International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

A Robust System for Detection of Artifacts from EEG Brain Recordings

Janga Vijaykumar, E Srinivasa Reddy

Abstract: ***Epilepsy is a chronic disorder and has the propensity of two or more unprovoked seizures which are clinical manifestation presumed to result from an abnormal and excessive discharge of a set of neurons in the brain. Analysis of EEG is the primary method for the diagnosis of epilepsy. Contamination of eye movement and blink artifacts presence in EEG data becomes more complicated to the doctors during the diagnosis period. Earlier detection of these artifacts gives a significant advantage of refining the Epilepsy identification process. In this regard, a robust subspace detection method is applied to detect the target signal in noise with possible interference-artifacts, then a dimensionality reduction model, with the combination of fast Independent and Robust Principal Component Analysis (FICA and rPCA) is implemented for identification of artifacts from EEG brain recordings. To perform this the proposed detection method uses synthetic data and artifact contaminated data. The extracted target subspace signal is considered as the input for rPCA and FICA. The ROC analysis is developed as a standard methodology to quantify the detectors' ability to correctly distinguish the target of interest (artifacts) from the background noise in the system.***

Keywords: electroencephalogram; artifact detection techniques; artifacts, PCA, FICA, ATGP

I. INTRODUCTION

In recent days it was observed that 65 million people of all ages have been confirmed to have epilepsy [1]. Due to the effects with particular epileptic seizures, that creates severe injuries, neurologists should be reviewed in patients with recurrent or prolonged seizures for early diagnosis and treatment. Electroencephalogram (EEG) is a non-invasive and effective procedure widely used to track brain activity and epilepsy diagnostics. EEG measurements were evaluated by neurologists to identify and categorize illness symptoms such as pre-ictal surges or convulsions. The visual analysis needs time and efficiency, and it takes several hours to review a patient's information documenting one day and includes specialist assistance. The review of patient records puts a heavy burden on neurologists and requires attention during the analysis. Such shortcomings have inspired efforts to develop and build computer systems to help neurologists identify epileptic seizures in the EEG.

Revised Manuscript Received on December 30, 2019.
***** Correspondence Author

Janga VijayKumar*, Research Scholar, Dept. of CSE, University College of Engineering, Acharya Nagarjuna University,Guntur, Andhra Pradesh, India.

Prof E Srinivasa Reddy, Professor & Dean, Dept. of CSE, University College of Engineering, Acharya Nagarjuna University,Guntur, Andhra Pradesh, India.

When a seizure happens and immediately affects the nervous system which seems to induce neurological shifts throughout the brain, this is well-thought-out as a general seizure. This happens if the brain part is damaged [2]. The existence of noise as well as artifacts in the data also makes it tough to know the brain structures of normal, ictal, and non-ictal instances. This challenge is further exacerbated by the variety of clinical seizure morphology [3].

Most findings have accepted a supervised learning framework that especially designed without manual operations for getting artifacts of EEG by machine learning. Irrespective of the type of the EEG data, the EEGs used to train identification systems are marked with prior knowledge. In [4-6] work focuses on the technique of neural network classification (NN) used for recognition of epilepsy affected people that achieves relatively good recognition performance. All of them used in support of vector machines (SVMs). Therefore, methods for the efficient detection and extraction of clean EEG data must be developed during encephalograms. Several methods for removing artifacts were proposed, but the removal study remains an open problem. The main objective of this article is to distinguish artifacts from EEG brain activity measurements such as eye blink and jaw movement. A traditional approach to detecting artifacts is to identify and neglect the corresponding data section. In an online environment, such as a brain-computer interface, this is not possible. Instead, a robust detector is preferable where the artifacts are presented as interference in a learned subspace. In the presence of artifacts, a robust subspace detection method [7] is applied to detect the target signal.

The main contributions and organization of this paper are summarized as follows: In section 2 we describe background details of EEG artifact detection. Section3 discusses the methods and methodology of work. Section 4 deliberates results and discussions. Finally, in section 5, we concluded the paper.

II. BACKGROUND WORKS

Epilepsy classify is an identification problem involving the detection and eventual recognition of specific features from EEG stimuli. There is also a need for a reliable method for the identification of inappropriate stimuli (called as technical artifacts such as cable motion or non-technical signals such as eye blink, jaw movement etc). EEG tracks random brain electrical activity and includes the voltage monitoring variations in brain activity [8, 9]. EEG signals occur at frequency from 0.01 Hz to 100 Hz, which can be divided into five frequency bands which, are summarized in Table 1.

