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Implementation of Self Organizing Feature Map for Analyzing Trends in Satellite Imagery

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ABSTRACT:
In the present Scenario, in Time Series Prediction, Artificial Neural Network have gained a lot of interest due to their ability to learn effectively about the dependencies which are non-linear, from a large amount of possibly noisy data using a learning algorithm. The Kohonen's standard, Self-Organizing Map (SOM) is adopted for exploratory temporal structure analysis. From these temporal sequences, unsupervised neural networks reveal useful information and reported power in dimensionality reduction &analyzing cluster. There is no need to pre-classify and pre-label the input data in unsupervised learning. For time series prediction, one of the unsupervised neural networks used is SOFM. The goal of time series prediction is to construct a model that can predict the future of the measured process under interest. For time series prediction various approaches have been used over the years & is still going on. It has application in different Research areas in diverse fields like forest survey, rural to urban change detection, remote sensing etc.In recent years advances in remote sensing technology & availability of high resolution images have motivated many researchers to study patterns in images for the purpose of trend analysis. This paper presents model to detect the temporal & spatial changes in Satellite Imagery using SOFM particularly to model a time series that can be used for forecasting.

KEYWORDS: ANN, Satellite Images, SOFM, SOM, Remote sensing, TKM.

I. INTRODUCTION:

A sequence of observations taken sequentially in time is called Time Series. Many sets of data appear as time series: a monthly sequence of the quantity of goods shipped from a factory, a weekly series of the number of road accident, hourly observation made on the yield of a chemical process and so on. Examples of time series abound in such field as economics, business, weather forecasting, speech recognition and remote sensing. An intrinsic feature of a time series is that typically adjacent observations are dependent. The nature of this dependence among observation of a time series is of considerable practical interest. In time series prediction the goal is to construct a model that can reveal the underlying process and can predict the future of the measured process under interest. In order to construct a model for a process, data is gathered by measuring value of certain variables sequentially in time. Usually data is incomplete and include noise. Stochastic and dynamic models for time series data have use in important application areas, such as forecasting of future value of a time series from current and past value, determination of the transfer function of a system subject to inertia, use of indicator input variable in transfer function models to
represent and assess the effect of unusual intervention events on the behavior of a time series, design of simple control schemes by means of which potential deviations of the system output from a desired target may, so far as possible be compensated by adjustment of the input series value[1].

Several computation techniques have been proposed to gain more insight into process and phenomena that include temporal information. Statistical methods based on linear (eg-AR and ARMA) and non- linear processes (eg-NARMAX and MARS) have been effectively used in many applications [2].
Recently neural networks have gained a lot of interest in time series prediction or to forecast certain outcomes by extrapolation due to their ability to learn effectively nonlinear dependencies from large volume of possibly noisy data with a learning algorithm. Many types of neural networks have been used in time series prediction. Traditional way of using neural networks in time series prediction is to convert the temporal sequence into concatenated vector via a tapped delay line, and to feed the resulting vector as an input to a network. This time delay neural network approach however has its well-known drawbacks, one of the most serious ones of being the difficulty to determine the proper length for the delay line[3].Therefore a number of dynamic neural network models have been designed for time series prediction to capture inherently the essential context of the temporal sequence without the need of external time delay mechanics. In these models learning equations are often described by differential or difference equation and the interconnection between the network units may include a set
of feedback connections, i.e. the network are recurrent in nature. Most recurrent neural networks are trained via supervised learning rules. However in temporal sequence analysis unsupervised network could reveal useful information from the temporal sequence at hand in analogy to unsupervised neural networks reported power in cluster analysis and dimensionality reduction. Also in unsupervised neural network, no preclassification or prelabling of the input data is needed [3]. In unsupervised learning or self organizing learning provision is made for task independent measure of the quality of representation that the network is required to learn, and free parameters of the network are optimized with respect to that measure, once the network has become tuned to form internal representation for encoding features of the input and thereby to create new classes automatically.

THIS PAPER IS ORGANIZED AS FOLLOWS: SECTION II:

We present an overview of the main concepts of SOFM, including the learning algorithms. Section III presents the introduction to Self-Organizing Feature Map (SOFM) to detect temporal changes in satellite imagery. In Section IV, we discuss the use of SOFM in classifying images. Section V provides a conclusion and an at last VI gives the outlook to future work.

