilepsy diagnosis. Soomro et al. [27] introduced a CCA-neural network for epileptic seizures prediction. Kiymik et al. [28] adopted power spectral density based approach. Although wavelet is popular, use of wavelet requires manual intervention [29]. That is use of wavelet function requires a trade-off in fixed frequency scale and sampling frequency. Choice of wavelet and level selection for effective model performance are essential. Further it uses wavelet coefficients extracted from specific signals which may not be feasible for analysis.

3. METHODOLOGY

A. EEG data set

A widely used public EEG data set was used in this analysis [30]. Data set consists of five sets A to E. Each set contains 100 single channel signals, each duration is 23:6 s. The data sets were recorded at the University Hospital Bonn, Germany with inbuilt amplifier and 12-ADC at sampling rate of

173:61Hz. The signals were filtered with band of 0-60 Hz. The number of samples in each recording was 4097. During data collection the healthy volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B). Sets C, D and E are originated from our EEG archive of pre-surgical diagnosis. Sets C and D were measured during seizure free interval while set E contained seizure activity. The study data set includes 150 recordings (50 A, 50 B and 50 E). In this study, we consider three group of data as shown in Fig.1. To conduct the experiment the data set is divided into training and testing sets.

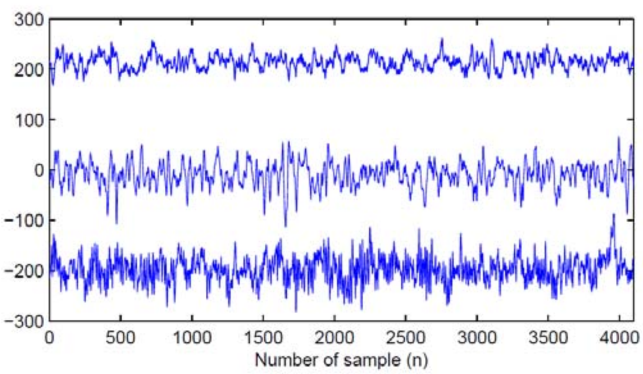


Fig. 1: Figure showing Three EEG patterns A, B and E (From top to bottom).

B. DCA based feature fusion model

1) Multi-dimensional features: A given data set with C study groups was divided into c subgroups. Each subgroup consists of q signals which were entered sequentially into multidimensional features X(i; j) = [x_1(p); : : : ; x_q(p)]^T , where p = 1; : : : ; 2n, refer to as multi-dimensional feature matrix. DWT was performed using daubechies wavelet function with two vanishing moments (db2) over signals and low frequency components were considered to derive statistically independent multi-view feature matrices [31]. It is due to fact biomedical signal falls in the low frequency range. The multi-view features were further decomposed to sets of sub-multi-view features for analysis.

2) Discriminant correlation and feature extraction: Both CCA and DCA are used as multidata processing methods to analyze the mutual relationships between two sets of variables [5]. Let us consider two sub-multi-view feature matrices X and Y . These features were subjected to the PCA to remove redundancy and irrelevant information [5]. Additionally, mean of each row from the reduced matrices were removed to make centered data matrices. It finds two linear transformations-

$$\left.\begin{aligned} u &= A_{x_1}x_1 + \cdots + A_{x_k}x_k = A_X^T X \\ v &= B_{y_1}y_1 + \cdots + B_{y_k}y_k = B_Y^T Y \end{aligned}\right\} \qquad (1)$$

CCA finds weight vectors $A_x = [A_{x_1}, \ldots, A_{x_k}]$ and $B_y = [B_{y_1}, \ldots, B_{y_k}]$ by optimizing the correlation ρ between u and v as below [18], [19]:

$$\max_{A_x, B_y} \rho(u, v) = \frac{E[uv]}{E[u^2]E[v^2]} = \frac{A_x^T C_{xy} B_y}{\sqrt{(A_x^T C_{xx} A_x)(B_y^T C_{yy} B_Y)}} \qquad (2)$$

where C_{xx} and C_{yy} are the autocovariance matrices and C_{xy} is the crosscovariance matrix of X and Y . It finds a set of pair features corresponding to d-correlations in descending orders. Each correlation indicates correlation between a pair of transformed feature in orthogonal space. To enhance the discrimination among the class features, DCA maximizes the between-class feature matrices of transformed features. The individual between-class feature matrix

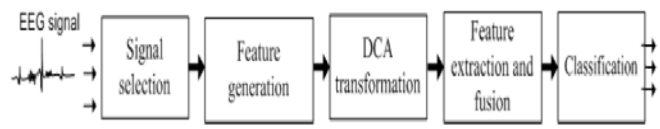
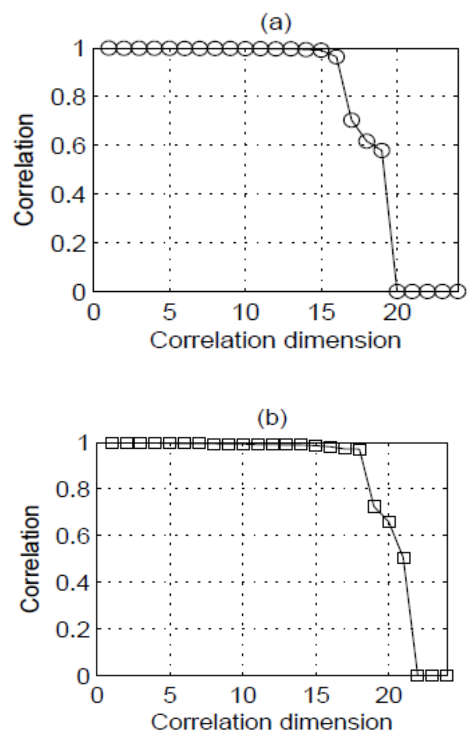


Fig. 2: Proposed DCA based decision model.