Table 1. Basic brain wave with their frequency.

EEG band	Frequency (Hz)
Delta	<4
Theta	4-8
Alpha	8-13
Beta	13-30
Gamma	>32

Seizures are broadly categorized into partial or focal and generalized seizure, which is represented in Fig.1.

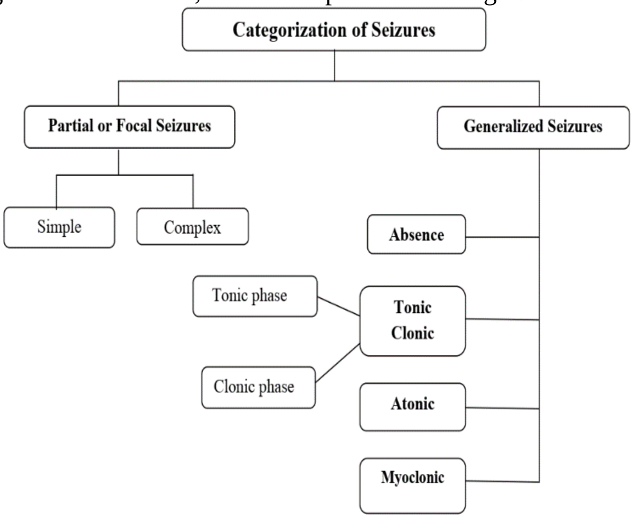

Fig.1. Broad Seizures categorization

EEG Artifacts:

Artifacts are unwanted signals from non-cerebral sources that alleviate the performance of biological signals. In terms of monitoring EEG, the major conflict is artifact recognition and elimination, as the occurrence of physiological and extra physiological artifacts. The patient-related artifacts are physiological artifacts (e.g. muscle movement, sweat, Jaw Clenching, ECG, eye movement) and technical artifacts, which have to be treated differently, for example (50/60 Hz artifacts, electrode popping).

III. METHODS AND METHODOLOGY

The process of detecting the artifacts' existence in the EEG data is illustrated the Fig.2. It consists of a processing stage, dimension reduction, Estimate Interference subspace, and detection of artifacts

Data recordings of EEG:

This system uses 16 channel EEG data recorded while the user tries to distinguish artifacts from the given EEG data. The EEG electrodes are fitted with the g. GAMMAcap (electrode cap). They have been arranged with O1, O2, F3, F4, FC, FC1, FC2, CZ, P1, P2, C1 C2, CP3, CP4 according to the International 10/20 model. A nonlinear 0.5–60Hz bandpass filter and a 60 Hz notch filter (the G.tec's built-in design) filtered the signals. The previously mentioned 1.5–42 Hz linear-phase bandpass filter is then used to filter signals. The filtered signals have been checked at 128Hz. Stimulus-on-start-locked periods of (0,500)ms for each channel have been taken as a stimulus-response for each channel [10]. An offline analysis using EEG data collected with RSVP Keyboard can be used for evaluating the suggested method [11-12].

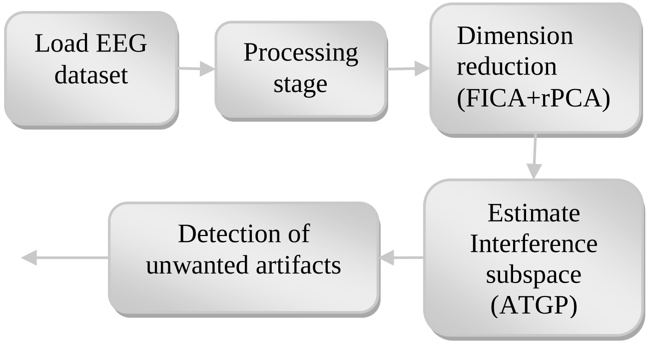

Fig. 2. Block diagram of the proposed scheme

A. *Processing stage:*

The EEG consists of artifact contaminated data, this happens because of either the faulty cable or the subject movement during the time of EEG recordings. For detecting the artifacts, there is a need for a good detector capable of detection in even it contains noise.