II. SELF ORGANIZING FEATURE MAP:

The Self Organizing Maps developed by Teuvo Kohonen in 80's has now become a well known tool, with established properties. A Self-Organizing Map(SOM) or self-organizing feature map (SOFM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map. Self-organizing maps are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space. The Self Organizing Feature Maps have been commonly used since their first description in wide variety of problems as classification, feature extraction, pattern recognition and other related application.
Self-organizing feature maps (SOFM) learn to classify input vectors according to how they are grouped in the input space. They differ from competitive layers in that neighboring neurons in the self-organizing map learn to recognize neighboring sections of the input space. Thus, self-organizing maps learn both the distribution (as do competitive layers) and topology of the input vectors they are trained on[5].
The neurons in the layer of an SOFM are arranged originally in physical positions according to a topology function. Distances between neurons are calculated from their positions with a distance function.
The Kohonen Self Organizing Feature Map can be defined as an Unsupervised Classification Algorithm from the artificial neural network paradigm.

It is characterized by the formation of topographic map of the input patterns in which the spatial locations (i.e. coordinates) of the neurons in the lattice are indicative of intrinsic statistical features contained in the input patterns, hence the name –self organizing map[4]. It is the vector quantization method with topology preservation. The training algorithm of the SOFM is based on unsupervised learning, where one sample, the input pattern x(n) from the input space V1 is selected randomly and compared against the weight vector wi of the unit i in the map space VM The best matching unit b to given input pattern x(n) is selected using some metric based criterion, such as-

$$||x(n)-w_b|| = \min_{i \in V_M} \{||x-w_i(n)||\} \qquad (1)$$

Where || || denote the Euclidean vector norm. Initially all weight vectors are set randomly to their initial positions in the input space. During the learning phase the weights in the map are updated towards the given input pattern x(n) according to

$$w_i(n+1) = w_i(n)+\gamma(n)h_{ib}(n)(x(n)-w_i(n)) \qquad (2)$$

Where $i \in VM$ and $\gamma(n), 0 <= \gamma(n) <= 1$, is a scalar valued adaptation gain. The neighborhood function hib(n), gives the excitation of unit i when the best matching unit is b. If the map is trained properly, i.e. the gain and the neighborhood function are properly decreased over training a mapping is formed, where weight vector specify centers of clusters satisfying the vector quantization criteria

$$E=\min \{ \sum^M j$$

III. SOFM TO DETECT TEMPORAL CHANGES IN SATELLITE IMAGERY:

In SOFM several improvements is made to learn to recognize temporal changes in a data taken at different time. One of them is Temporal Kohonen Map (TKM).It is not only capable of separating different input patterns but is also capable of giving context to patterns appearing sequences. TKM differs from the SOFM only in its output. The outputs of the normal SOFM are reset to zero after presenting each input pattern and selecting the best matching unit. Hence the map is sensitive to last input pattern. TKM will fire all of its neurons to varying degree of excitation. The output of each neuron is a leaky integrator unit, so there is a time delay involved [5]. Leaky integrators are influenced by past output as well as by present outputs, resulting in an overall network output that is a domain response to a time domain signal. The modeling of the output in the TKM is close to the behavior of natural neurons, which retain electrical potential on their membranes with decay.

III.A CHANGE DETECTION:

Change detection is a process of showing changes between two images of the same area, collected at different times. Typically, pixel-by-pixel comparisons are made and output is generated when corresponding pixels have sufficiently different grey value. To detect the change in the given image of different time we first extract feature of given image. Feature extraction is a process of extracting features from imagery, such as roads, railways, and water bodies that can be displayed on maps or in Geographic Information System (GIS). On the basis of that feature we compare two images and detect the change.

III.B SATELLITE IMAGES:

In the earth sciences, digital satellite images have become an important source of information. These images are taken at various temporal resolutions. A satellite image is not a photograph taken by a camera with film in it but is an image. All Commercial satellites acquired with digital sensors. The sensor has thousands of tiny detectors that measure the amount of electromagnetic radiation reflecting from earths surface and object on it. These are called Spectral Measurements. Each spectral reflectance value is recorded as a digital number. These numbers are transmitted back to Earth where they are converted by computer into colors or

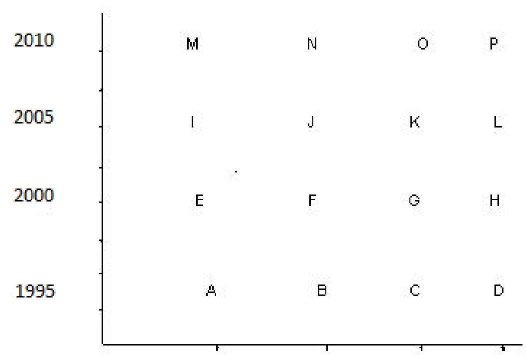
gray scale converts them brightness levels to create an image that look like a photograph. Depending on the desired sensitivity of the detectors, sensor can measure reflectance of energy in the visible, near infrared, thermal infrared, and microwave radar portions of the EM spectrum [6]. Most remote sensing satellite measure energy in very specific well defined wavelength of the spectrum.
Multispectral satellite images are acquired by a digital sensor that measures reflectance in many bands. For instance, one set of detector may measure reflected visible red energy, while another set may measure near infrared energy. These multiple reflectance values are combined to create color images. Current multispectral remote sensing satellites measure reflectance in three to seven different bands at once.

