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Classification of EEG Spectrogram using Adaptive Resonance Theory-2

Engineering

KEYWORDS : EEG classification, Adaptive Resonance Theory-2

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ABSTRACT

Electroencephalography (EEG) is a well Known tool to capture the human brain signals. This paper uses the time frequency approach known as spectrogram image processing technique for analyzing the EEG signal, which was generated by the technique Short Time Fourier Transform. The features were extracted by using the Gray Level Co-occurrence Matrix (GLCM). The four feature mean, variance, standard deviation and range were extracted using the Gray Level Co-occurrence Matrix (GLCM). The extracted features were given as the input to the Adaptive Resonance Theory-2 (ART2) classifier. Then the Adaptive Resonance Theory-2 (ART2) classifier was employed to classify the EEG spectrogram image. The results showed that the Adaptive Resonance Theory-2 (ART2) classifier was able to EEG spectrogram image with accuracy of 96%.

1. INTRODUCTION

The Human brain is a complex system which exhibits a rich spatiotemporal dynamics [1]. The electrical activity i.e the variation of the surface potential distribution on the scalps reflects functional activities of the brain. This electrical activity is recorded by affixing an array of electrodes to the scalp, and measuring the voltage between pairs of these electrodes the obtained data is called the Electroencephalogram (EEG) signal [2]. The diagnosis of the activity of the brain is vital issue. The detection and classification of the EEG data by visual screening is a complex and time consuming operation. EEG signals are non-stationary; hence the visual analysis of EEG signal in time domain is not sufficient. So the brain waves recorded in the form of amplitude versus time i.e. time based are usually translated into frequency based using the Fourier transforms. The brain wave can also be analyzed with a technique called time-frequency based which is known as spectrogram image. The spectrogram image has been used in the study of heart abnormalities from the ECG signal [3]. The spectrogram image can be analyzed using texture analysis in image processing called as Gray Level Co-occurrence Matrix (GLCM). The GLCM technique is also popular in biomedical image analysis to detect disease in liver and brain [4, 5]. The main aim of classification of EEG signal is for diagnose of the brain signal. In our project we are using the EEG spectrogram image obtained from the STFT. The features are extracted from the spectrogram image using the GLCM technique. The extracted features are classified using the Adaptive Resonance Theory-2 classifier which is a kind of neural network classifier which has high stability and plasticity. The uses of ANN classifiers are done before, but by using the ART-2 classifiers we can achieve high rate of accuracy .Thus the classification of EEG spectrogram is carried out using the Adaptive Resonance Theory-2 algorithm.

2. IMPLEMENTATION

A. DATA COLLECTION:

For the data acquisition, electrodes of 8 mm of silver-silver chloride fixed on C3 and C4 of the international system of positioning 10-20 electrode system were used. Signal amplification was made through amplifier EEG of 8-channel model Procomp Infinity. The sampling frequency is of 256 Hz. A digital band-pass filter has been implemented between 0.5 and 30 Hz in real time to especially eliminate the noise originating from the mains and other sources.

B. PREPROCESSING:

As shown in fig 1, the raw EEG signals need to be cleaned the EEG preprocessing consists of two steps; artifacts removal and low pass filter. In data preprocessing, the artifacts is removed by using a threshold value. The value was set to eliminate the EEG signal when the values are exceeded 100µV and less than -100µV. The program was designed using MATLAB. The Low pass filter was used to remove the DC components. The preprocessing is necessary to clean the EEG signal because the raw signal is contaminated which when used with good classifier also provides average results due to the artifacts present in the signal. Hence the raw EEG signal is preprocessed.

