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Feature Fusion: An Application To Biomedical Signal Classification

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Abstract: Development of a feasible support system for automating staging of neural disorder based on Electroencephalogram (EEG) is essential to speed-up diagnosis process by improving the burden of the clinician of analyzing large volume data and to accelerate large scale research. In this work Discrete wavelet transform (DWT) has been applied to extract statistically independent features and fused the features for effective classification of various EEG signal. The aim of this paper is to present a comparative study of two feature fusion approaches namely Canonical Correlation Analysis (CCA) and Discriminant Correlation Analysis (DCA). Further, our proposed method can be extended to develop a graphical user interface and promote real time implementation.

Keywords: EEG, Feature fusion, CCA, DCA

I. INTRODUCTION

Biomedical signal is generally a representation of a collective electrical signal achieved from any organ, signifying a physical variable of interest. The complexity or non-stationary natures of the signals are their integral properties and for which learning from various collections of information is not sufficient for getting an operative output. EEG is the recording of electrical signal shaped by brain. It offers lots of information to evaluate the status of a person. But due to the inherent complex properties the information is very much error prone. Now days in pattern recognition feature fusion is more challenging one. It is thought to be more effective to increase the performance of the model. Feature fusion is the combination of two or more related information into a single one having more discriminative power. Recently Multi View Learning (MVL) [1-2] has captured an enormous attention through feature fusion technique. MVLs are nothing but setting information having same or different statistical nature. The aim of the MVL is to differentiate an object by making span of information space. In this paper work discrete wavelet transform (DWT) played a significant role. We have used DWT to extract the statistical features of the EEG segment. In non-stationary signal analysis DWT is very popular. During DWT implementation the EEG signal is passed through both high pass and low pass filter. The high pass filter yields detail coefficients where as approximation coefficients are provided by low pass filter. In our model we have used approximation coefficient as it significantly improves the performance of the model. In learning method, the importance of curse of dimensionality is supreme. Large dimensionality degrades the performance of the model. The classification problems become more efficient and attractive by reducing the dimensionality with the help of some conservative techniques like PCA- principal components analysis, LDA- linear discriminant analysis, and unsupervised-LDA. Recently in pattern recognition the feature fusion scheme canonical correlation analysis (CCA) have drawn a wide attention which can be used to measure the correlation between two sets of features. CCA is used in other applications also like artifact removal, multiuser myoelectric interface, and multi-modal fusion. Recently used feature fusion scheme DCA is nothing but extension of CCA which includes much more class related feature space information

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II. VARIOUS STATE-OF-ARTS-METHODS

EEG-Electroencephalogram is the electrical signal having the information of the brain related to physiological function. EEG was first recorded in 1929 by externally attaching several electrodes on the human skull through which the information for the abnormalities of a human being can be assessed.

In recent years several works have been carried out in this track. Use of discrete wavelet transform is reported in various research works. Orhan *et al.* [3] has performed two machine learning methods namely k- means clustering technique and multi-layer perception neural network for the classification of EEG signal and the feature extraction has been performed by Discrete Wavelet Transformation (DWT). Kousarrizi *et al.* [4] have designed a Brain Computer Interface and then classification of extracted data was done by neural networks and SVM. Murugesan *et al.* [5] proposed a feed forward neural network for an automatic detection of brain tumour. They have extracted the features using Fast Fourier Transform. Jia [6] has classified the EEG signal by deploying artificial neural network (ANN) and probabilistic neural network (PNN). Before that the EEG signal preprocessing was carried out by using time domain regression method and feature has been extracted using AR- Autoregressive model coefficients. Ioannides *et al.* [7] have used wavelet transform technique for feature extraction and using neural network classified the EEG signal. Fusion at feature level includes the integration of feature sets corresponding to multiple modalities.

In multimodal biometric system S. K Bhardwaj [8] proposed an ensemble algorithm for feature level fusion. N. Poh *et al.* [9] discussed about fusion technique. According to the fusion technique are divided into two classes and those are fusion before matching and fusion after matching. Gajic *et al.* [10] used a time frequency and nonlinear analysis method for detecting epileptiform activity and accordingly achieved a very encouraging result. Hassan *et al.* [11] used tunable Q-factor wavelet transform and spectral features and proposed a decision support system for unconscious sleep staging using EEG signal.

