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Correlation Dimension Based Performance Analysis of Alcoholic EEG data with PCA and PSO Classifiers

Harikumar Rajaguru, Vigneshkumar Arunachalam

Abstract: Excessive drinking Alcohol is a serious problem in the world as it causes a lot of health issues. It causes heavy damage in the human brain and problems like lack of memory and concentration accompanied by impaired decision making takes place. The electrical activity of human brain is identified by, Electroencephalography (EEG) signals. An EEG signal depicts multiple patterns for various neurological disorders. Hence, it is widely preferred one in clinical diagnosis. A chronic alcoholic patient's EEG and the Correlation Dimension (CD) features are analyzed. The obtained CD features are classified with the Principle Component Analysis (PCA) and Particle Swarm Optimization (PSO) Classifiers. The bench mark parameters such as Good Value(GV), AUC, Specificity and Sensitivity are compared in both optimization. The PSO Classifier out performed PCA Classifier with higher AUC of 97.92% when compared with PCA's AUC of 96.85%.

Keywords: EEG, Correlation Dimension, Particle Swarm Optimization (PSO), Principle Component Analysis (PCA)

I.INTRODUCTION

The human brain is a fascinating and a greater amount of research activities have been performed in the past few decades . As the brain is quite complex and uncertain, may unresolved issues are there to be addressed. A low amplitude and low frequency waveforms profile of brain signals indicates the healthy nature of brain. The EEG signal interpretation and analysis plays a vital role in areas of clinical medicine and psychology. Analyzing the EEG signals is one of the best techniques to monitor the state of the alcoholic patient and so it serves as an effective tool to analyze the problems occurring in the brain due to alcoholism [1]. Cognitive problems and health issues are the derivative of Alcoholism. Due to this problem, the vital parts of the human body are affected severely thereby leading to dire consequences. A lot of works have shown the works related to alcoholism by the EEG signal processing. The analysis of sample entropy of both the alcoholic and normal people was done by Zou et al [1]. The effects of alcohol on both the neuro behavioural functions and the brain were analyzed by Berman and Marinkovi [2]. Wu et al [3] performed a study on the human brain using EEG signals after the consumption of alcohol.

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***Correspondence Author(s)**
Harikumar Rajaguru, Professor, Department of Electronics and Communication Engineering, Bannari Amman Institute of Technology, Sathyamangalam, India
Vigneshkumar Arunachalam[2] Assistant Professor, Department of Computer Science and Engineering, Bannari Amman Institute of Technology, Sathyamangalam, India

Rajaguru and Prabhakar [4] utilize the Softmax Discriminant Classifier for the classification of alcoholic level from EEG signals. A study of an extracted Correlation Dimension (CD) features from a single alcoholic patient and the effect of Principle Component Analysis (PCA) and Particle Swarm Optimization (PSO) classifiers are discussed and compared. The block diagram for Alcoholic Epilepsy Classifier is shown in Figure I.

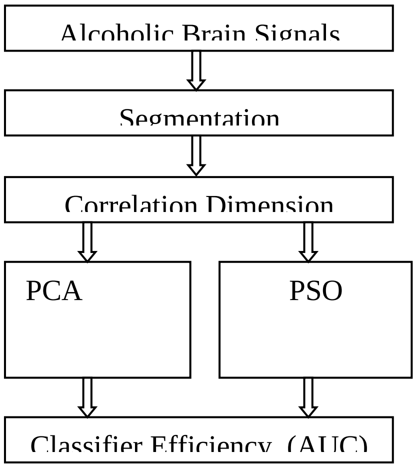

Figure I Alcoholic Epilepsy Classifier

Section I Introduces the concepts of the article. The materials and methods and Correlation Dimension feature extraction is discussed in section II. Section III & section IV explains the methodology of PCA and PSO Classifiers respectively. Results are discussed in the section V. The article is concluded in Section VI.

II.MATERIALS AND METHODS

For a single chronic alcoholic patient, through single trial 64 channels and with three electrodes, the EEG signals are obtained. The sampling of the signal is done at 256 samples/second with a 12 bit Analog to Digital Converter (ADC) implemented with signed representation. For 10 second duration, each channel is acquired and so (256 x 10= 2560) samples per particular channel are obtained. Therefore 2560 samples are assumed to be a bin and so as there are 64 channels, 1, 63,840 samples are present which can be totally grouped in 64 bins. The human brain is surely affected by the consumption or influence of alcohol. According to the [3], D.Wu etal had evaluated the correlation dimension of an alcoholic patient to be 5.6. However, in this paper, Correlation Dimension features are extracted from EEG signals for further classifications.