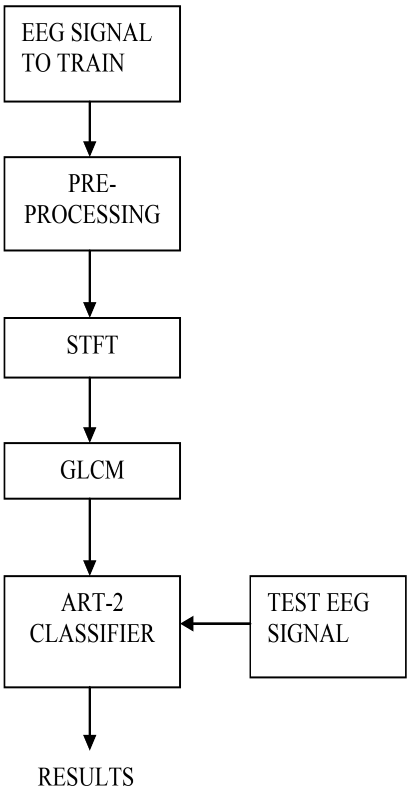

Fig 1 Block diagram to classify the EEG signal using Adaptive Resonance Theory-2

C. SPECTROGRAM IMAGE:

The processed signal i.e the cleaned signals are in the time based form. It is translated into the frequency based form by using the Fourier transform. One of the mathematical methods with greater application in signal processing is the Fourier Transform (FT), Fourier analysis is as a mathematical technique for transforming our view of the signal from time-based to frequency-based using the equation (1)

$$X(f) = \int x(t)e^{-2j\pi ft}\, dt \qquad (1)$$

For many signals, Fourier analysis is extremely useful because the signal's frequency content is of great importance, but it has a serious drawback. In transforming to the frequency domain, time information is lost. When looking at a Fourier transform of a signal, it is impossible to tell when a particular event took place, because the analysis coefficients X(f) denote the distribution of the signal in the frequency domain for the entire record, that is, with no time resolution[2].

If the signal properties do not change much over time that is, if it is what is called a stationary signal this drawback isn't very important. However, most interesting signals, like the EEG signals, contain numerous non-stationary or transitory characteristics: drift, trends, abrupt changes, and beginnings and ends of events. These characteristics are often the most important part of the signal, and Fourier analysis is not suited to detect them.

In an effort to correct this deficiency, Dennis Gabor (1946) adapted the Fourier transform to analyze only a small section of the signal at a time[2]. This intuitive solution consists of multiplying the signal x(τ) with a temporal window function h. The resulting transform, called the Short-

$$STFT(t,f) = \int X(\tau)h^{*}(\tau - t)e^{-2j\pi ft}\, d\tau \qquad (2)$$

Thus the frequency- time based signal is called as the spectrogram image. For non stationary signals like EEG these spectrogram images are used study the abnormalities of the EEG signals. The spectrogram image was obtained using the matlab functions.

D. FEATURE EXTRACTION

The spectrogram image was analyzed by using the texture analysis method using the Gray level co-occurrence matrix. Thus the features are extracted using the above four equations. The 160 features were extracted using the GLCM technique. The GLCM was calculated by the inbuilt functions present in the matlab. For each EEG data 160 features were determined .These extracted features are given as input to the ART-2 classifier, where the classifier classifies the EEG signal by comparing these extracted features by the GLCM texture analysis method[6].

3. CLASSIFICATION.

Adaptive resonance theory based artificial neural networks (ART) form a particular family of pattern recognition methods. They were introduced by G. Carpenter and S. Grossberg to overcome the so-called stability plasticity dilemma. It is said, that ART networks solve the stability-plasticity dilemma*:* "they are stable enough to preserve significant past learning but they remain adaptable enough to incorporate new information"[7]. In other words: they are always able to learn new patterns without forgetting the past. The ART network is able to create stable recognition codes by self organization in response to arbitrary sequences of

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input pattern. Adaptive Resonance Theory, or ART, is a cognitive and neural theory of how the brain autonomously learns to attend, categorize, recognize, and predict objects and events in a changing world[15].

The topology graph of ART-2 in fig 2 shows the F1 Feature representation field with M processing units each one composed of three layered feedback system: top, middle and bottom. The neurons are represented by the circles. It has a vigilance parameter ρ which is used as a threshold value for finding the perfect match.