A robust subspace detection method is applied to detect the signal of interest in noise with possible interference-artifacts. The current model assumes a modified Gaussian distribution for each class, signal of interest and no- signal of interest in the feature space.

Let us consider there is only the signal of interest and unknown interference

Let us consider there is only the signal of interest and unknown interference

$$a = x_l + x_m + N \quad (1)$$

$$a = Y\theta + Z\psi + N \quad (2)$$

Consider for each feature vector a windowed in time segment can be expressed as a sum of the signal of interest, x_l, an unknown interference x_m, and noise *N*.

Given the model above we desire a hypothesis test for the presence of the signal, that should work, even if is non-zero and *Z* is unknown

$$H_0 : Z\psi + N \quad (3)$$

$$H_1 : Y\theta + Z\psi + N \quad (4)$$

We apply a likelihood ratio test, which after taking the log yields the test statistics for the no interference (conventional, Equation 5) and interference (Equation 6) cases.

$$\lambda(k) = \left(\frac{1}{w_1}\|k - l\hat{\theta}\|_2\right)^2 + \left(\frac{1}{w_0}\|k\|_2\right)^2 \quad (5)$$

$$\lambda(k) = \left(\frac{1}{w_1}\|k - L\hat{\theta}\|_2\right)^2 + \left(\frac{1}{w_0}\|k - p\hat{\theta}\|_2\right)^2 \quad (6)$$

A geometric interpretation of the problem is useful for the next step in the derivation. Consider the feature vector *k* to be in a space with components in the direction of and orthogonal to the signal subspace, *Y*.

We assume use of a maximum likelihood estimate for the $\hat{\theta}$ unknown gain; this distance $\|k - l\hat{\theta}\|_2$ is the projection of *k* onto the subspace *L*.

$$P_L = L^T (L^T L)^{-1} L^T \qquad (7)$$

With no interference, in the case where the noise variance is known, we can set a threshold for the magnitude of the projection of k into L for detection. This results in the χ^2 test. In the case where the noise variance is unknown, we can consider the ratio of the portion of x in the subspace of S and in the orthogonal space $P = L_{\perp}$.

B. *Feature reduction subspace:*

There are several techniques available for reducing the dimension of feature among them PCA is widely used because of the simplified pattern of estimation of signal subspace for identification purposes. It fails for low-dimensional data representation and has computational complexity. To overcome this ICA can be applied to data which separates components independently. Also, ICA deals with low-dimensional data because of statistical independence.

RobustPCA (rPCA):

This function applies PCA on each channel of EEG data for all trials matrix. Consider the group of data vectors $D = d^1, d^2, \ldots d^q$ for p trials which makes the column matrix of $p\times q$ order.

The mean of data vector for all components is given by

$$\bar{D} = \frac{1}{q} \sum_{k=1}^{q} d^k \qquad (8)$$

Next, the covariance matrix is calculated as

$$C = \frac{1}{q-1} \sum_{k=1}^{q} \left(d^k - \bar{D}\right)(d^k - \bar{D})^T \qquad (9)$$

The operation is done on all eigenvectors with the help of covariance matrix C. In a similar manner PCA is applied on the EEG channel which is segmented into g windows and later this will form a matrix for further processing. Then the extraction of the principal component from each channel is done thus the result is data with removed low variance components.

FastICA (FICA):

It is used to reduce the feature dimension especially suitable for significant features from the EEG data. Before performing the operation, it segments components independently and compute analysis on components.

Consider there are q linear set of vectors generated with associated mixtures namely M_1, M_2, ….. M_k with k trials. In the same way there exist d source vector obtained with d_1, $d_2, \ldots d_k$. Then all together components $a_{i,j}$ denoted with weighted matrix model is given as

$$M = Wd \qquad (10)$$

More specifically model can express in mathematical form as

$$M = \sum_{i=1}^{q} a_i d_i \qquad (11)$$

From the Eq. (10) it is evident that FICA is supposed to be treated as model in which all the independent components. It is clear that gather data are generated with the process of collection of all independent components d_i

Subsequently the reverse process of weighted matrix can be represented as

$$M = Ad \qquad (12)$$

C. *Estimate Interference subspace (ATGP):*

An Automated Target Generation Process (ATGP) accompanied by a Target Classification Process (TCP) may implement the proposed algorithm. The ATGP generates a set of potential targets without prior knowledge from the signal data in an unsupervised manner. The obtained ATGP targets are then categorized accordingly into TCP order to perform the artifact detection process. Next, the TCP processes the targets produced by the ATGP, which classifies each of the ATGP targets generated. The classifier used in the TCP is the OSP type in which ATGP is treated as unsupervised target detection technique. It implements an orthogonal subspace projector to find a set of potential targets with the maximal orthogonal projections (OPs) from the signal. The orthogonal subspace projector of ATGP can be given by eq. (7).

