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SATELLITE SCENE RECOGNITION USING SPEEDED UP ROBUST FEATURE EXTRACTION

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ABSTRACT---In the field of Satellite image and Remote sensing, The Satellite image classification goals to provide two objectives are:

1) Firstly, Involves visual attention into the satellite images TSC-Two layered sparse coding model is proposed to discover the true neighbors of objects and retrieve the similar images in the database which are relevant and similar to that images.

2) Secondly, by applying SURF- Speeded up Robust Feature, feature extraction is introduced to extract the local features of the images. It relaxes the other feature extraction like color and texture. SURF makes the clear vision of the feature extraction in terms of the key points. The key points can be detected and decrypted using this SURF features. SVM is a tool to classify the class of the scene. the accuracy of this work is nearly 93.63%.The Experimental comparisons is based on a real satellite image database

KEYWORDS—Satellite Image Classification, High Resolution Image, SURF (Speeded Up Robust feature), SVM (Support Vector Machine)

I.INTRODUCTION

Satellite images are rich and plays vital role in providing geographical information. Satellite images have become available enabling accurate earth observation and topographic measurements. satellite and remote sensing images provides quantitative and quality information that reduces the complexity of field work and also the study time. satellite image classification is the process of grouping the pixels into meaningful classes. In high resolution satellite images the structures and objects dominate the image category, to overcome these drawbacks the Two layered sparse coding model is discovered, that will more concentrate on the structures and interesting objects. Two layered sparse coding plays major role for discovering the similar objects in the database and reconstruct that images whether the images belonging to same category or not.

The main objective of this paper is ,classification of object from the satellite image to categories the area of scenes among various scenes of area with the help of classifier. SURF and SVM plays an important role for image classification. some of the sample images are shown below. This paper have the classification of five areas such that they are Airport, Bridge, Commercial Area, Desert, Forest.

AIRPORT

BRIDGE

COMMERCIAL AREA

DESERT

FOREST

Fig 1. Sample satellite images

II. RELATED WORK

[1] The extraction of texture features from high resolution remote sensing imagery provides a complementary source of data for those applications in which the spectral information is not sufficient for identification or classification of spectrally heterogeneous landscape units. However, there is a wide range of texture analysis techniques that are used with different criteria for feature extraction: statistical methods (grey level concurrence matrix, semivariogram analysis); filter techniques (energy filters, Gabor filters); or the most recent techniques based on wavelet decomposition

[2]This paper presents the soft margin regularized AdaBoost method for the classification of images acquired by satellite sensors. The regularized AdaBoost algorithm combines a number of RBF neural networks as base learners efficiently. The method is theoretically motivated by noting the need of regularization and soft margin in the standard AdaBoost method, particularly in the context of high-dimensional possibly noisy problems, such as those posed in the classification of hyper spectral images.

[3] This paper proposes a novel pixel-based system for the supervised classification of very high geometrical (spatial) resolution images. This system is aimed at obtaining accurate and reliable maps both by preserving the geometrical details in the images and by properly considering the spatial-context information.

[4] Image classification methods require an intensive learning/training stage (using SVM, Boosting, etc.) In contrast, non-parametric nearest-neighbor (NN) based image classifiers require no training time and have other favorable properties. However, the large performance gap between these two families of approaches rendered NN-based image classifiers useless. We claim that the effectiveness of non-parametric NN-based image classification has been considerably undervalued.

[5] This paper presents a method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene. The features are invariant to image scale and rotation, and are shown to provide robust matching across aa substantial range of affine distortion, change in 3D viewpoint, addition of noise, and change in illumination. The features are highly distinctive, in the sense that a single feature can be correctly matched with high probability against a large database of features from many images.

[6] Moments and functions of moments have been extensively employed as invariant global features of images in pattern recognition. In this study, a flexible recognition system that can compute the good features for high classification of 3-D real objects is investigated. For object recognition, regardless of orientation, size and position, feature vectors are computed with the help of nonlinear moment invariant functions. Representations of

objects using two-dimensional images that are taken from different angles of view are the main features leading us to our objective.

[7] The notion of complex moments is introduced as a simple and straightforward way to derive moment invariants. Through this relation, properties of complex moments are used to characterize moment invariants. Aspects of information loss, suppression, and redundancy encountered in moment invariants are investigated and significant results are derived. The behavior of moment invariants in the presence of additive noise is also described. The purpose of this paper is to provide an analytic characterization of moment invariants as features for pattern recognition

