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Image Classification using SOM and SVM Feature Extraction

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***Abstract*— Support Vector Machines (SVMs) are a relatively new supervised classification technique to the land cover mapping community.SVM are machine learning techniques that are used for segmentation and classification of medical pictures, as well as segmentation of white matter hyper-intensities (WMH). Although there are various techniques implemented for the classification of image, here combinatorial method of clustering and classification. Here the feature extraction using SVM based training is performed while SOM clustering is used for the clustering of these feature values. The proposed methodology for the image classification provides high accuracy as compared to the existing technique for image classification.**

***Index Terms*—SVM, MLC, Fuzzy Classifier, ANN, Genetic Operator, Fitness Value.**

I. Introduction

Clustering is the unsupervised classification of patterns (i.e. observations, data items, or feature vectors) into groups (clusters). Clustering is a not easy problem combinatorial, and discrepancy in guessing and contexts in different communities has prepared to the transfer of valuable generic concepts and methodologies slow to take place. Cluster analysis tries to identifying groups of similar objects and, consequently helps to discover distribution of patterns and interesting correlations in large data sets. It has been area under discussion of wide research since it arises in many application domains in engineering, social sciences and business. Particularly, in the last years the ease of use of enormous transactional and experimental data sets and the take place prerequisites for data mining produced needs for clustering algorithms that extent and can be applied in assorted domains.

Clustering is think about an interesting come within reach of come across similarities in data and putting similar data into groups. Clustering partitions a data set into quite a lot of groups such that the correspondence inside a group is larger than that among groups. The design of data grouping, or clustering, is simple in its nature and is close to the human way of thinking; at any time they are nearby with a large amount of data, humans are frequently be inclined to go over this huge number of data into a small number of groups or categories in arrangement to more smooth the progress of its analysis. Additionally, nearly all of the data collected in many problems give the impression to have some intrinsic properties that provide themselves to natural groupings. On the other hand, discovering these groupings or make an effort to categorize the data is not an effortless task for humans unless the data is of small dimensionality.

Clustering technologies are significant for the reason that many applications such as search engine, document analysis, bio-information, financial analysis, and human face recognition, rely on the clustering technologies. Recently, how to find an estimated result to a clustering problem, which is NP-hard, in a realistic time has turn out to be a very important research area somewhat because the dataset size has become larger and larger and partially because finding the optimum solution to a clustering problem takes an unusual amount of time. To accurately segment an image within a general framework is a challenging task because there exist many diverse objects and large variations between them. The performance of a clustering algorithm such as in [35-37], is highly dependent on the type of the features used and domain information concerning the objects in that image. This raises an interesting question about which features produce the best results for which type of image, thereby limiting the generalization capability of such clustering algorithms. This drawback provided the motivation to explore embedding shape information within the segmentation process. Popular fuzzy shape-based clustering techniques include the Gustafson-Kessel (GK) algorithm [38], ring-shaped (FKR) [39], circular shell (FCS) [40], c-ellipsoidal shells (FCES)[41] and elliptic ring-shaped clusters (FKE) [42].

Definition and Terminology of Clustering and Its Steps

The clustering [9] difficulty can be conditioned basically as follows:

Here they present a finite set of data, X, build up a grouping method for grouping the objects into classes. The number of classes and the characteristics of the classes are indefinite and should be find out.

In classical cluster analysis, these classes are necessitate to form a partition of X such that the degree of association is physically powerful for data within blocks of the separation and weak for data in different blocks. On the other hand, this requirement is excessively strong in a lot of practical applications, and it is thus popular to put back it with a weaker requirement. When the requirement of a crisp partition of X is reinstated with a weaker requirement of a fuzzy partition or a fuzzy pseudo partition on X , we submit to the rising problem area as fuzzy clustering. Fuzzy pseudo partitions are often called fuzzy c-partitions, where c assigns the numeral of fuzzy classes in the partition.