***Automatic Target Generation Process*:**

1) Initial condition:

Select an initial target signature of interest denoted by t_0. Let ε be the prescribed error threshold.

Set

2) Apply $P_{t_0}^{\perp}$ to all signal vectors **r** in the signal.

3) Find the first target signature, denoted by t_1 which has the maximum orthogonal projection

$$t_1 = \arg\left\{\max_r [(P_{t_0}^{\perp} r)^T \left(P_{t_0}^{\perp} r\right)]\right\} \qquad (13)$$

4) If $\eta_1 = t_0^T P_{U_0}^{\perp} r < \varepsilon$, forward to step 8. Else, set the value $i = i + 1$ and then continue.

5) Obtain the i^{th} target $\boldsymbol{t}_i$ produced at the i^{th} stage by **t**.

$$t_i = \arg\left\{\max_r [(P_{t_0 U i-1}^{\perp} r)^T \left(P_{t_0 U i-1}^{\perp} r\right)]\right\} \qquad (14)$$

6) Consider i^{th} target signature matrix, compute it at the same time relate it with set threshold.

7) Stopping rule: If $\eta_1 < \varepsilon$ return to step 5. Else, continue.

8) In this phase the ATGP is halted and matrix of required target **U**i in which target signatures does not contains initial target $\mathbf{t}_0$

IV. RESULTS AND DISCUSSION

In this paper, the bandpass filter is used for EEG data with a frequency of 0.5-40Hz. The simulation is carried out with Matlab 2013a, separate functions are written for individual operations. The operations are run on PC with a configuration of 2.7GHz with 8GB RAM. The operations are done for all sixteen channels, which should be possible by operating directly on the matrix array. It can label the channels 1 through 16. Choose a 10-second segment of the data the sampling rate was 256 samples per second. The total number of observations for the entire simulation is 1000.

ROC analysis provides a systematic tool for quantifying the impact of variability among individuals' decision thresholds.

True Positive Rate (TPR) or Sensitivity: The true positive rate is the proportion of the individuals with a known positive condition for which the test result is positive.

False Positive Rate (FPR): The false-positive rate is the proportion of the individuals with a known negative condition for which the test result is positive.

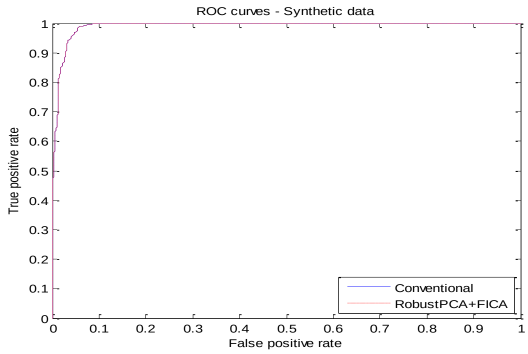

Fig.3. ROC curves of original synthetic EEG data

Fig. 3 illustrates the ROC curves of synthetic data shows same detector performance for the two schemes conventional and RobustPCA+FICA because of no artifacts in the EEG recordings.

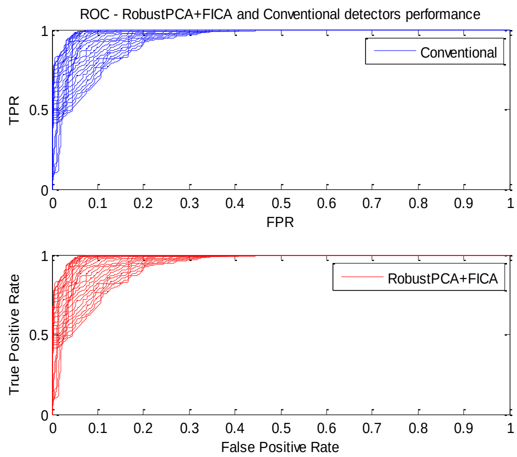

Fig. 4. Performance of conventional and RobustPCA+FICA detector

Fig. 4 illustrates the ROC curves of both the detectors performance for 16 channels of EEG data applied for RobustPCA+FICA and conventional scheme for obtaining the area under curve (AUC) purpose.

