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# An Exhaustive Analysis of Code Converters as Pre-Classifiers and K means, SVD, PCA, EM, MEM, PSO, HPSO and MRE as Post Classifiers for Classification of Epilepsy from EEG Signals

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**ABSTRACT**

The aim of this paper is to compare and learn the performance measures by considering the code converter as a one-level classifier and K-means Clustering, Singular Value Decomposition (SVD), Principal Component Analysis (PCA), Expectation Maximization (EM), Modified Expectation Maximization (MEM), Particle Swarm Optimization (PSO), Hybrid Particle Swarm Optimization (HPSO) and Minimum Relative Entropy (MRE) as post classifiers for the classification of the epilepsy risk levels obtained from Electroencephalography (EEG) signals. From the EEG signals the seven features such as variance, energy, spike and sharp waves, positive and negative peaks, events, average duration and covariance are extracted. Out of the seven parameters extracted, four parameters like the positive and negative peaks, the waves which include spike type and sharp type waves, events and average duration are extracted using only Haar wavelet transform performed with Hard Thresholding method. Performance Index (PI) and Quality Values (QV) are the two parameters that are used to assess the performance of the code converter and classifiers.

**KEY WORDS:** EEG, Code Converter, EM, MEM, PSO.

## 1. INTRODUCTION

In a variety of ways, the activities of the brain can be measured such as Magneto Encephalogram (MEG) and optical images (Celement, 2003). However, the most famous and popular technique used is EEG. It has always been an important clinical tool for diagnosis, management and monitoring of neurological disorder such as dementia, epilepsy etc. (Gabor and Seyal, 1992). The large amount of data generated by the monitoring of EEG is generally difficult for visual analysis (Gustavo and Renato, 1979). When treatment of epilepsy is done, the clinicians rely on robust algorithms for seizure detection and prediction (Joel, 2004). Therefore automated systems for recognizing EEG became the need of the hour (Leon, 2003).

The organization of the paper is as follows: Section 1 introduces the paper and materials and methods are discussed in the Section 2. Section 3 describes about the analysis of Post Classifiers such as K-means Clustering, Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Expectation Maximization (EM), Modified Expectation Maximization (MEM), Minimum Relative Entropy (MRE), Particle Swarm Optimization (PSO) and Hybrid Particle Swarm Optimization (HPSO) for epilepsy risk level classification. Results are discussed and concluded in Section 4.

## 2. MATERIALS AND METHODS

**Data Acquisition of EEG Signals:** The data acquisition is done as per the Figure.1.

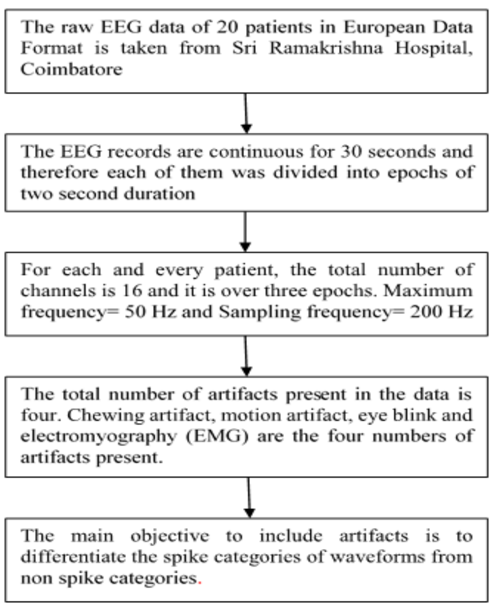


**Figure.1. Block Diagram of the Data Acquisition**

For the classification of the risk level of the patients, some parameters were chosen and it is detailed below

a) The energy is calculated as follows for each epoch and is given by

$$E = \sum_{i=1}^{n} x_i^2$$

Where, $x_i$ – signal sample value, n – Number of such samples.

b) The dynamics of underlying EEG can be understood if the variance of the signal is calculated in consecutive non overlapping windows. The variance is given by