There are so many definitions of data clustering have been proposed over the years. In this work, we give the definition as conditioned in [9]

Let ‘X’ be the data set defined as:

$$X = \{x_1, x_2, \dots, x_N\}$$

(2.1)

The partition of X into m sets (clusters): $C_1,\dots,C_m$ is defined as an m-clustering of X, so that the following conditions are met:

$$C_i \neq \emptyset, i = 1, \dots, m$$

(2.2)

$$\cup_{i=1}^{m} C_i = X$$

(2.3)

$$C_i \cap C_j = \emptyset, i \neq j, i, j = 1, \dots, m$$

(2.4)

The vectors surrounded in a cluster are more similar to each other and much less comparable to other clusters. Different measures have been build up to measure this similarity, since the different data will form unusual kinds of clusters. A number of examples of data cluster types are shown in Figure 1.

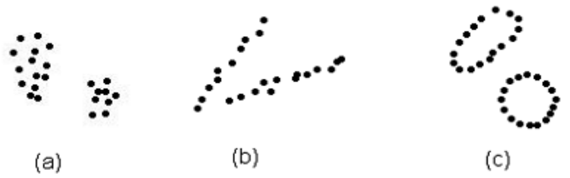

Figure 1 – Examples of data cluster types: a) cloud-type b) line-type c) circle or shell types

Consecutively to grow a clustering task [9], the following are the steps that should be followed:

• Feature **selection** – data features must be decided on appropriately so that they are the most excellent representation with as much information as probable concerning the task of importance.

• **Proximity measure** – a evaluation that compute the similarity between two feature vectors. It should be make certain that all selected features give uniformly to the computation of the proximity measure.

• Clustering **criterion** – is mainly which clustering method should be preferred based on the data interpretation given by skilled. The clustering criterion may be expressed by way of a cost function.

• Clustering **algorithms** – is a variety of a precise algorithm that finds the clustering structure of the data.

• **Validation of the results** – is a procedure of verifying the correctness of the outcomes obtained by clustering. Several tests are proposed for such reason.

• Analysis **of the results** – performed by an expert in the application field.

CLUSTERING TECHNIQUE

There are so many different types of clustering techniques have been developed. The main types of clustering techniques are hierarchical agglomerative, partition, robust and unsupervised.

- **Hierarchical Agglomerative Clustering**

A hierarchical clustering technique consign that each data sample to one cluster, merges clusters in an iterative process, and stops when there is only one cluster remaining [2]. Clusters are merged based on some distance perception or similarity measure.

- **Partition Clustering**

A partition clustering technique begins with a selection of k samples from the data set to be clustered. Such samples define the early set of candidate cluster midpoints. Next, it allocates samples to such clusters based on some distance perception or similarity measure. Finally, the candidate cluster centers are recomputed. This procedure is frequent in anticipation of various stopping criteria is achieved [2]. Typically, this stopping criteria is defined according to some optimization function.

- **Robust Clustering**

Many clustering techniques have relied on the guessing on that a data set go after a definite distribution and is free of noise. Actually, if noise is initiated, several techniques based on the least square approximation are destroyed [6]; such is the case with k-means [10] and fuzzy k-means [4]. Several approaches have make an effort to deal with this problem; some of them are based on robust statistics [6], and others are based on transforming the purpose of the fuzzy centroid mean to formulate the consideration estimate more robust with respect to noise[12]. A clustering technique that is proficient to manage noisy information is called robust.

- **Unsupervised Clustering**

Although clustering techniques are unsupervised learning techniques, many of them require the number of clusters in advance. A clustering technique that does not requires the number of clusters in advance is called unsupervised [13].

CLASSIFICATION

Classification of remotely sensed data is used to assign corresponding levels with respect to groups with homogeneous characteristics, with the aim of discriminating multiple objects from each other within the image. Classification will be accomplished on the basis of spectral or spectrally defined features, such as texture, density etc. in the aspect space. It can be assumed that classification splits the feature space into several classes based on a decision rule. The concept of classification of remotely sensed data.