III.C METHODOLOGY:

The processing of multi spectral and multi temporal satellite images is divided into the following three phases

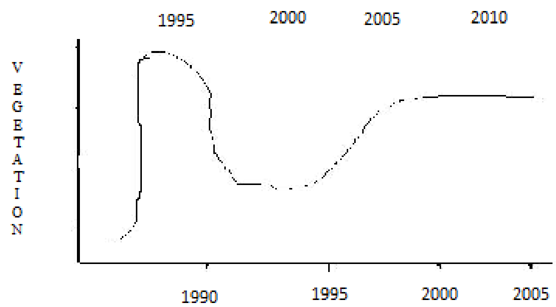
1. Generation of Feature Space
2. Classification using SOFM neural
a. network
3. Design a Temporal Kohonen Map
4. Testing

To process the data with SOFM we have to feed the features of images, which are important for change detection. Selection of features from multi spectral and multi temporal images is to be done with the help of the standard Digital Image processing Techniques such as principal component analysis, band ratioing etc [7]. These features are time dependent and non-linear in nature. The features extracted from the images are fed to a SOFM network. Self-organizing models group the input sample into self-similar classes based on some specific measure of similarity. The output of this phase is a classified image using SOFM. Which in turn is used to detect the temporal changes? There are three ways to represent the changes. First, we represent the change detected between the images by a single image. The Single image shows the change between all the images on those we perform comparisons. Second, we represent the change detected between the images by tabular form. In this we represent the change between the areas of the images by numeric value.



Vegetation Water Urban Forest

In the above figure, A, B, C………….alphabets represents the numeric value of different changes between the areas after each 5 years. Third, change detected between the images by the graph. The graph shows the changes between the areas of the satellite images of different years.



For trend analysis we need to design a Temporal Kohonen Map. The entire work is carried out on a High Resolution PC Platform in MATLAB. Use of MATLAB has definite advantage of flexibility and expandability because most work on ANN is carried out worldwide using MATLAB. In the next section we present the results on classification of satellite images.

III.D EXPERIMENTAL RESULT:

A SOFM classification is experimented on a IRS/1D L3 Image over a specific area for a specific period. This image of size 1200*900 consists of 4 bands 0.52 - 059 microns (B2), 0.62 - 0.68 microns (B3), 0.77 - 0.86 microns (B4) and 1.55 - 1.7 microns (B5). The aim of the classification is to distinguish between dense vegetation, coarse vegetation, water body and urban area. The important requirement of the classification is the Features of the Image. Features are the characteristics of the images quantified e.g. statistical features such as mean, minimum, maximum, variance, covariance, correlation and standard deviation. Other examples of the features are band ratio and difference between two images of the same area (i.e. taken at difference of time span).

The statistical feature identified in the present study for the specific image is given in Table 1.

Feature	**Band 1**	**Band 2**	**Band 3**
Mean	60.9483	49.7930	57.6082
Max	255	255	255
Min	0	0	0

TABLE 1: Statistical features used for classification

ANN model had been constructed to represent these images. A 3 x 8 Neural Network (with hexagonal topology) has been used in this study. The neurons in the layer of an SOFM are arranged originally in physical positions according to a "hextop" topology function. The hextop arrange the neurons in a hexagonal topology (Figure 1). One such image with its classified version is shown in figure 2 (a) and (b). Such classified images of the same area over a long period of time can be modeled by SOFM to detect changes/predict trends.