III. PROPOSED METHODOLOGY

A. Dataset

We have used publicly available EEG signal database obtained from Bonn University, Germany. Five set of classes namely A, B, C, D and E are there for five different neurotic and normal human cases as described in the table: 1given below.

Table-I: Information from Bonn University database

Dataset	Description
Set A	EEG data of a healthy person with open eyes
Set B	EEG data of a healthy person resting with closed eyes.
Set C	EEG signal recorded when the persons were free from seizure (opposite to the epileptogenic zone of electrode placement)
Set D	EEG signal during the seizure free intervals (The electrode placement was within the epileptogenic zone)
Set E	EEG data were recorded when the persons were in merely seizure state.

For each dataset 100 single channel were recorded at the University Hospital Bonn, Germany with inbuilt 128 channel amplifier. The sampled rate of the data was 173.61 samples per second and 12 bit ADC was used to record the signal. So the number of total samples present in the single channel recording is around 4097 samples. The range 0.53-40 Hz (12db/Octave) [12] is the band pass filter. In our research work we have used the combination of A, B, E out of five datasets.In our experiment the complete dataset is arbitrarily separated into two sets namely training and testing. But the same subject data is not used for both the data sets. Fig-1 shows the workflow diagram of our proposed methodology.

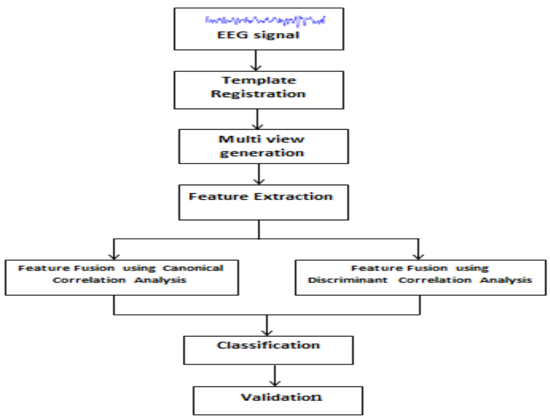


Fig 1: Block diagram of proposed methodology

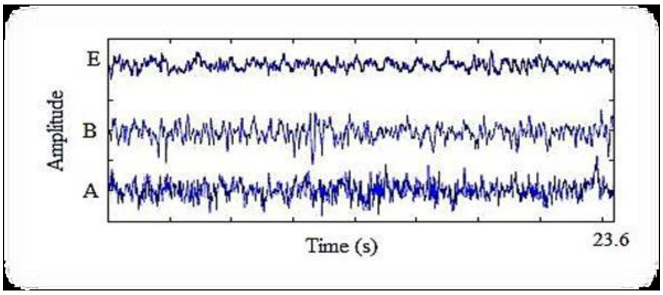


Fig 2: EEG pattern of three sets (A, B and E)

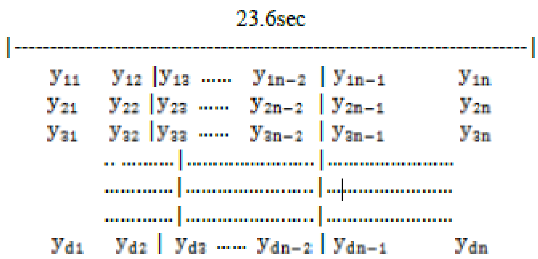


Fig 3: Matrix representation of EEG signal collected for duration of 23.6 sec.