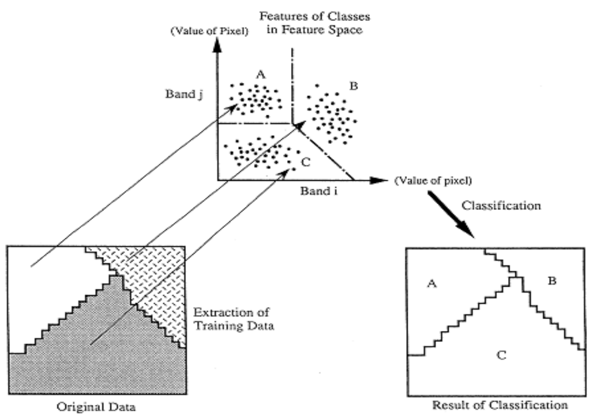

Figure: 2 Concept of Classification of Remotely Sensed Data

Classification [8] between the objects is easy task for humans but it has proved to be a complex problem for machines. A simple classification system consists of a camera fixed high above the interested zone, where images are captured and consequently processed. Classification includes image sensors, image preprocessing, object recognition, object segmentation, quality extraction and object classification. Classification system consists of database that contains predefined patterns that compares with detected object to classify in to proper category. Image classification is an important and challenging task in various application domains, including biomedical imaging, biometry, video-surveillance, vehicle navigation, industrial visual inspection, robotic navigation, and remote sensing. Classification process [8] consists of following steps:

A. Pre-processing- atmospheric correction, noise removal, image transformation, main component analysis etc.

B. Detection and extraction of a object- Detection includes detection of position and other characteristics of moving object image obtained from camera. And in extraction, from the detected object estimating the trajectory of the object in the image plane.

C. Training: Selection of the particular attribute which best describes the pattern.

D. Classification of the object: Object classification step categorizes detected objects into predefined classes by using suitable method that compares the image patterns with the target patterns.

IMAGE CLASSIFICATION TECHNIQUE AND ITS PROCEDURE

Image Classification: Assumptions Similar features have similar spectral responses. The spectral response of a certain feature is unique when compared to other features of interest. By measuring the spectral reply of a recognized characteristic, we can use this information to discover all occurrences (instances) of that aspect.

Supervised Image Classification

• Idea: Using samples with known identities (i.e., assigned pixels to information classes), the algorithm classifies pixels with unknown identities.

• Classification Procedure: The procedure starts by the user selecting and naming areas on the image, which correspond to the classes of interest. These classes correspond to information classes. Then, the image classification algorithm will find all similar areas which are algorithm dependent.

Unsupervised Image Classification

• Concept: The image is automatically segmented into spectral classes based on natural groupings found in the existing data.

• Classification procedure: The user inputs some classification parameters. The algorithm proceeds by finding pixels with similar spectral properties. After the classification, the user names each class (i.e., the user relates the spectral classes to the relevant information classes).

In several cases, classification will be assumed by means of a computer, with the employ of mathematical classification techniques. Classification will be prepared according to the following methods as shown:

Step 1: Definition of Classification Classes: Depending on the objective and the characteristics of the image data, the classification classes should be clearly defined.

Step 2: Selection of Features: Features to discriminate between the classes should be established using multi-spectral and/or multi-temporal characteristics, textures etc.

Step 3: Sampling of Training Data: Training data should be sampled consecutively to find out suitable decision rules. Classification techniques such as supervised or unsupervised learning will then be decided on the basis of the training data sets.

Step 4: Estimation of Universal Statistics: Various classification techniques will be compared with the training data, so that an appropriate decision rule is selected for subsequent classification.

Step 5: Classification: Depending up on the decision rule, all pixels are classified in a particular class. There are two methods of pixel by pixel classification and per-field classification, with respect to segmented regions.

Step 6: Verification of Results: The classified results should be checked and verified for their accuracy and reliability.

Supervised & Unsupervised [3] Classification

• Supervised image classification procedure: Select training data, Classify the image, Accuracy assessment.

• Unsupervised image classification procedure: Classify the image, Identify clusters, Accuracy assessment.