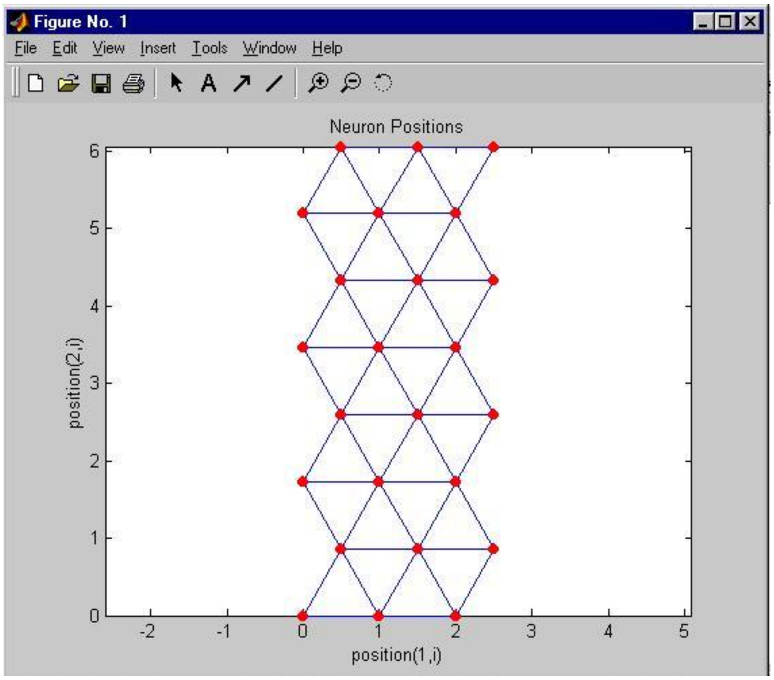


Figure1. SOFM Architecture

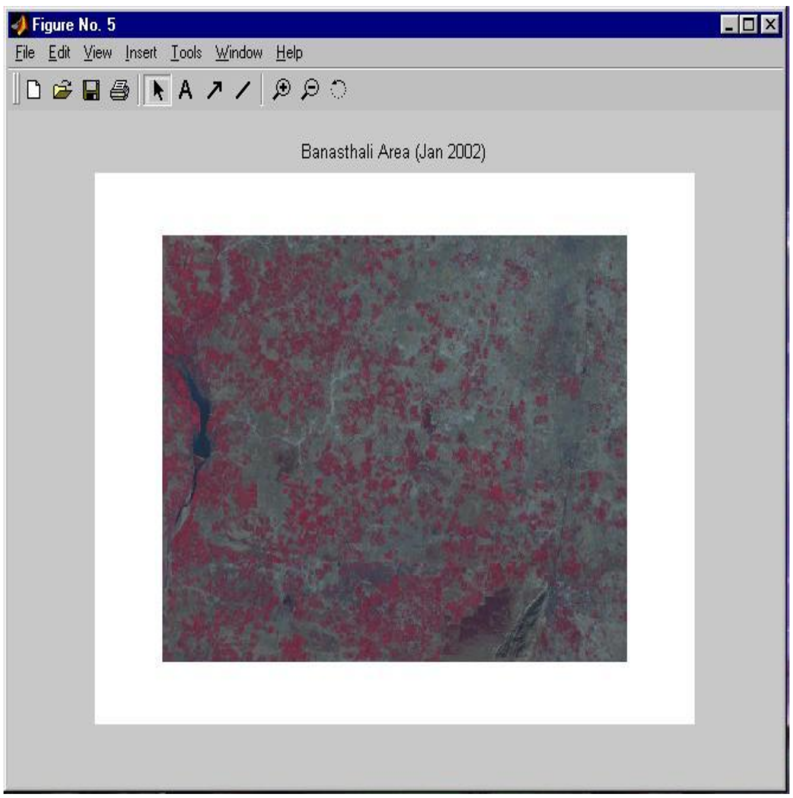
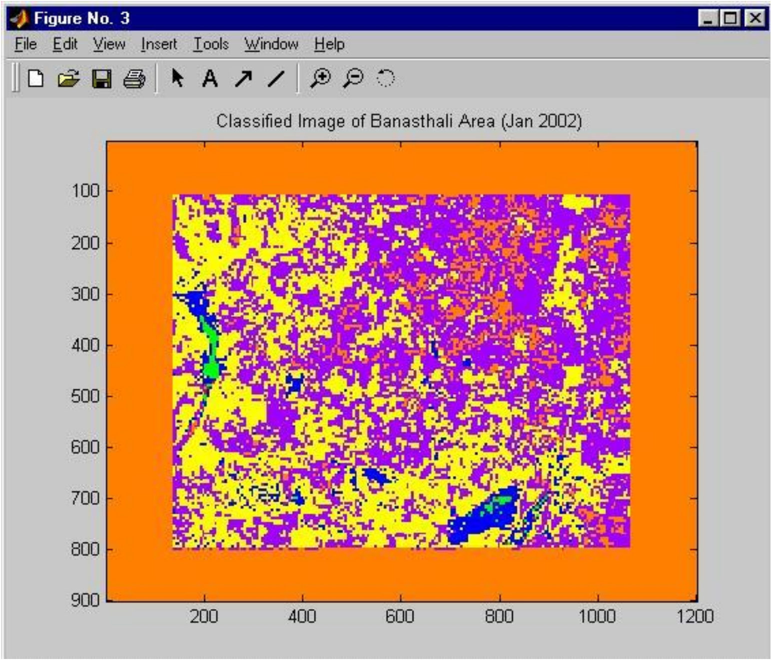