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}$$

Where, μ - average amplitude of the epoch

c) The covariance of duration for the average variance is determined by using the equation below

$$CD = \frac{\sum_{i=1}^{p}(D - t_i)^2}{pD^2}$$

With the help of morphological filters and wavelet transforms the following four parameters are obtained.

a) The positive and negative peaks is found above the threshold level

b) Spikes are detected for zero crossing function if it is lies between 20milli seconds - 70milli seconds and sharp waves are detected if the zero crossing function lies between 70milli seconds – 200 milli seconds

c) After the detection process is over, the events are determined to be the total number of spikes and sharp waves

d) The duration for these waves is examined by the relation:-

$$D = \frac{\sum_{i=1}^{p} t_i}{p}$$

Where, $t_i$- Peak to peak duration, P – Number of such durations

**Wavelet Transforms for Feature Extraction:** Using the wavelet transform the features are extracted as follows. A wavelet transform applied to a particular function f (t) can be obtained as follows (Sukanesh and Harikumar, 2006).

$$wf(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}^{*}(t)dt$$

Where, $\psi^*$ (t) – complex conjugate of the wavelet function ψ (t)

On the careful analysis, from the mother wavelet ψ (t) the wavelet family can be deduced

$$\psi_{a,b}^{*}(t) = \frac{1}{\sqrt{2}}\psi\left(\frac{t-b}{a}\right)$$

Where, a - dilation parameter, b – Translation parameter

The feature extraction process is easily initialized by studying the effect of simple Haar threshold function

$$\psi(t) = \begin{cases} 1; 0 \le t < 1/2 \\ -1; \frac{1}{2} \le t < 1 \\ 0 : otherwise \end{cases}$$

Wavelet Thresholding is actually a signal estimation technique which explains the capabilities of wavelet transform applicable for signal Denoising or smoothing techniques. The efficacy of Denoising is determined by the choice of a threshold parameter. The hard threshold is the standard threshold operators for Denoising. In general Hard threshold is defined as follows

$$\rho_T(x) = \begin{cases} x, if\ |x| > T \\ 0, if\ |x| \le T \end{cases}$$

Where T is denoted as the threshold level.

The parameter extraction from EEG signals can be done with the help of both hard Thresholding and soft Thresholding methods. The wavelets such as Haar, dB2, dB4 and Sym8 wavelets with Hard Thresholding and four types of soft Thresholding methods such as Heursure, Minimaxi, Rigrsure and Sqtwolog can be applied generally but in this paper, only Haar wavelet with Hard thresholding is implemented. With the help of expert's knowledge for five linguistic risk levels such as very low, low, medium, high and very high ranges and according to the clinical description the following parametric ranges have been identified. The table I shows the various parameter ranges for different risk levels

**Table.1. Parameter Ranges for Various Risk Levels**

| Risk Level | Representation |
|---|---|
| Normal | U |
| Low | W |
| Medium | X |
| High | Y |
| Very High | Z |

The output of the code converters is always encoded into string of seven codes which corresponds to each and every signal parameter (Harikumar, 2003). The noise is present in the expert defined threshold values in the form of overlapping ranges.

**Code Converter as a Pre Classifier:** With the encoding method, the output values which are sampled are processed easily as an individual code. To process numbers with a perfect decimal accuracy seems to be very difficult while working with definite alphabets is much easier (Harikumar, 2003). Performing operations on numbers is difficult whereas processing alphabets is quite easier. By the easy encoding of each risk level in one of the five states, for each of the sixteen channels a string of seven characters is obtained (Sunil Kumar and Harikumar, 2015). The Performance Index of the code converter is given by the following formula

$$PI = \frac{PC - MC - FA}{PC} \times 100$$

Where, PI – Performance Index, PC – Perfect Classification, MC Missed Classification, FA – False Alarm.