KOHONEN SELF ORGANISING FEATURE MAPS

Kohonen Self Organising Feature Maps (SOM) [11] were originated by a man named Teuvo Kohonen, they provide a way of representing multidimensional data in much lower dimensional spaces - typically one or two dimensions. This progression, of reducing the dimensionality of vectors, is mainly a data compression technique known as vector quantisation. Besides that, the Kohonen technique makes a network that stores information in such a way that any topological links within the training set are maintained. The most important goal of an SOM is to change an incoming signal pattern of arbitrary dimension into a one or two dimensional discrete map, and to execute this transformation adaptively in a topologically arrangement way. Consequently SOM can be set up by placing neurons at the nodes of a one or two dimensional lattice. Higher dimensional maps are also feasible, but not so familiar. The neurons turn out to be selectively adjusted to various input patterns (stimuli) or classes of input patterns at some stage in the course of the competitive learning. The places of the neurons so tuned (i.e. the winning neurons) turn out to be generated and a meaningful coordinate system for the input features is generated on the lattice. The SOM consequently types they have need of topographic map of the input patterns. The self organization procedure involves four major components:

Initialization: All the connection weights are initialized with small random values.

Competition: For each input pattern, the neurons calculate their relevant values of a discriminated function which provides the basis for competition. The particular neuron with the smallest value of the discriminant function is declared the winner.

Cooperation: To be successful neuron discover out the spatial location of a topological neighbourhood of excited neurons, in that way as long as the basis for cooperation along with neighbouring neurons.

Adjustment: The excited neurons decrease their character values of the differentiated function in relation to the input pattern throughout appropriate adjustment of the combined connection weights, such that the comeback of the winning neuron to the subsequent application of a comparable input pattern is improved.

II. Related Work

Shanmugam et al. [5], classifying war scene from the natural scene by extracting wavelet features. By using after extracting wavelet features they are classified by using Artificial Neural Network and then Support Vector Machines (SVM). This paper also compares Artificial Neural Network and Support Vector machine and determining which one is best to classify war scene. First from the input image wavelet features are extracted and then that extracted features are given to normalization in order to maintain the data so that performance of classifier can be improved. Normalized features are given as input to Artificial Neural Network and also to Support Vector Machine. ANN classify the image using backward propagation algorithm and SVM classify the image using radial basis kernel function with p=5. In the case of SVM, it gives only 59% classification rate and in the case of ANN, it gives only 72.5% classification rate. Thus ANN provides good classification result in classifying war scene by extracting wavelet features when compared with SVM.

Hua Zhang, Wenzhong Shi, and Kimfung Lium[15], propose a novel fuzzy-topology integrated support vector machine (SVM) (FTSVM) classification method for remotely sensed images based on the standard SVM. It make threshold fuzzy protocol is comprised into the standard SVM. Two different experiments were performed to estimate the performance of the FTSVM technique, in evaluation with standard SVM, maximum likelihood classifier (MLC), and fuzzy-topology-integrated MLC. The FTSVM method performs better than the standard SVM and other methods in terms of classification exactness, thus providing an successful classification method for remotely sensed images. FTSVM when compared with the standard SVM, MLC, and FTMLC, the FTSVM obtains a comparatively high accuracy. These evince that the FTSVM is a very effective classifier for multispectral remotely sensed images. With this, the misclassified pixels are reclassified; consequently, the problem of misclassification in the traditional SVM methods is thus solved to a certain extent, particularly for those pixels located at the boundary of between classes.

Junfei Chen, Jiameng Zhong,[17] proposed a new integrated model is put forward for selecting 3PL providers based on support vector machine (SVM) and fuzzy analytic hierarchy process (FAHP). In the first stage, the support vector machine (SVM) is used to classify the primary 3PL provider samples into four types which are admirable, good, medium and bad correspondingly. Then we can find the outstanding samples which are the candidates for the second stage selection. In the next phase, the FAHP is used to evaluate the selected excellent samples in the primary phase, so we can obtain the sorting results for the excellent samples and the optimal samples. The method separates 3PL provider selection into two stages. SVM is used in the first stage to classify all the enterprises to be elected. Then fuzzy AHP is adopted to estimate the excellent enterprises which were selected in the first stage. Compared with the traditional method, the model based on SVM-FAHP can improve the selection efficiency and reduce the computational cost during decision-making process and the cost of information collection. The FAHP model can solve the uncertainty problem effectively when converting the qualitative case to quantitative ones. The example study shows that the SVM-FAHP model is feasible and effective. The research can provide decision-making for enterprises to select 3PL providers.