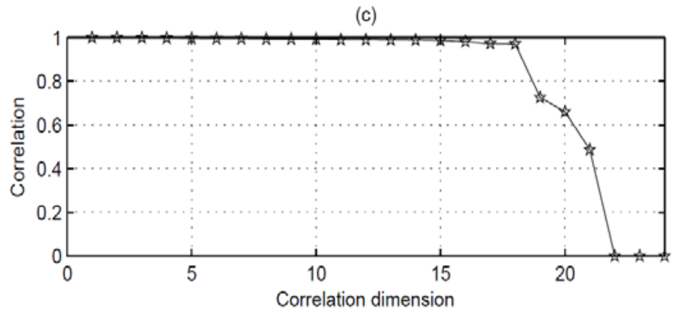


Fig. 3: Correlation between sub-multi-view features for three groups - a) A-group, b) B-group and c) E-group

(i.e., S_B) of transformed features was evaluated and diagonal zed using the method in [5]. However, DCA was applied on direct and wavelet feature spaces and consequently feature fusion was performed by using summation rule similar to CCA as follows:

$$Z_{ij} = A_x^T X + B_y^T Y + C_{x1}^T X_1 + D_{y1}^T Y_1$$

where X_1 and Y_1 are transformed wavelet features. Z_{ij} is canonical variates and canonical correlation discriminant features (CCDF) of i_{th} sub-group of j_{th} group respectively. CCDFs are evaluated for four pairs of features and combination was used as feature descriptor to improve the quality of extracted feature space [20]. It could be regarded as a multimodal fusion and use of such scheme in our method was inspired from the success of the methods in [14], [15], [17], [20].

Correlation _ indicates how close the projected features A_1 and B_1 in two orthogonal subspace. Fig.3 shows the variation in correlations of transformed features. Features corresponding to higher order correlations are used to capture the underlying statistics of input features in terms of loworder feature structure which can preserve most of the energy contents of input feature sets [32]. Such features are widely used in many applications and thus it is an useful mean for automatic staging of ECG patterns. In this analysis taking _ = 8 as threshold we estimated global feature descriptors (i.e., Z_{ij}) for two pairs of consecutive sub-multi-view features. Finally mean feature descriptor were used for analysis.

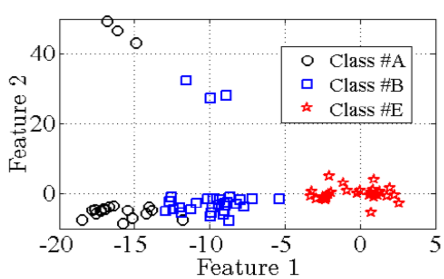


Fig. 4: Scatter plot of three group-A, B, and E features.

TABLE I: Mean output performances of various combined models in terms of accuracy Ac_, sensitivity Sn_E (for E) and specificity Sp_A Sp_B (for A and B). The highest values are indicated in boldface

Classifiers	Sn_E	Sp_A	Sp_B	Ac_μ
Discriminant Analysis (Linear)	99.43	98.09	98.57	98.70
Discriminant Analysis (Quadratic)	98.00	98.00	100.0	99.33
k-nearest neighbors	**100.0**	**98.66**	**100.0**	**99.73**

4. RESULTS AND DISCUSSION

8-dimensional feature matrices are subjected to one-way analysis of variance (ANOVA) with p < 0:05 which was carried out in MATLAB at 95% confident level [23], [24]. Any feature having p > 0:05 was considered as insignificant and significant features were evaluated for analysis. Fig.4 shows scatter plot distribution of significant features used in this analysis. It shows that the features employed in our method have good discriminant ability. Thus, it can be expected to provide good algorithm performance while fed them into classifiers. The experiment was carried out in MATLAB (The MathWorks, Inc., Natick, United States) on a computer with an Intel (R) Xeon (R) machine (Precision T3500), 2.8 GHz processor and 8 GB of RAM.

A set of well-known classifiers were employed to explore efficacy of proposed fusion model. It was intended to show how models behave with proposed feature fusion scheme. This confirms that the algorithm is pragmatic and feasible in realworld scenarios. It includes classifiers as outlined in Table I.

Use of various classifiers in this analysis are due to their widespread use in various classification problems. Table I shows the average results of five repeated measurements. For k-NN, measurements were performed for k = 2; : : : ; 10 and the best results were reported. Discriminant analysis uses linear and quadratic discriminant functions. Table I shows promising classification accuracies. k-NN emerges as the best among the conventional classifiers. However the results in terms of accuracy, sensitivity and specificity [33]–[36] are very close to each other which apparently indicate the superiority of proposed feature fusion scheme.

5. CONCLUSION

The article presents feature fusion based classification schemes utilizing multi-view information extracted from 1- D EEG signals. The proposed model does not involve any assumption and complicated steps and is entirely data-driven which make it attractive choice for processing and analyzing of EEG signals. The algorithm significantly reduces the dimensionality and the results suggested that information extracted from multi-view inputs yield excellent classification accuracy upto 99.73% with promising parameters values. Moreover, it can control the complexity, feature biasing and over-fitting. Thus it can further be extended to develop a graphical user interference so as to speed up the diagnosis process in real time setting.

6. ACKNOWLEDGMENT

The authors would like to thank technical staff of Guwahati Neurological Research centre (GNRC), Ghy, India for their helps during acquisition of data.

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