The code converters performance is around 44.81%. When the physician agrees with the classic epilepsy risk level then it represents the perfect classification. The missed classification generally represents a high level as low level. With the help of the diagnosis of the physician the false alarm represents a Low level as High level. The other performance measures are also defined as below

The Sensitivity $S_e$ and Specificity $S_p$ are represented as

$S_e$= [PC/(PC+FA)]*100, (0.5/0.6)*100=83.33%, $S_p$= [PC/(PC+MC)] *100, (0.5/0.7)*100=71.42%

Average Detection (AD)= (Sensitivity+Specificity)/2, AD=78.875, Relative Risk= Sensitivity/ Specificity =1.166

For determining whether a classifier is a stable one or a sensitive one, the relative risk factor has to be taken into consideration. The relative risk will be unity for an ideal classifier. Slow response classifier will have a relative risk lower than unity and more sensitive classifier will have a relative risk slightly above than unity (Nurettin Acir, 2005). A value of just 40% for Performance Index and sensitivity, specificity, average detection and relative risk for the code converter is about 83.33%, 71.42%, 8.8% and 1.66 respectively. It is very vital to optimize the output of the code converter due to the low performance measures.

**Analysis of Post Classifiers:** Our main objective is to combine the representation of the epilepsy risk level with capabilities such as approximate reasoning while maintaining both the uncertainty handling and gradual processing of former with factors such as comprehensibility, popularity and easy handling.

**K – Means Clustering Algorithm*:*** It is mainly based with respect to the cluster similarity distance measures and the main factor considered here is computational expensiveness (Sunil Kumar and Harikumar, 2015). In the data analysis field, more attention has been given on data clustering as a robust technique in the last decade. The pattern data which is most often represented as multidimensional space in the clusters is described by the unsupervised classification of the clustering or data grouping.

**Principal Component Analysis for Optimization of Code Converter Outputs:** To various kinds of data, Principal Component Analysis (PCA) is applied as dimensionality reduction technique. In reality, PCA is the most optimal linear transform used and for any choice PCA always returns back the subspace where the highest variance is retained (Subasi and Gursoy, 2010). PCA can be used for the optimization of the code converter outputs. PCA is actually a mathematical technique which allows the reduction of the complex system of correlations where a relative smaller number of dimensions are present.

**Singular Value Decomposition as a Post Classifier:** In this section of the paper, SVD is chosen as a post classifier for the classification of epilepsy risk levels from EEG signals. It is widely used for the dimensionality reduction purposes and it is used to determine the modes of a dynamic system which is both complex and linear (Sunil Kumar and Harikumar, 2015). SVD is considered as a vital tool for the emphasis of modern numerical analysis and also in the field of numerical linear algebra.

**Expectation Maximization as a Post Classifier:** The Expectation Maximization (EM) is actually a statistical technique which maximizes the complex likelihoods and also it handles the incomplete data problem (Jinlong, 2011). It generally consists of two main steps namely the expectation step and the maximizations step.

**Expectation Step (E Step):** The expected value is initially computed for a particular data $x_{1,}$ which has an estimate of the parameter and the observed data.
**Maximization Step (M Step):** From the expectation step, the maximizations step is obtained. In the expectation step, the data was used which is used to actually measure the Maximum Likelihood estimate of the parameter A set of unit vectors is assumed to be as X when considering the code converter outputs.
**Modified Expectation Maximization Algorithm:** In this paper, a modified Expectation Maximization (EM) algorithm for pattern optimization processes is used with the help of maximum likelihood function. It is more or less very similar to the conventional EM algorithm and this algorithm is alternated between estimation of the E-Step and M-Step (Zhou, 2000). The evaluation of the ML function is generally difficult and therefore modifications are made to the EM algorithm.
**Minimum Relative Entropy (MRE) for Optimization of Wavelet Outputs:** The theoretic approach to the pattern recognition applications has received a considerable interest in recent years. The two main concepts that have been widely used here as recognition criteria are Shannon's entropy and the relative entropy (Srinivasan, 2007). From these entropies factors such as information centre, cross entropy and the directed divergence could be easily found out. Shannon's entropy generally allows to measure the information content of a particular group of patterns and the relative entropy enables to enhance the discrepancy between any two groups of patterns.
**Particle Swarm Optimization (PSO) Algorithm:** The two vital steps of PSO are outlined below (Coello, 2003)
a) Initialization Process: Here the generated particles in a random manner are called as "Particles", where N is being considered as the total number of parameters to be optimized and each such particle is assigned a velocity which is very random.
b) Velocity updates: In the hyperspace, the particles "fly" while it also updates its own velocity function followed by the accomplishment of consideration of its own part flight along with that of the neighboring companions.
**Hybrid Particle Swarm Optimization:**
**Step 1:** Rescale data sheet and separate training and testing set inputs of EEG (Hema, 2008).
**Step 2:** Calculate average of each attribute of the data set.
**Step 3:** Create population of PSO
**Step 4:** Evaluate the fitness value of each set by converting it through Continuous Genetic Algorithm (CGA) with highest fitness is gbest value.
**Step 5:** Calculate velocity and adjust position of each particle.
**Step 6:** Repeat steps 4 and 5 up to specified number of iterations.
**Step 7:** Convert gbest particle back into structure of PSO Algorithm.
**Step 8:** Perform local search by using PSO Algorithm.
**Step 9:** Once the search is over the patients with and without seizure is recognized by analyzing the obtained risk values.