Giorgos Mountrakis, Jungho Im, [20] studied a wide range of methods for analysis of airborne- and satellite-derived imagery continues to be proposed and assessed. SVMs are particularly appealing in the remote sensing field due to their ability to generalize well even with limited training samples, a frequent restriction for remote sensing applications. Though, they also experience from parameter assignment problem that can significantly affect obtained results. SVM classifiers, characterized by self-malleability, swift learning pace and limited needs on training size have proven a fairly reliable methodology in intelligent processing of data acquired through remote sensing. Past applications of the technique on equally real-world data and simulated environments have shown that SVMs exhibit superiority over most of the alternative algorithms.

Zhibin Liu, Haifen Yang, Shaomei [14] overcome the inadequacy of traditional linear SCDA assessment method, proposes an enhanced support vector machine (SVM) evaluating method based on the multistage dynamic fuzzy decision, takes the multistage dynamic fuzzy judgment as the sampling establishment, uses the SVM principle to begin evaluation model. This technique not only can exert the single advantages of multi-layer SVM classifier, but also trounce the difficulty of looking for the high grade training sample data. The accuracy and generalization ability of SVM is excellent relatively, because the model is based on the principle of structural risk minimization, It solves the problem of "more learning" and "less learning", gains the overall optimum solution, and overcomes the deficiency of neural network can only get partial optimal solution.

Yan LI, Li YAN, Jin LIU [21] explained the changes in remote sensing classification from two aspects: basic thought and new classification algorithms. The basic thought of remote sensing classification has changed from per-pixel multispectral-based approaches to multiscale object-based approaches. New categorization algorithms contain support vector machine, evolutionary algorithm, fuzzy clustering algorithm, as well as Artificial Neural Networks. This is lead to the development in remote sensing image classification in the past decade, including the multi scale object-based approaches and some new classification algorithms, such as SVM, EA, fuzzy clustering algorithm, ANNs. The fact that the data types and suppliers are far more than the past made us understands the real world better. However, the great challenge is how to use these multisource imagery (multispectral, hyper spectral, radar, LIDAR to optical infrared sensors) to improve the classification accuracy in order to boost the remote sensing application.

Qiu Zhen Ge, Zhang Chun Ling ,Li. Qiong, Xin Xian Hui, Guo Zhang [26] presented the image categorization problem as an image texture learning problem by viewing an image as a collection of regions, each obtained from image segmentation. An approach performs a helpful quality mapping through a chosen metric distance function. Thus the segmentation problem becomes solvable by a regular categorization algorithm. Sparse SVM is adopted to radically decrease the regions that are needed to classify images. The chosen regions by a sparse SVM estimated to the target concepts in the traditional diverse density framework. Thus, the SVM classification approach was found very promising for Image Analysis. It has been shown that it can produce comparable or even better results than the Nearest Neighbor for supervised classification. A very good feature of SVMs is that only a small training set is needed to provide very good results, because only the support vectors are of importance during training.

Farid Melgani, Lorenzo Bruzzone [28] considered the problem of the classification of hyper spectral remote sensing images by support vector machines (SVMs). First, we suggest a hypothetical conversation and experimental analysis aimed at understanding and assessing the potentialities of SVM classifiers in hyper dimensional feature spaces. Thus, the considered dataset allow to identify the following three properties: 1) SVMs are much more effective than other conventional nonparametric classifiers (i.e., the RBF neural networks and the K-nun classifier) in terms of categorization accurateness, computational time, and constancy to parameter setting; 2) SVMs seem more effective than the traditional pattern recognition approach, which is based on the combination of a feature extraction/selection procedure and a conventional classifier.

F. Emecki, O.D. Sahin, D.Agrawal, A. El Abbadi, [16] consider a scenario where multiple data sources are willing to run data mining algorithms over the union of their data as long as each data source is guaranteed that its information that does not pertain to another data source will not be revealed. The focus is on the classification problem in particular and presents an efficient algorithm for building a decision tree over a n arbitrary number of distributed sources in a privacy preserving manner using the ID3 algorithm. Thus an efficient method is proposed to verify the correctness of the final results even when a large number of parties are involved. The method uses communication and computation techniques to construct the decision tree in a privacy preserving manner and thus it can scale up to thousands of data sources.