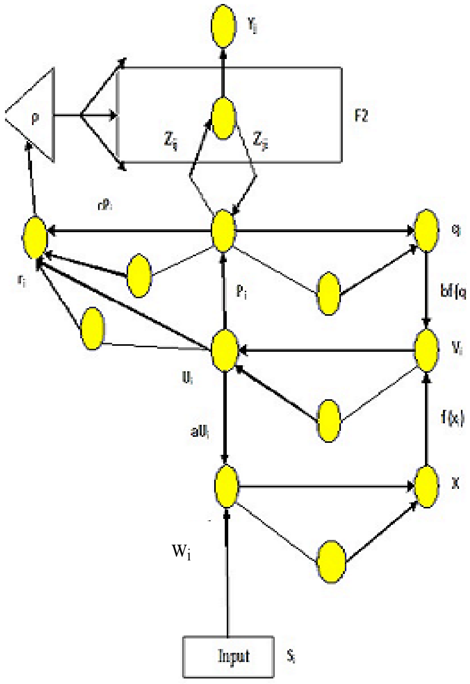

Fig 2 Topology of ART-2

A. The STM equations of feature representation field F1[7,8]:

The input is given to a three layered feedback system which has the nodes w_i, x_i, u_i, v_i, p_i, q_i, the Short term memory activities of the F1 field are given by the dimentionless equations (3 to 8)

$$u_i = \frac{v_i}{e + \|V\|} \quad (3)$$

$$w_i = s_i + au_i \quad (4)$$

$$p_i = u_i + \sum_{j=M+1}^{N} g(y_j) z_{ji} \quad (5)$$

$$q_i = \frac{p_i}{e + \|P\|} \quad (6)$$

$$x_i = \frac{w_i}{e + \|W\|} \quad (7)$$

$$v_i = f(x_i) + bf(q_i) \quad (8)$$

where $f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$

where $\|W\|$ denotes the normalised value of W it is given as $\|W\| = \sqrt{\sum w^2}$. The variables a,b,c,e are the constants. where I is the output signal from the jth F2 node and is the LTM trace in the path from the jth F2 node to the ith F1 node.

B. The STM equations of Category representation field F2[7,8]:

The function of the F2 layer is to determine the winning neuron by competitions, whose weight vectors have a maximum similarity to input vectors. Suppose the input vector of node j in F2 is the winner node then,

$$T_j = \sum_i p_i Z_{ij} \quad (j = M+1.......N) \quad (9)$$

The winner node is then taken as

$$T_j^* = \max(T_j) \quad (j = M+1........N) \quad (10)$$

F2 can also be resetted by using the gated dipole field network in F2. When a new input reaches the F2 gated dipole field the nodes are resetted. When node j^* is the maximum activated node, other nodes should be deactivated. The gated dipole can be characterized as

$$g(y_j) = \begin{cases} d, & j = j^* \\ 0, & j \neq j^* \end{cases} \quad (11)$$

While d is the top-bottom feedback parameter should be, 0 < d < 1. The constant c and d are related $\frac{cd}{1-d} \leq 1$.
From this eqn (6.9) the eqn (6.3) can be written as

$$p_i = \begin{cases} u_i + dz_{ji}, & j = j^* \\ u_i, & j \neq j^* \end{cases} \quad (12)$$

C.Weight regulation equations[7,8]

The weights are updated adaptively by the adaptive filters in the Long term memory (LTM).