## 3. RESULTS AND DISCUSSION

For various types of classifiers based on the Performance Index, Quality values, Sensitivity, Specificity, Time and Accuracy the results are computed and tabulated. The following table shows the exhaustive analysis of the performance analysis of various types of classifiers. The Tables 2 and 3 shows the consolidated analysis of all the post classifiers for the perfect classification of epilepsy risk levels from EEG signals.

**Table.2. Consolidated Analysis of all the Post Classifiers for the Classification of Epilepsy Risk levels from EEG Signals (PI, Sensitivity, Specificity)**

| Classifiers | PI (%) | Sensitivity (%) | Specificity (%) |
|---|---|---|---|
| K means | 95.83 | 98.12 | 97.91 |
| VD | 90.81 | 98.54 | 93.12 |
| PCA | 86.64 | 92.71 | 95.83 |
| EM | 75.79 | 89.58 | 91.25 |
| MEM | 81.86 | 95.83 | 89.17 |
| MRE | 85.35 | 95.41 | 93.54 |
| PSO | 73.65 | 97.08 | 83.33 |
| HPSO | 76.80 | 94.59 | 88.75 |

**Table.3. Consolidated Analysis of all the Post Classifiers for the Classification of Epilepsy Risk levels from EEG Signals (Time, Quality Values, Accuracy)**

| Classifiers | Time (sec) | Quality Values | Accuracy |
|---|---|---|---|
| K means | 2.04 | 22.83 | 98.02 |
| SVD | 2.29 | 21.50 | 95.83 |
| PCA | 2.02 | 19.32 | 94.27 |
| EM | 2.14 | 17.11 | 90.41 |
| MEM | 2.35 | 18.96 | 92.50 |
| MRE | 2.16 | 20.54 | 94.48 |
| PSO | 2.60 | 18.09 | 90.21 |
| HPSO | 2.34 | 18.73 | 91.67 |

The Performance Index of K-means algorithm is highest as of 95.83 % when compared to the performance indices of the other parameters. The Performance Index of SVD is next to the K means algorithm and it is of the range of 90.81%. If the accuracy parameter is concerned, then the post classifiers provide an average accuracy of more than 90% but the highest accuracy is obtained when K means clustering algorithm is applied and the value is found to be approximately 98.02%. This is followed when the post classifier used in SVD and it provides an average of about 95.83%. The accuracy of MRE and PCA comes third and fourth respectively with 94.48% and 94.27% respectively but the performance indices of both MRE and PCA is less as of 85.35% and 86.64% respectively. Thus it is concluded that the K means algorithm is the best post classifier for the classification of epilepsy risk levels from EEG signals.