Bart Kuijpers, Vanessa Lemmens, Bart Moelans [25] consider privacy preserving decision tree induction via ID3 in the case where the training data is horizontally or vertically distributed. Furthermore, they consider the same problem in the case where the data is both horizontally and perpendicularly distributed, a state we refer to as lattice partitioned data. They give an algorithm for privacy preserving ID3 over horizontally partitioned data involving in excess of two parties. For the grid partitioned data, we discuss two different evaluation methods for preserving privacy ID3, namely, first merging horizontally and growing vertically or first merging vertically and next rising horizontally. Now next to introducing privacy preserving data mining over grid-partitioned data, the major donation of paper is that we illustrate by means of an intricacy study that the former evaluation method is the more efficient. Here the datasets when partitioned horizontally, vertically and later than the clustering algorithm is applied performs better performance than on the whole datasets.

Fuzzy topology helps to deal with the mixed pixel problem of image classification. Wenzhong Shi, Kimfung Liu, and Changqing Huang [29] analyzed that due to the existence of object boundary with uncertainties, fuzzy topological theory is one of the theories that can be applied to study the uncertain boundary that is between spatial objects and their backgrounds. Fuzzy topology is a generalized form of ordinary topology [18],[22-24],[27]. This generalization can be of help in understanding fuzzy relations between spatial objects and is applied to describe fuzzy relations numerically [19][30] [32-34]. Based on fuzzy topology, the topological relations between spatial objects can be modeled, and the relations can be applied for spatial query and topological consistency checking in geographic information systems (GISs), for example. Two operators in fuzzy topology, i.e., interior and closure operators, have been defined in previous work. These two operators further induce open and closed sets, respectively, where the open and closed sets are coherent with each other, i.e., the complement of an open set is a closed set and vice versa. In addition, K. F. Liu and W. Z. Shi, [31] proposes a thresholding fuzzy topological space is proposed. In order to implement the theoretical concept of fuzzy topology in image processing, the sense of a fuzzy set in a fuzzy topological space should be introduced. The induced threshold fuzzy topological space enables the decomposition of spatial objects into three parts: an interior, a boundary, and an exterior.

Due to low image resolution, complexity of ground substances, diversity of disturbance, etc., many mixed pixels exist in a remotely sensed image. In addition, the spatial autocorrelation of pixels is not commonly considered in the classification; frequently, the classification result map comprises much "salt and pepper" noise. This affects the performance of the SVM classifier in terms of accuracy. In order to make SVM obtain a higher accuracy, Hua Zhang, Wenzhong Shi, and Kimfung Liu introduced the new fuzzy-topology-integrated SVM (FTSVM) method by induced threshold fuzzy topology, which is integrated into the standard SVM, is proposed. In the FTSVM, we will describe the spectral space classification in the fuzzy topological space. To do this, the optimum threshold is needed to decompose the classes into interior, boundary, and exterior parts. Hence the result is such that the fuzzy boundary pixels, which contain many misclassified ones, are able to be reclassified, providing improved classification accuracy. The FTSVM method performs better than the standard SVM and other methods in terms of classification exactness, thus providing an successful classification method for remotely sensed images. FTSVM when compared with the standard SVM, MLC, and FTMLC, the FTSVM obtains a comparatively high accuracy. These evince that the FTSVM is a very effective classifier for multispectral remotely sensed images. With this, the misclassified pixels are reclassified; consequently, the problem of misclassification in the traditional SVM methods is thus solved to a certain extent, particularly for those pixels located at the boundary of between classes.

Jiang et al. [7], proposed a scene oriented hierarchical classification of blurry and noisy images. Three strategic approaches used are global pathway for essential capture, local pathway for highlight detection and thirdly hierarchical classification. In this firstly extracting global features by using gabor filter, from that gabor image extract only real part and then applying Principle Component Analysis (PCA) to reduce dimensionality. Then get then visual context by combining real part of gabor image and PCA. Secondly, pseudo restoration is done directly on blurry and noisy images and from that pseudo restored image highlight detection ie set of local features has been finded and then extract conspicuous local features by using Harris Affine detector and thirdly combining both features by using log linear model and clustered by using Monte Carlo approach. Finally, these clustered features are classified by using Self Organizing Tree Algorithm (SOTA). The classification rate is 81.95%.