The weight equation from F2→F1 is given as

$$\frac{dz_{ji}}{dt} = d(p_i - z_{ji}) \quad (13)$$

The weight equation from F1→F2 is given as

$$\frac{dz_{ij}}{dt} = d(p_i - z_{ij}) \quad (14)$$

When F2 has a winning neuron j^* for $j \neq j^*$ then

$$\frac{dz_{ij}}{dt} = 0 \quad and \quad \frac{dz_{ji}}{dt} = 0$$

If $j = j^*$ then the weights are concluded as

$$\frac{dz_{ji*}}{dt} = d(1-d)\left(\frac{u_i}{1-d} - z_{ji*}\right) \qquad (15)$$

$$\frac{dz_{ij*}}{dt} = d(1-d)\left(\frac{u_i}{1-d} - z_{ij*}\right) \qquad (16)$$

The weights Z_{ij} and Z_{ji} are initially taken by the equations

$$Z_{ij} = 0 \quad and \quad Z_{ij} = \frac{1}{[(1-d)\sqrt{M}]}$$

where I = 1,2,…, M; j = M+1,……. M+N)

D. The orienting subsystem reset equation[7,8]

When a similarity is not determined the F2 is resetted. The matching equation is defined by

$$r_i = = \frac{u_i + cp_i}{e + \|U\| + \|cP\|} \qquad I = 1,2,\ldots,M \qquad (17)$$

Set threshold ρ, 0 < ρ < 1 $\|R\|$ is the m odulus of similarity, if $\|R\|$ < ρ then the orienting subsystem resets the field F2.

E. Implementation of the learning algorithms of ART-2[11, 12, 14,16]

Step 1: Initialize the parameters) a, b, c, d, e, α, ρ). Also specify the number of epochs of training and the number of learning itertation w have taken a = b = 8, c = 0.1, d = 0.9, e = 0, α = 0.5, ρ = 0. 75. The values of c and d should satisfy the equation $\frac{cd}{1-d} \leq 1$. The α is the learning rate; ρ is the vigilance parameter which should be 0.7 < ρ < 1; the weights are initialzed using the Equation $Z_{ij} = 0$ and $Z_{ij} = \frac{1}{[(1-d)\sqrt{M}]}$. Where M is the attribution of the training pattern.

Step 2: For each training pattern perform step 3 to 12 for number of epochs time. (nep = 100)

Step 3: Update F1 unit activation

$$u_i = 0 \quad ; \quad w_i = s_i$$
$$p_i = 0 \quad ; \quad x_i = \frac{w_i}{e + \|W\|}$$
$$q_i = 0 \quad ; \quad v_i = f(x_i)$$

Step 4: Update F1 unit equations again using following equations

$$u_i = \frac{v_i}{e + \|V\|} \quad ; \quad w_i = s_i + au_i$$
$$p_i = u_i + dt_{ji} \quad ; \quad x_i = \frac{w_i}{e + \|W\|}$$
$$q_i = \frac{p_i}{e + \|P\|} \quad ; \quad v_i = f(x_i) + bf(q_i)$$

Step 5: Calculate the F2 activation layer using

$$Y_j = \sum_i p_i Z_{ij}$$

Step 6: If reset is true , perform steps 7 and 8

Step 7: Find the winning neuron j in the F2 layer with maximum activation

Step 8: Test for the vigilence by calculating,

$$u_i = \frac{v_i}{e + \|V\|}$$

$$p_i = u_i + dt_{ji}$$

$$r_i = = \frac{u_i + cp_i}{e + \|U\| + \|cP\|}$$

If $\|r_i\|$ < (ρ-e) then y_j = -1 hence inhibit j, Reset is true. Perform step 5

If $\|r_i\| \geq$ (ρ-e) then calculate the equations;

$$w_i = s_i + au_i$$
$$x_i = \frac{w_i}{e + \|W\|}$$
$$q_i = \frac{p_i}{e + \|P\|}$$
$$v_i = f(x_i) + bf(q_i)$$

If reset is false proceed with step 8

Step 8: Perform steps 9 to 11 for specified number of learning iterations

Step 9: Update the weights for winning unit j:

$$z_{ji} = \alpha du_i + \{1 + \alpha d(d-1)\} z_{ji}$$
$$z_{ij} = \alpha du_i + \{1 + \alpha d(d-1)\} z_{ij}$$

Step 10: Update the F1 activations:

$$u_i = \frac{v_i}{e + \|V\|} \quad ; \quad w_i = s_i + au_i$$
$$p_i = u_i + dt_{ji} \quad ; \quad x_i = \frac{w_i}{e + \|W\|}$$
$$q_i = \frac{p_i}{e + \|P\|} \quad ; \quad v_i = f(x_i) + bf(q_i)$$

Step 11: Check for the stopping condition of weight updation ; whether the number of stop iterations is reached or not.