Figure 2 :(a) IRS/1D L3 example image



(b) Classified image-using SOFM

IV. CLASSIFICATION OF SATELLITE IMAGES USING SOFM:

In the present work self-organizing feature map network identifies a winning neuron using the same procedure as employed by a competitive layer. However, instead of updating only the winning neuron, all neurons within a certain neighborhood of the winning neuron are updated using the Kohonen rule. The weights of the winning neuron (a row of the input weight matrix) are adjusted with the Kohonen learning rule. Supposing that the i^{th} neuron wins, the elements of the i^{th} row of the input weight matrix are adjusted as shown below.

$$iIW1,1(q) = iIW1,1(q-1) + \alpha(p(q) - iIW1,1(q-1))$$

The Kohonen rule allows the weights of a neuron to learn an input vector, and because of this it is useful in recognition applications. Thus, the neuron whose weight vector was closest to the input vector is updated to be even closer. The result is that the winning neuron is more likely to win the competition the next time a similar vector is presented and less likely to win when a very different input vector is presented. As more and more inputs are presented, each neuron in the layer closest to a group of input vectors soon adjusts its weight vector toward those input vectors. Eventually, if there are enough neurons, every cluster of similar input vectors will have a neuron that outputs 1 when a vector in the cluster is presented, while outputting a 0 at all other times. Thus, the competitive network learns to categorize the input vectors it sees.

Finding the negative distance between input vector p and the weight vectors and adding the biases b compute the net input. If all biases are zero, the maximum net input a neuron can have is 0. This occurs when the input vector p equals that neuron's occurs when the input vector p equals that neuron's weight vector. After this computation all neurons within a certain neighborhood Ni*(d) (2) of the winning neuron are updated using the Kohonen rule. Specifically, we adjust all such neurons as follows.

$$iIW1,1(q) = iIW1,1(q-1) + \alpha(p(q) - iIW1,1(q-1))$$

or

$$iw(q) = (1 - \alpha)\, iw(q - 1) + \alpha p(q)$$

Here the neighborhood Ni*(d) (2) contains the indices for all of the neurons that lie Within a radius " d " of the winning neuron i* (1).

$$N_i(d) = \{ j , d_{ij} \le d \}$$

Thus, when a vector is presented the weights of the winning neuron and it's close neighbors move toward. Consequently, after many presentations, neighboring neurons will have learned vectors similar to each other [6].

V. CONCLUSION:

In the present work the classifications for multispectral satellite images using self organizing feature map have been done. The classification difference taken over a period of time can be used for trend analysis using SOFM. Such techniques can indeed be applied for a variety of purposes such as remote sensing, deforestation, archeology, urban planning and development, damage assessment, defense intelligence, and environmental monitoring, weather forecasting etc. The work is executed using the Image Processing and Neural Network toolboxes of MATLAB because of the definite advantage of flexibility and expandability.

VI. FUTURE WORK:

The work can be done in future to classify the satellite images on the basis of different patterns and features using both Supervised & Unsupervised classification techniques.

REFERENCES:

1. Time Series Analysis:Forecasting & Control (3rd Edition) by George Box,Gwilym M. Jenkins, Gregory Reinsel.
2. A.S.Weigend &N.Gershenfeld,editors.Time series prediction: forecasting the future and understanding the past.Wesley,1993
3. T.Koskela, M. Varsta, J.Heikkonen, and K. Kaski. Time series prediction using recurrent SOM with local linear models. Int. J. of knowledge-Based Intelligent Engineering System, 2(1):60-68,1998
4. AB. Yegnarayana, "Artificial Neural Networks", Prentice Hall of India Pvt. Ltd, New Delhi, 1999.
5. Rafael C. Gonzalez, Richard E.Woods. Digital Image Processing, Pearson Education, Inc Second Edition.
6. Website:- www.nrsa.gov.in
7. Wikipedia 'Article on Satellites'