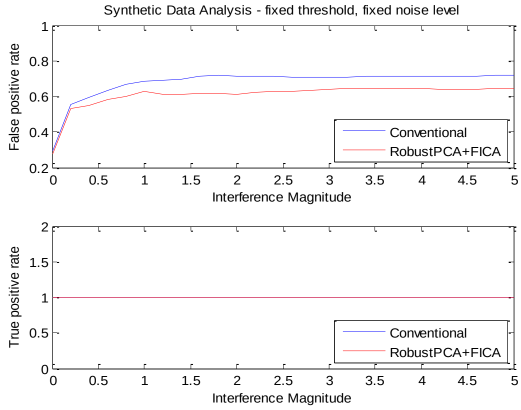

Fig. 5. Data analysis of original EEG data for fixed threshold

Figure 5 shows that FPR values are high for Robust scheme with respective to all the interference values shows the out performance of detector.

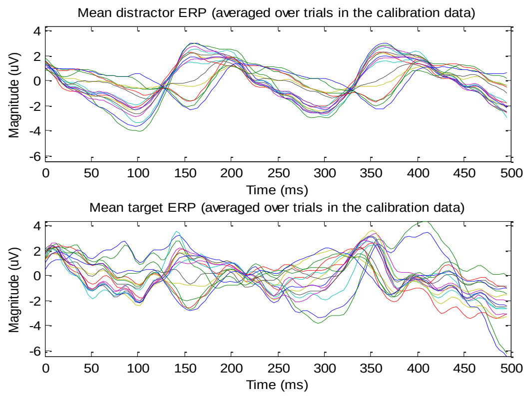

Fig. 6. Averaged over trials for each channel, for clean data

Fig.6 illustrates the different magnitude levels of channels of clean data for 500ms. It is clear from the plot that mean distractor and target Event related potentials (ERP) has high magnitude during time of 430ms.

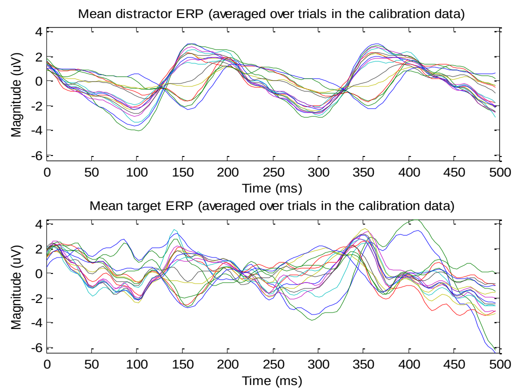

Fig.7. Averaged over trials for each channel, for eye blink contaminated data

Fig.7 illustrates the different magnitude levels of channels of artifact contaminated data for 500ms. It is clear from the plot that mean distractor and target Event related potentials (ERP) has high magnitude during time of 400ms.

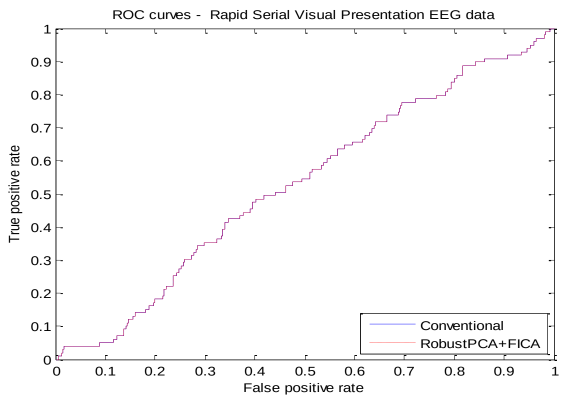

Fig. 8. ROC curves for FPR and TPR

Fig. 8 shows the receiver operating characteristic (ROC) curves that was plotted for FPR versus TPR of proposed model, and the conventional model for EEG data. It is clear from the plots the proposed model outperforms as related to the conventional scheme.