Step 12: Check for the stopping condition for number of epochs ; whether the number of stop epochs is reached or not.

After the network is trained by the learning algorithm the classification is done by the unsupervised method of the Adaptive resonance theory-2. The extracted features from the GLCM were used as the input to the classifier to test and evaluate by ART-2 neural network. The performance measures of accuracy of classifier are given by the sensitivity, specificity and the total accuracy of these algorithms will also be presented using as training and testing data sets.

4. RESULT AND CONCLUSION

The raw EEG signals are shown in the fig 3 which is time based signals. The preprocessing of the signal is done using two steps one is artifact removal and the other is low pass filter. In data preprocessing, the artifacts is removed by using a threshold value. The value was set to eliminate the EEG signal when the values are exceeded 100µV and less than -100µV. The program was designed using MATLAB. The low pass filter was used to remove the DC components. The fig 4 shows the preprocessed EEG signal. After the preprocessing the spectrogram image of the EEG signal is obtained which is the Frequency –time based system. The 160 features were extracted using the GLCM technique. These features were given as the input to the Adaptive resonance theory-2 classifier with the following parameters given in table 1.The classification is shown in the fig 7.

Table 1 : parameters for the learning algorithm of ART-2

Parameters	Values assigned
Vigilance parameter (ρ)	0.75
Learning rate (α)	0.5
a	8
b	8
c	0.1
d	0.9
e	0