## 4. CONCLUSION

This paper compares the performance by considering the code converter as a one-level classifier and K-means Clustering, Singular Value Decomposition (SVD), Principal Component Analysis (PCA), Expectation Maximization (EM), Modified Expectation Maximization (MEM), Particle Swarm Optimization (PSO), and Hybrid Particle Swarm Optimization (HPSO) as post classifiers for the classification of the epilepsy risk levels obtained from Electroencephalography (EEG) signals. From the EEG signals the seven features such as variance, energy, spike and sharp waves, positive and negative peaks, events, average duration and covariance are extracted. Performance Index (PI) and Quality Values (QV) were the two parameters that were used to assess the performance of the code converter and classifiers. When comparing all the classifiers, if code converter acts a pre-classifier and K-means Clustering algorithm is used as the post classifier then it is found to produce a higher accuracy of 98.02% when compared to the other classifiers. Future works plans to incorporate the use of different classifiers for the perfect classification of epilepsy risk levels from Electroencephalography signals.

## REFERENCES

Celement C. Pang, Upton A.R.M, Shinge G, and Kamath M.B, A Comparison of Algorithms for Detection of Spikes in the Electroencephalogram, IEEE Transaction on Bio Medical Engineering, 50 (4), 2003, 521-26.

Coello CA, Luna EH, Aguirre AH, Use of particle swarm optimization to design combinational logic circuits, Lecture Notes in Computer Science (LNCS), 2606, 2003, 398-409.

Gabor A.J, and Seyal M, Automated Interitical EEG Spike Detection using Artificial Neural Networks, Electroenceph. Clin. Neuro physiol., 83, 1992, 271-280.

Gustavo B, and Renato D, Contribution to the automatic processing of electrocardiograms using syntactic methods, IEEE trans on BME, 26 (3), 1979, 125-136.

Harikumar R, Sukanesh R, and Sabarish Narayanan B, Application of Aggregation operator in Fuzzy logic based classification of Diabetic Epilepsy risk level, National Conference IEEE India council, ACE 2003, Pune, 2003.

Hema CR, Paulraj MP, Nagarajan R, Yaacob S, Adom AH, Application of Particle Swarm Optimization for EEG Signal Classification, BMFSA, 2008.

Jinlong X, Jianwu L, & Yang Y, A new EM acceleration algorithm for multi-user detection, IEEE Int. Conf. Measuring Technol. Mechatronics Automation, 1, 2011, 150-153.

Joel J, Detection of Seizure Precursors from Depth EEG using a Sign Period gram Transform, IEEE Transactions on Bio Medical Engineering, 51 (4), 2004, 449-458.

Leon D. Iasemidis, Deng-Shen Shiau, Chao Valit Wongse W, Sacellares J.C, and Pardalos P.N, Adaptive Epileptic Seizure Prediction System, IEEE Transactions on Biomedical Engineering, 50 (5), 2003, 616-627.

Nurettin Acir, Oztura I, Kuntalp M, Baklan B, & Vuzelis C, Automatic Detection of Epileptiform Events in EEG by a Three-Stage Procedure Based on Artificial Neural Networks, IEEE Transaction on Biomedical Engineering, 52 (1), 2005, 30-40.

Srinivasan V, Eswaran C, & Sriraam N, Approximate entropy-based epileptic EEG detection using artificial neural networks, IEEE Trans. Inform. Technol. Biomed., 11 (3), 2007, 288-295.

Subasi A, & Gursoy MI, EEG signal classification using PCA, ICA, LDA and support vector machine, Expert Syst. Appl., 37 (12), 2010, 8659-8686.

Sukanesh R, and Harikumar R, Removal of Gaussian Noise from Photo-Plethysmography (PPG) Signals Using Wavelet Transforms, Cairo 3rd International Biomedical Engineering Conference, CIBEC'06 -Cairo-EGYPT, 2006**.**

Sunil Kumar Prabhakar, Harikumar Rajaguru, Performance Comparison of Fuzzy Mutual Information as Dimensionality Reduction Techniques and SRC, SVD and Approximate Entropy as Post Classifiers for the Classification of Epilepsy Risk Levels from EEG Signals, Proceedings of 2015 IEEE Student Symposium in Biomedical Engineering and Sciences (ISSBES), Universiti Teknologi Mara, Malaysia, 2015.

Zhou Y, Jim P, & Lee Y, A modified expectation maximization algorithm for maximum likelihood, IEEE Conf. Signals Syst. Comput., 1, 2000, 613-617.