A. Theory of Chaos And Non-Linear Dynamics

Chaos represents a complex behavior of a well-behaved system. A Chaotic system exhibits erratic and random response under steady state condition. One theory said that a chaotic system is free of noise and deterministic. The chaos of the system lies between the conflicting notions of randomness and determinism[5]. Chaos is a field of study which is known as nonlinear dynamics. A nonlinear system is represented by the nonlinear time domain equations comprising the dynamical property of the variables in their non linear form.

B. Representation of Correlation Dimension

The correlation integral is approximated by the correlation dimension [5] and represented as

$$\mathbf{D_2} = \lim_{r \to 0} \frac{\log [C(r)]}{\log (r)}$$

$$C(r) = \frac{1}{N(N-1)} \sum_i \sum_j V(r, |W_i\text{-}W_j|) \qquad (i \neq j)$$

In the above equations, r denotes the (radius) and ε denotes the criterion distance. Using above procedure Correlation Dimension was calculated for alcoholic EEG signal under study. Each channel of EEG signal produced ten correlation dimensions and hence, we attained 640 CD values for a single patient. We can visualize the presence of non linearity in CD through Histogram plot. Figure II shows the histogram of Correlation Dimension of Alcoholic EEG Signal. It is observed from figure II is a skewed one. Further substantiate our claim for the presence of non linearity in the CD features a histogram plot of statistical features like, Mean, Variance, Skewness, and Kurtosis were depicted in the figure III. Figure III also shows the presence of nonlinearity in CD features of the EEG signals. Hence, it will prove that CD features were the true representative of EEG signal in the embedded domain.

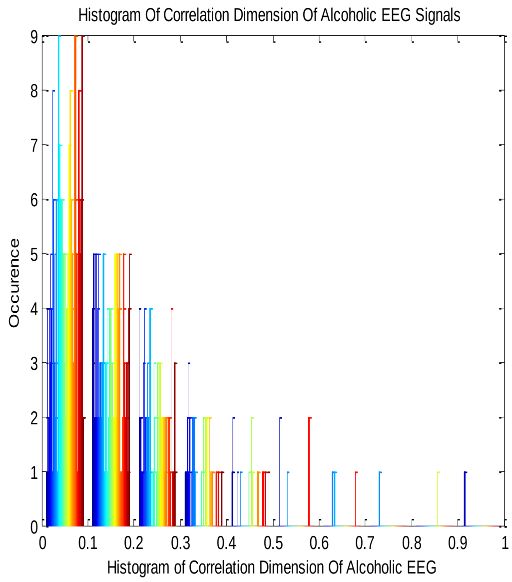

Figure II. Histogram of Correlation Dimension of Alcoholic EEG Signal

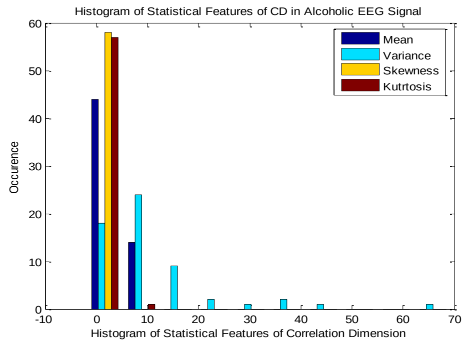

Figure III Histogram of Statistical Features of Correlation Dimension (CD) in Alcoholic EEG Signal

The following section of the paper explains the usage of Principal Components Analysis (PCA) as Classifier for Alcoholic Epilepsy from CD features.

III. PRINCIPAL COMPONENTS ANALYSIS (PCA) AS CLASSIFIER FOR ALCOHOLIC EPILEPSY FROM CD FEATURES

Orthogonal projections of variables are quite important in the analysis non linear features and Principal Component Analysis (PCA) is one among them [7]. Eigen value based PCA is maintained the nonlinearity and converged it to the ranking point of the input variables. Consider the correlation dimension values are N observations is a matrix of

$$e = [e_1 \quad e_2 \quad e_3 \quad .. \quad e_n]$$

The covariance matrix is computed as follows

$$C = \frac{1}{N}\sum_{m=1}^{n} \delta_m \delta_m^T = \frac{1}{N} A \times A^T$$

If υ_i denotes the prominent values of AXA^T and its scalar is indicated by

$$A^T A\upsilon_i = \mu \upsilon_i \; U_i = A \upsilon_i$$

The principal component of every signal e_i is obtained,

$$w_k = u_k^T \times (e_i - \delta)$$

The vector w_k represents the ranking of the CD features in the principle axes as the classification. The PSO is discussed as below.

IV. PARTICLE SWARM OPTIMIZATION (PSO) AS CLASSIFIER FOR ALCOHOLIC EPILEPSY

Kennedy and Eberhart in 1995 introduced this famous algorithm [8]. The algorithm comprises of a group of elements moving in a social colony and search space. The elements are represented as the function of position, distance, velocity and convergence. The better position indicates the optimization and solution to the search problem.