Noridayu et al. [1], proposed a new approach for improving performance of object class recognition by combining different features with local features. In this, the features are extracted from the image, which are boundary-based shape features and local features. The first type of feature is based on the outline of segmented objects while the second are based on the interior information of objects. Two features thus obtained are combined and then concatenating those features in a new single feature vector by using feature fusion approach. Then features are classified by using Support Vector Machine. The classification accuracy is 70%.

III. Proposed Methodology

1. Take an input image.
2. Select the region of interest.
3. Apply SOM based clustering to group the similar features of the image.
4. Apply SVM to train the model.
5. Calculate Posterior Probability of each pixel.
6. Calculate optimal threshold value of each pixel.
7. Compare the values of Posterior Probability with the threshold value.
8. If Posterior Probability <= threshold value
9. Classify each of the pixels and use connected components to combine the boundary regions.
10. Else
11. Classification of the interior pixels.

SOM based clustering algorithm

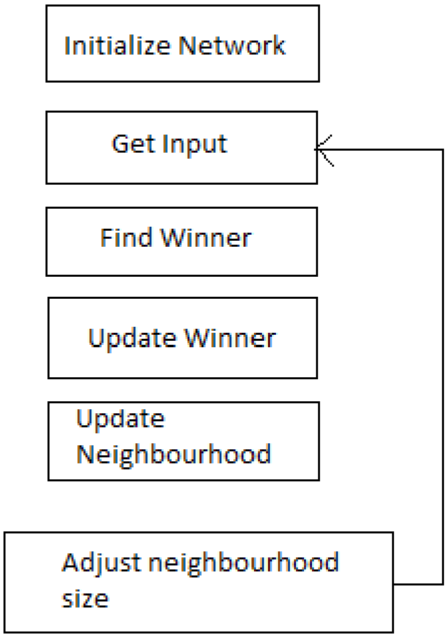

Figure 3. Outline of the SOM clustering

The main goal of the SOM is to transform an incoming pattern of arbitrary dimension into a one- or two-dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion. Each output neuron is fully connected to all the source nodes in the input layer. This network represents a feed forward structure with a single computational layer consisting of neurons arranged in 2D or 1D grid. Higher dimensions > 2D are possible but not used very often. Grid topology can be square, hexagonal, etc. An input pattern to the SOM network represents a localised region of “activity” against a quiet background. The location and nature of such a “spot” usually varies from one input pattern to another. All the neurons in the network should therefore be exposed to a sufficient number of different realisations of the input signal in order to ensure that the self-organisation process has the chance to mature properly.

Let m be the dimension of the input space. A pattern chosen randomly from input space is denoted by:

$\mathbf{x}=[x_1, x_2,\ldots, x_m]^T$

The synaptic weight of each neuron in the output layer has the same dimension as the input space. We denote the weight of neuron j as:

$\mathbf{w}_j=[w_{j1}, w_{j2},\ldots, w_{jm}]^T, \quad j=1,2,\ldots,l$

Where l is the total number of neurons in the output layer.

To find the best match of the input vector **x** with the synaptic weights $\mathbf{w}_j$ we use the Euclidean distance. The neuron with the smallest distance is called i(**x**) and is given by:

$i(\mathbf{x})=\arg\min_j \|\mathbf{x} - \mathbf{w}_j\|, j=1,2,\ldots,l$

- The neuron (i) that satisfies the above condition is called *best-matching* or *winning neuron* for the input vector **x**.