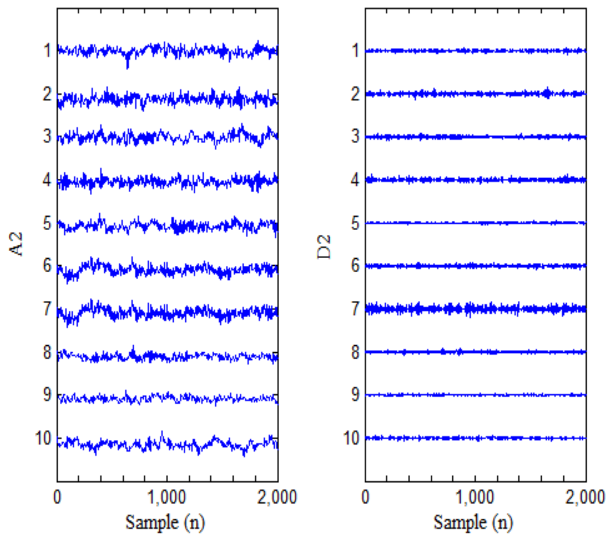
B. Generation of multi-dimensional view

In this work for all the studied groups Multi-dimensional views are produced. Registered *q* templates sequentially for each subgroup consist of *n* subjects.

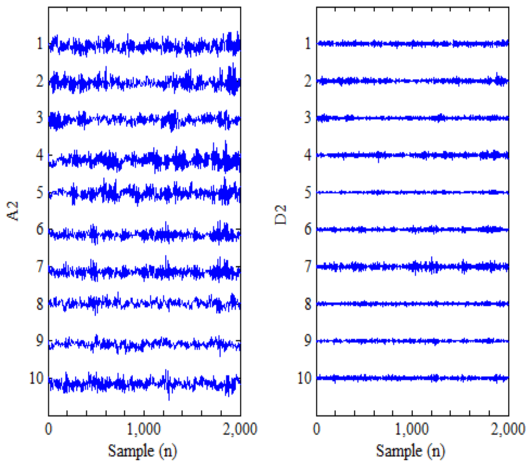
$$Y(i,j) = [y_1(n), y_2(n), \ldots, y_q(n)]$$

Here, Y is the multi-view feature.

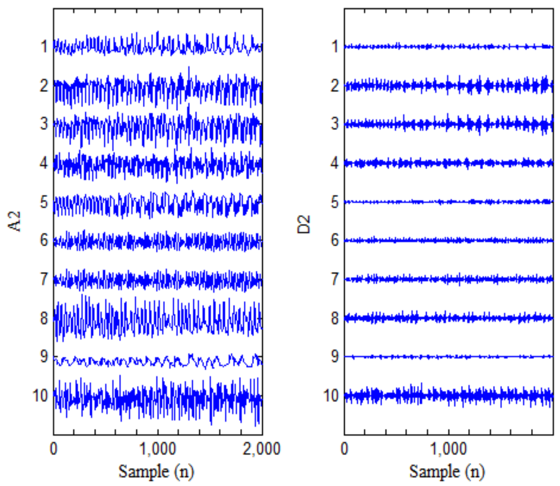
Fig-3 is the feature matrix represents the EEG signal with each element. We have performed Discrete Wavelet Transform over the signals and used daubechies wavelet function to find the low frequency component. The decomposition of sub multi-view feature for analysis is showed in fig-4.



(a)



(b)



(c)

Fig 4: Discrete Wavelet Transform of EEG pattern

C. Performance measure

Performance of the EEG classification is evaluated by calculating the rate of sensitivity (SE), Specificity (SP) and percentage of Accuracy (AC) or Overall accuracy (OA) as shown in Table-II.

Table-II: Confusion matrix

		Actual value		
		P	N	
Prediction	P	TP	FP	P
	N	FN	TN	N
		P	N	

Here TP= True Positive FP = False Positive
FN=False Negative TN= True Negative

IV. FEATURE FUSION USING CANONICAL CORRELATION ANALYSIS

Canonical correlation is used to investigate the overall correlation between two sets of variables and it is also called as multivariate extension of correlate analysis. In this work *X* and *Y* are considered two multi-view feature matrices. Also, from the reduced matrices we have removed the mean of each row to make them centered data matrices. Then we have defined linear transformations which are also called as canonical variates of feature matrices:

$$u = A_{x1}x_1 + \cdots + A_{xk}x_k = A_X^T X$$
$$v = B_{y1}y_1 + \cdots + B_{yk}y_k = B_Y^T Y \quad (1)$$

Where, u and v are canonical variates. Using CCA we can finds the weight vectors $A_x = [A_{1,\ldots\ldots}A_k]$ and $B_y = [B_{1,\ldots\ldots\ldots},B_k]$ and solving the optimization problem i.e equation 2, the correlation ρ between the variate u and v can be maximized.