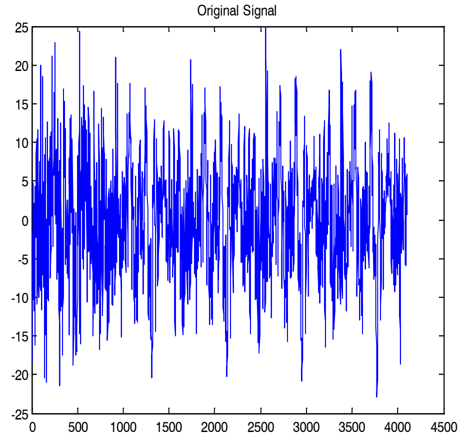

Fig 4 Original EEG signal

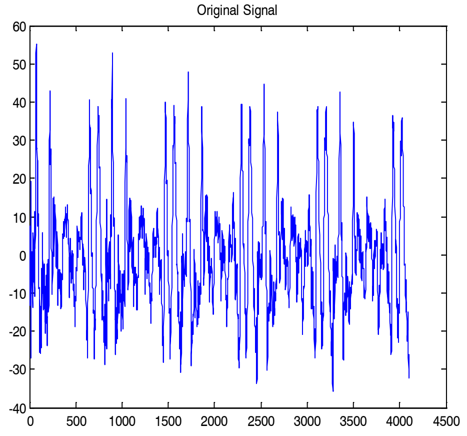

Fig 5 Processed EEG signal

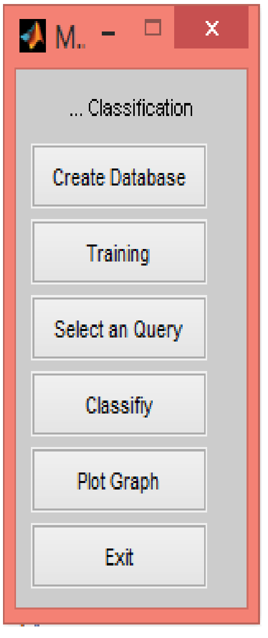

Fig 6 menu window

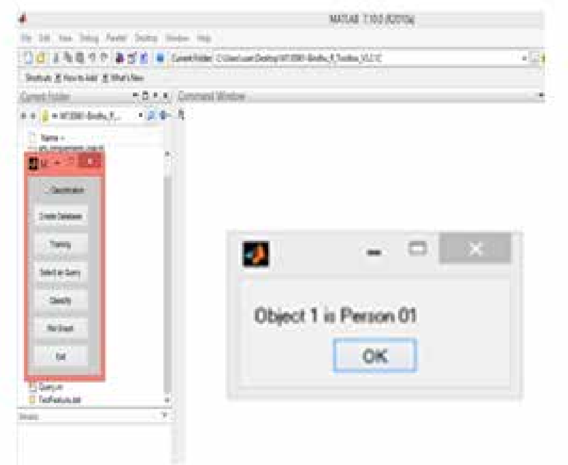

Fig 7 classification using ART-2

Fig 6 and 7 shows the matlab code implementation and classification output. The menu window the EEG signals are stored in the data base. The 50% of the data is used for training the remaining 5% is used for the testing, after selecting a test signal the classify signal classifies the test signal which is taken as object 1 as person 1. The plot of ROC is obtained which is shown in fig 8.

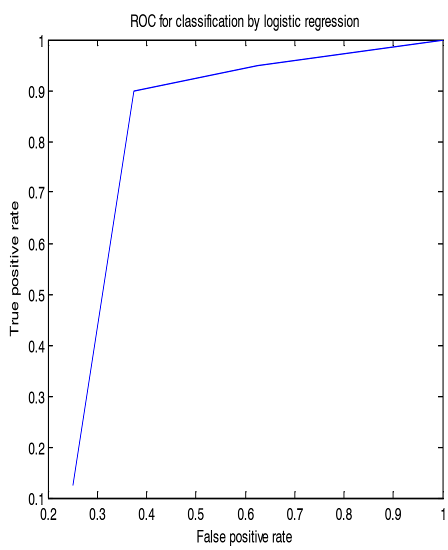

Fig 8 Roc for classification

A ROC graph is a plot with the false positive rate on the *X* axis and the true positive rate on the *Y* axis. It gives the increasing rate of specificity and sensitivity at the learning process of the classifier. After the learning process it was at 90% which tremendously gave an higher accuracy after the learning process was complete. This graph gives the probability of the sensitivity and specificity at the time of the learning of algorithm ART-2. For all the sets of EEG data the performances were obtained as the specificity of 95.4% , sensitivity of 97.3% and a overall accuracy of 96.67% was obtained.

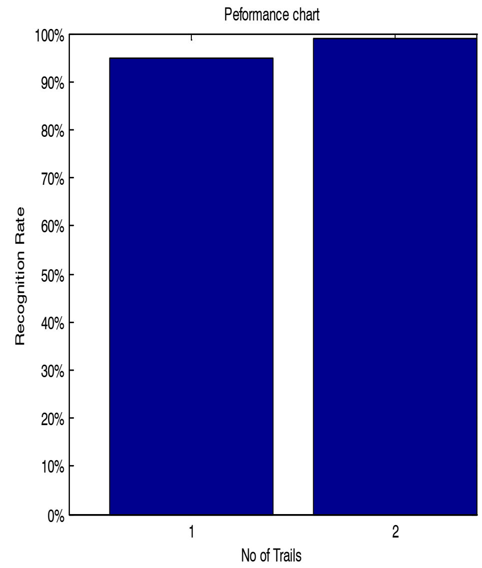

Fig 9 Performance chart

In the performance chart shown in the fig 9 we had taken two trials by varying the vigilance parameters of the classifier. In the first trail the classifier gave an accuracy of 95% and the same input signals when classified again with the same classifier by varying the vigilance parameter gave an accuracy of 98%. By taking the average of the two trails the overall accuracy of the classification is given as 96%.