V. CONCLUSION

In this paper, we proposed a scheme in which, the detection of artifacts in the presence of noise is examined. To achieve a good detector for artifacts from EEG data, a single PCA technique is not adequate for reducing the number of features. So, in this paper, two techniques rPCA and FICA are combined for transforming features into a lower dimension. To show the performance of the proposed model, a publicly available dataset is used. The various FICA and rPCA components were evaluated for extracting features following the implementation of the dimensional reduction models. Moreover, it evaluated the model to measure different statistical parameters. It has been found that taking features from a combined reduction scheme (rPCA+FICA) offers better quality than taking features from individual models.

REFERENCES

1. D. Thurman, E. Beghi, C. Begley, A. Berg, J. Buchhalter, D. Ding, D. Hesdorffer, W. Hauser, L. Kazis, R. Kobau *et al.*, “Standards for epidemiologic studies and surveillance of epilepsy,” *Epilepsia*, vol. 52, no. 7, pp. 2–26, 2011.
2. R. Fisher, J. Cross, C. D’souza, J. French, S. Haut, N. Higurashi, E. Hirsch, F. Jansen, L. Lagae, S. Moshe´ *et al.*, “Instruction manual for the ILAE 2017 operational classification of seizure types,” *Epilepsia*, vol. 58, no. 4, pp. 531–542, 2017.
3. McShane, T. (2004). A clinical guide to epileptic syndromes and their treatment. *Archives of disease in childhood*, *89*(6), 591.
4. He, Q.; Wu, B.; Wang, H.; Zhu, L. VEP Feature Extraction and Classification for Brain-Computer Interface. In Proceedings of the 8th International Conference on Signal Processing, Guilin, China, 16–20 November 2006.
5. Boser, B.E.; Guyon, I.M.; Vapnik, V.N. A Training Algorithm for Optimal Margin Classifiers. In Proceedings of the Annual Workshop on Computational Learning Theory, Pittsburgh, PA, USA, 27–29 July 1992; pp. 144–152.
6. Fu, K.; Qu, J.; Chai, Y.; Zou, T. Hilbert marginal spectrum analysis for automatic seizure detection in EEG signals. *Biomed. Signal Process. Control* **2015**, *18*, 179–185.
7. M.N. Desai and R.S. Mangoubi. Robust Gaussian and non-gaussian matched subspace detection. *IEEE Transactions on Signal Processing*, 51(12):3115 3127, December 2003.
8. Niedermeyer, E.; Lopes da Silva, F.H. *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, 5th ed.; Raven Press: New York, NY, USA, 2005; pp. 654–660, ISBN 978-0781789424.
9. Minguillon, J.; Lopez-Gordo, M.A.; Pelayo, F. Trends in EEG-BCI for daily-life: Requirements for artifact removal. *Biomed. Signal Process. Control* **2017**, *31*, 407–418.
10. Umut Orhan, Deniz Erdogmus, Brian Roark, Barry Oken, and Melanie Fried-Oken. Offline analysis of context contribution to ERP-based typing BCI performance. *Journal of neural engineering*, 10(6):066003, December 2013.
11. Hild K, Orhan U, Erdogmus D, Roark B, Oken B, Purwar S, Nezamfar H, Fried-Oken M. An ERP based brain-computer interface for text entry using rapid serial visual presentation and language modeling. Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies. 2011:38–43.
12. Orhan, U.; Hild, K.; Erdogmus, D.; Roark, B.; Oken, B.; Fried-Oken, M. Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on. IEEE; 2012. Rsvp keyboard: An EEG based typing interface; p. 645-648.

AUTHOR PROFILES

Janga Vijaykumar, Research Scholor in Computer Science and Engineering Department, University college of Engineering, Acharya Nagarjuna university, Guntur, Andhra Pradesh, India. He published his works in 8 international journals and attended 2 international conferecnes. His ares of reaserach interests are Artificial Intelligence, Machine Learning and Kowledge Extraction systems.

Prof E Srinivasa Reddy, former principal, Professor & Dean University college of Engineering, Acharya Nagarjuna University, Guntur, Andhra Pradesh, India. He had 25 years of teaching and 15 years of research Experience with the publications count over 70 including prestigious journals and conferences. His area of research includes Digital image processing and pattern recognition.