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

Here, C_{xx} and C_{yy} are the auto covariance matrices and C_{xy} is the cross covariance matrix of X and Y. The solution of the above equation gives d-sets of transformed vectors are $A_x = [A_{x1,\ldots\ldots}A_{xd}]$ and $B_y = [A_{y1,\ldots\ldots}A_{yd}]$ corresponding to d-correlations (d = rank(X, Y)) are in descending order. In orthogonal subspace there is correlation between a pair of the transformed feature. The solving of the optimization problem requires solving the following standard eigenvalue equation.

$$XY^T(YY^T)^{-1}YX^TA = \alpha^2 XX^TA \quad (3)$$

$$YX^T(XX^T)^{-1}XYB = \alpha^2 YY^TB \quad (4)$$

Here α^2 is the diagonal matrix with d non-zero elements. The solution gives a set of features pair conforming to d-correlations which are in descending orders. With the help of canonical correlations we can get the closeness of the projected vectors in orthogonal subspace. The higher value of diagonal elements specifies close contiguity of vectors of two subspaces. It is noteworthy that CCA includes both optimization and singular value decomposition that distinctly diminish the curse of dimensionality. We can have feature level fusion either by concatenation or summation of the transmuted feature vector.

$$Z1 = \begin{bmatrix} X_1^* \\ \vdots \\ X_{22}^* \end{bmatrix} = \mathrm{diag}[A \ldots . D]^T \begin{bmatrix} X_1 \\ \vdots \\ X_{22} \end{bmatrix} \quad (5)$$

$$Z2 = X_1^* + \cdots + X_{22}^* = \begin{bmatrix} A \\ \vdots \\ D \end{bmatrix}^T \begin{bmatrix} X_1 \\ \vdots \\ X_{22} \end{bmatrix} \quad 6)$$

Here, Z1 and Z2 are the Canonical Correlation Discriminant Features (CCDFs).

V. FEATURE FUSION USING DISCREMINANT CORRELATION ANALYSIS

One of the feature fusion methods is Discriminant Correlation Analysis (DCA) which considers the class association in feature sets.

The DCA maximizes the between class feature matrices of transformed features and thus enhance the discrimination among the class features. In DCA [13], the individual between-class feature matrices of changed features are calculated and digitalized. Similar to the CCA, feature level fusion is performed using summation of the transformed features. The transformed features for the first set using feature fusion summation technique [14] is as follows-

$$T_t = A_x^T X + B_y^T Y = T_1 + T_2$$

Likewise, by using summation method we have the feature fusion for the second set of transformed feature vector is

$$T_t = C_{x1}^T X_1 + D_{y1}^T Y_1 = T_3 + T_4$$

Here as shown in below the discriminant feature vector can be found merging two independently estimated features -

$$Z_{ij} = \sum_{t=1}^{4} T_t = A_x^T X + B_y^T Y + C_{x1}^T X_1 + D_{y1}^T Y_1$$

Where X1 and Y1 are the transformed wavelet features. T_t is canonical variates and Z_{ij} is canonical correlation discriminant features of the {i,j}th feature pairs. Here the number of variates is indicated by t=1……4.

VI. RESULT ANALYSIS

Using DWT, curse of dimensionality can be reduced for wide inconsistency of templates though it requires human interpolation and sub band statistics; however it may not realistic. Additionally intrinsic nonlinearity nature of template, result variety can be found using DWT features. Table-III and IV shows the analysis of the performance using feature fusion technique CCA.

Table-III: Formulation of average confusion matrix of feature extraction strategy implementing LDA-kNN

Actual Class	Predicted Class					
	A		B		E	
	μ	σ	μ	σ	μ	σ
A	49	1	1	0	0	0
B	0	0	50	0	0	0
E	0	0	0	0	50	0

Table-IV: Mean performance. S_pA and S_pB represent specificities of A and B respectively

#Strategy	S_nE (%)		S_pA (%)		S_pB (%)	
	μ	σ	μ	σ	μ	σ
MVL	98.0	0.50	98.0	0.50	100	0.00

In this work the projected algorithm misclassified the one case (A) which probably owing intrinsic similarity of patterns. Due to the well-defined feature extraction and fusion strategy the integrity of the proposed method decreases the complexity.