5. CONCLUSION

The EEG signal is one of the diagnose tool to detect the brain activitydetect it is usually corrupted with unwanted interference. The artifacts and interfaces are removed by the preprocessing of the signal. The spectrogram image is obtained foor the cleaned EEG signal. Using the technique of GLCM feature extraction the features are extracted. These features are applied to the Adaptive Resonance Theory-2 neural network which classifies the EEG signal. Neural Network is applied for EEG signal characterizing, noise reduction. The neural network architecture is used to detect and characterize the EEG signal. The most important advantage of the proposed method is the reduction of data size as well indicating and recognizing the main characteristics of signal.Furthermore, it can reduce memory space, shorten pre-processing needs, the network size and increase computation speed for the classification of an ECG signal**.** In order to achieve a stable classifier the Adaptive resonance theory-2 classifier is used. By using the ART-2 algorithm to classify the EEG signals an overall accuracy was 96% was obtained

REFERENCE

| [1] Abdul hamit subbasi, Ergun Ercelebi, "Classification of EEG signals using neural network and logistic regression", computer methods and programs in bio-medicine(2005)78, 87-99 | | [2] Jorge baztarrica ochoa, "EEG signal classification for brain computer interface applications. March 28th 2002. | | [3] M. Saad, M. Nor, F. Bustami, and R. Ngadiran, "Classification of Heart Abnormalities Using Artificial Neural Network," Journal of Applied Sciences, vol. 7, pp. 820-825, 2007. | | [4] H. Ming-Huwi, "An ultrasonic image evaluation system for assessing the severity of chronic liver disease," Computerized Medical Imaging and Graphics, vol. 31, pp. 485-491, 2007. | | [5] M. Arora, "Detection of Abnormalities in MRI Images Using Texture Analysis," M.S. thesis, Thapar University, 2009. | | [6] R. M. Haralick, K. Shanmugam, and I. H. Dinstein, "Textural Features for Image Classification," IEEE Trans. on Systems, Man and Cybernetics, vol. 3, pp. 610-621, 1973. | | | [7]Shujie Du, "Influence on ART-2 Clustering Algorithm with different adjusting learning rate". Communications in information science and management engineering sept 2012, vol. 2 iss.9, PP:30-34 | | [8] Gail A. Carpenter and Stephen Grosserberg, "ART2: Self organization of stable category recognition codes for analog input patterns". Applied optics volume 26, number 23, December, 1987. | . | [9]Fritz albregtsen, " Statistical texture measures computed from Gray level Co-occurance matrices", November 2008. | | [10]Gail. A. carpenter and Stephen Grossberg, "Adaptive resonance theory", THE handbookof brain theory and neural networks, April 2002. | | [11] L W Freriks, P J M cluitmans, M J Van gils, "The adaptive resonance theory network : (clustering) behavior in relation with brainstern auditory evoked potential pattern". ISBN 90-6144-264-8. | | [12] R.J Kuo, J.L Liao, C.Tu, "Integration of ART-2 neural network and genetic K-means algorithm for analyzing web browsing paths in electronic commerce" Decision support systems 40(2005) 355-374 | | [13] Dietrich Wienke , Lutgarde Buydens, "Adaptive resonance theory based neural network forsupervised chemical pattern recognition (Fuzzy ARTMAP) part 1: theory and network properties, Chemometriscs and intelligent laboratory systems 32(1996) 151-164 | | [14] Dr. T.R gopalakrishnan Nair, P. Jayarekha, "Pre allocation stratergies of computational resources in cloud computing using Adaptive resonance theory-2" Intyernational journal on cloud computing/; services and architecture(IJCCSA), vol 1, no 2, august 2011 | | [15] Dr. S Grossbergwww.scholarpedia.org/article/ Adaptive resonance theory | [16] Chiung-Yao Fang, Sei-Wang Chen and Chiou-Shann Fuh, Environmental Change Detection System Regarding Roads(NSC 89-2218-E-003-001) |