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A. Steps involved in PSO

The steps of PSO are as follows:

i.The CD features are the elements and is represented in a D-dimensional space as

Yi=(yi1,yi2,yi3,…yiD)

ii. The elements position are(P1,P2,P3,..PD) is the better solution towards the social interaction and its best value is the attainable solution.

iii. The elements are moving in the search space with the velocity associated with their positional values and its social interaction. The elite value of the position is the local best one.

iv. The global value will be the objective function or the possible solution.

v. The movements of elements are monitored by the velocity as well as their distance measures from the objective function.

vi. The acceleration function will converge the algorithm.

vii. The stopping criteria will be number of iterations or minimum error condition.

viii. After reaching the stopping condition the elements are ranked in the descending order and the best one is selected as the solution.

Figure IV demonstrates the performance of MSE in number of iteration for PSO at different weights and it is observed from the figure 4 that the optimum weight is chosen at w=0.5 with lower MSE values when compare with other weight values. In this case inertia (w) is set at 0.5 and η1, η2 are fixed as 1.

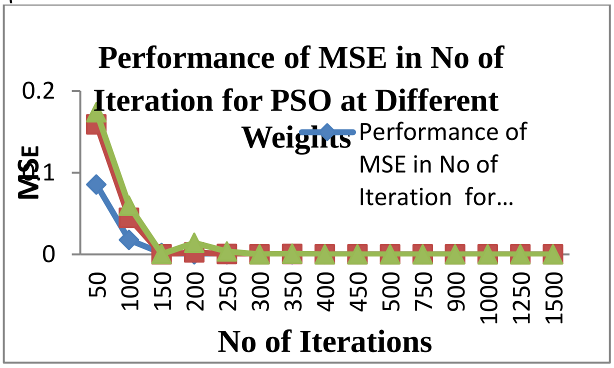

Figure IV Performance of MSE in Number of Iteration for PSO at different weights(inertia)

B Training and Testing of Classifiers

The efficacy of PCA and PSO classifiers are analyzed by the training and testing error. S-fold validation method is used in the training process. The Mean Square Error (MSE) is defined as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(O_i - T_j)^2$$

Oi is the output at time i, Tj is the fitness of the row j; j=1-10, and N is the total number of observations which is 64. The stopping criteria for PCA and PSO training is fixed by the number of iterations and is set at thousand iterations. The MSE for PCA and PSO classifiers are tabulated in Table 1.

Classifiers	**Mean Square Error**	
	Training	**Testing**
Principle Component Analysis (PCA)	3.3E-07	1.6E-05
Particle Swarm Optimization (PSO)	5.2E-10	1E-08

Table 1: Average MSE for CD Features in PCA and PSO

As shown in table 1 that the training error for both the classifiers are settled at higher value in the range of 10^{-7}, which is the direct influence of the number iterations in PCA and PSO algorithm.

V.RESULTS AND DISCUSSION

The effectiveness of PCA and PSO Classifiers are assessed by the metrics like Good Value (GV), Sensitivity, Specificity, and Area under Curve of ROC (AUC) in classifying the alcoholic EEG signals. The average results are tabulated in Table 2. The Good Value (GV), Sensitivity, Specificity and AUC are defined as

$$GV = \left(\frac{T - M - F}{T}\right)\times 100$$

Where True Division- T, Missed Division- M and the False Division- F. The Sensitivity, Specificity and AUC are expressed as

$$Sensitivity = \frac{T}{T+F}\times 100$$

$$Specificity = \frac{T}{T+M}\times 100$$

$$AUC = \frac{Sensitivity + Specificity}{2}$$

It is observed from table 2 that the PSO classifier settled at higher side of classification in Good Value, Sensitivity, Specificity and AUC when compared with PCA. The PSO classifier is ruined by the missed division which is not present in the PCA classifiers. Hence PSO Classifier will be labeled as high threshold one with lower specificity and PCA classifier is labeled as low threshold with lower sensitivity.

Parameters	PCA as a Classifier	PSO as a Classifier
True Division (%)	93.71	95.83
Missed Division (%)	0	4.16
False Division (%)	6.27	0
Good Value (%)	93.17	95.65
Sensitivity (%)	93.71	100
Specificity (%)	100	95.83
AUC (%)	96.85	97.92

Table 2 Performance Analysis of PCA and PSO Classifiers

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VI CONCLUSION

In this paper, the classification of chronic alcoholic from EEG signals for was analyzed from Correlation Dimension (CD) features with the two types of post classifiers like PCA and PSO. PCA classifier produces an average classification AUC of 96.85% with an average GV of 93.71%. For PSO classifier is ebbed with an average classification AUC of 97.92% with GV of 95.83%. The future research will be in the direction of biologically inspired classifiers for classification of alcoholic EEG signals.

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