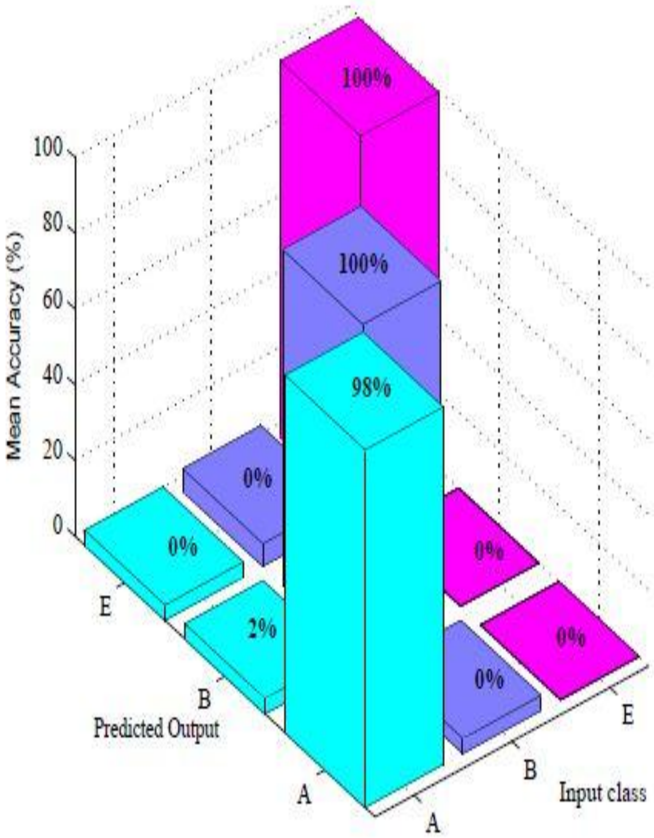


Fig-5: 3-D bar diagram of Table-III

Table–V shows the various combined model of EEG classification using feature fusion technique DCA.

Table-V: Mean performance of various combined model

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	100.00	99.33
k-NNs	100.00	98.66	100.00	99.73

VII. PERFORMANCE COMPARISON

The performances of our proposed methods are compared along with the other state-of-art methods to explore the usefulness of our proposed feature fusion schemes. The details of the comparison are explained in Table-VI reporting all the evaluation parameter.

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Table-VI: Mean performance of various combined model

Method	Feature type	Classifier	Study group	Accuracy
Multilayer perceptron Neural Network[15]	Discrete wavelet features	K – means algorithm	5/10	97.00
Mixture of experts Neural Network[16]	Discrete wavelet features	Neural Network	2/10	94.50/93.20
Adaptive neuro-fuzzy inference system[17]	Adaptive neuro-fuzzy	Adaptive neuro-fuzzy	5/10	92.55
Non-linear[3618]	Time, time-frequency feature	Quadratic classifiers	3/10	98.73
Proposed method	Statistical features and fused features using CCA	kNN	3/10	99.32
Proposed method	Fused feature using DCA	Discriminant Analysis (linear)	3/10	98.70
Proposed method	Fused feature using DCA	Discriminant Analysis (quadratic)	3/10	99.33
Proposed method	Fused feature using DCA	kNN	3/10	99.73

VIII. CONCLUSION

In this work, we have presented a relative study of two different feature fusion strategies namely Canonical Correlation analysis and Discriminant Correlation Analysis. The feature fusion strategies efficiently work in categorizing three categorical publicly available dataset of EEG patterns (A, B and E). We have compared the results with other state-of-arts method also. Following the results, it can be found that the output of DCA is high when compared to CCA. Here we have compared CCA and CCA extension namely DCA, while there are still many extension of CCA likes LS-CCA, Sparse CCA etc. which are also competent to classification problem. Furthermore the efficacy of our proposed strategies is essential to explore various categories of signal with various signals that can provide the consistent performance.

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