- The above equation leads to the following observation: *A continuous input space of activation patterns is mapped onto a discrete output space of neurons by a process of competition among the neurons in the network.*
- Depending on the application's interest the response of the network is either the index of the winner (i.e. coordinates in the lattice) or the synaptic weight vector that is closest to the input vector.
- The winning neuron effectively locates the center of a *topological neighbourhood*.
- From neurobiology we know that a winning neuron excites more than average the neurons that exist in its immediate neighbourhood and inhibits more the neurons that they are in longer distances.
- Thus we see that the neighbourhood should be a decreasing function of the *lateral distance* between the neurons.
- In the neighbourhood are included only excited neurons, while inhibited neurons exist outside of the neighbourhood.

IV. Result Analysis

As shown in the below figure is the outcome of the existing work using fuzzy- SVM methodology. The figure shows the outline and inner boundary pixels of the image and the inner pixels are classified into 4 regions.

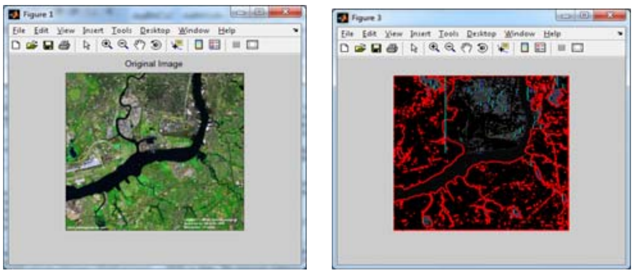

Figure 4. Classification of Satellite Image using Fuzzy-SVM

The Table shown below is the result analysis of the existing work. The Image Classification using Fuzzy-SVM classifier when applied on Satellite Image provides four different regions to classify the image into buildings, Woodland, Water, and Farmland.

	Building	Woodland	Water	Farmland	Total
Building	8	410	264	666	1348
Woodland	402	256	146	666	1470
Water	146	402	658	256	1462
Farmland	256	256	154	666	1332
Total	812	1324	1222	2254	5612
Accuracy		86.3363			
Kappa		0.9405			

Figure 5. Result Analysis of Fuzzy-SVM based Technique

As shown in the below figure is the outcome of the Proposed work using SOM- SVM methodology. The figure shows the outline and inner boundary pixels of the image and the inner pixels are classified into 4 regions.

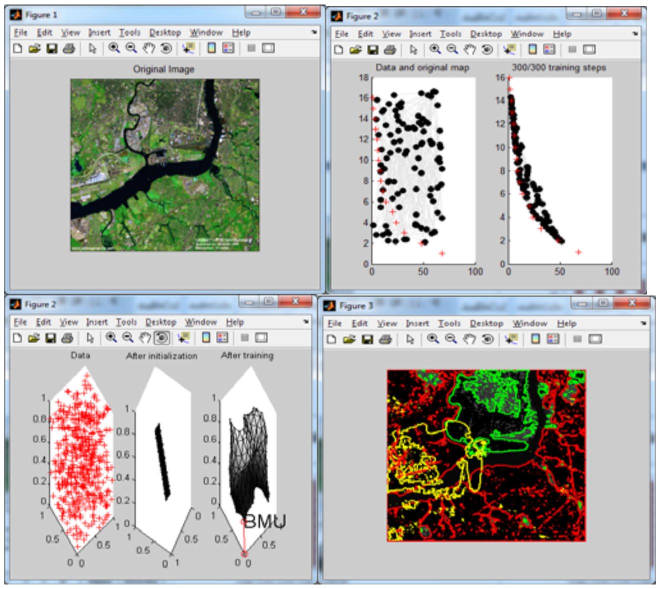

Figure 6. Classification of Satellite Image using SOM-SVM

The Figure shown below is the result analysis of the proposed methodology. The proposed methodology shows the accuracy is better as compared to the previous work.

	Building	Woodland	Water	Farmland	Total
Building	410	8	146	658	1222
Woodland	402	256	146	666	1470
Water	666	402	658	248	1974
Farmland	256	256	154	666	1332
Total	1734	922	1104	2238	5998
Accuracy		91.1411			
Kappa		0.9407			

Figure 7. Result Analysis of SOM-SVM based Technique

V. Conclusion

The proposed technique implemented here is an efficient one for the classification of images using the hybrid combinatorial method of SOM and SVM based feature extraction. The experimental results show the performance of the proposed technique. The proposed technique provides high classification ratio, hence the accuracy is more.

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