III. PROPOSED WORK

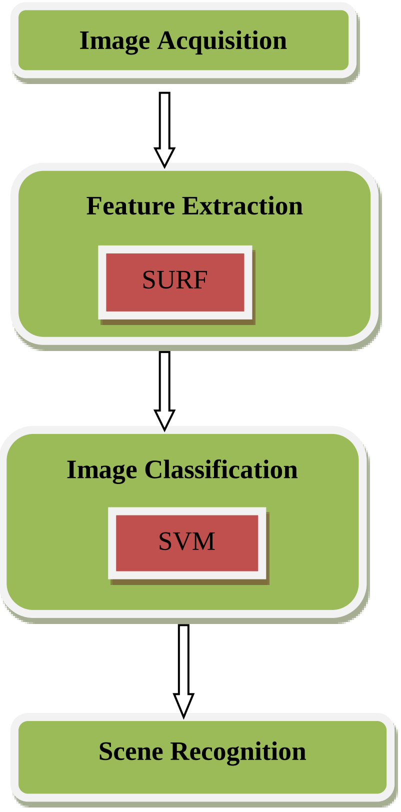


Fig 2. Block diagram of proposed work

The block diagram for proposed system is shown in the figure. 2. It is an image recognition system for identifying the scene that first involves image acquisition and then scene recognition. This work does not involve any color and shape feature extraction techniques instead it uses SURF (Speeded Up robust Feature) for extracting the local features in images that have sharp changes in intensities by filtering images at multiple scales and patches of interest. Then the scene of the object can be recognized by means of the SVM(Support vector Machine) classifier

IV IMPLEMENTATION

1. Image Acquisition

In this session, input image should be get. In each class we collect 40 set of samples images from (Google Inc). From this website we can collect images, Totally 200 images should be trained from all five classes. Then all images can be taken for further processing that means Image Acquisition, Feature Extraction, and finally then all images should be labeled as per the class name of the image. Then all class of image should be finally categorized according to their class

From the total 200 images of five class, 40 images of each class should be seperated in the training part. For testing we taken totally 50 images that carries 10 images from each class. The images can be tested and categorize the class of that input image.

In this section, we can take any kind of images like (.*bmp,.*bitmap,.*png,.*jpg) the image may be taken, firstly the color image is converted into gray image, then applying the gabour filter the images may be filtered with the removal of unwanted noise, accuracy of the image is visualized and by means of the quantization principle the quantity of the image may be measured and the weight of the image is also quantized.

2. Feature Extraction

SURF is a detector and a descriptor for points of interest in images where the image is transformed into coordinates, using the multi-resolution pyramid technique, to make a copy of the original image with Pyramidal Gaussian or Laplacian Pyramid shape to obtain an image with the same size but with reduced bandwidth. Thus a special blurring effect on the original image, called Scale-Space, is achieved. This technique ensures that the points of interest are scale invariant.

Algorithm and features

The SURF algorithm is based on the same principles and steps as SIFT; however, details in each step are different. The algorithm has three main parts: interest point detection; local neighborhood description; and matching.

Interest point detection

The SIFT approach uses cascaded filters to detect scale-invariant characteristic points, where the difference of Gaussians (DoG) is calculated on rescaled images progressively. In SURF, square-shaped filters are used as an approximation of Gaussian smoothing. Filtering the image with a square is much faster if the integral image is used, which is defined as:

$$S(x,y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i,j)$$

The sum of the original image within a rectangle can be evaluated quickly using the integral image, requiring four evaluations at the corners of the rectangle.

SURF uses a blob detector based on the Hessian matrix to find points of interest. The determinant of the Hessian matrix is used as a measure of local change around the point and points are chosen where this determinant is maximal. In contrast to the Hessian-Laplacian detector by Mikolajczyk and Schmid, SURF also uses the determinant of the Hessian for selecting the scale, as it is done by Lindeberg. Given a point p=(x, y) in an image I, the Hessian matrix H(p, σ) at point p and scale σ, is defined as follows:

$$H(p,\sigma) = \begin{pmatrix} L_{xx}(p,\sigma) & L_{xy}(p,\sigma) \\ L_{xy}(p,\sigma) & L_{yy}(p,\sigma) \end{pmatrix}$$

where $L_{xx}(p,\sigma)$etc. are the second-order derivatives of the grayscale image.

The box filter of size 9×9 is an approximation of a Gaussian with σ=1.2 and represents the lowest level (highest spatial resolution) for blob-response maps.

Scale-space representation and location of points of interest

The interest points can be found in different scales, partly because the search for correspondences often requires comparison images where they are seen at different scales. In other feature detection algorithms, the scale space is usually realized as an image pyramid. Images are repeatedly smoothed with a Gaussian filter, then they are sub sampled to get the next higher level of the pyramid. Therefore, several floors or stairs with various measures of the masks are calculated:

The scale space is divided into a number of octaves, where an octave refers to a series of response maps of covering a doubling of scale. In SURF, the lowest level of the scale space is obtained from the output of the 9×9 filters.

Hence, unlike previous methods, scale spaces in SURF are implemented by applying box filters of different sizes. Therefore, the scale space is analyzed by up-scaling the filter size rather than iteratively reducing the image size. The output of the above 9×9 filter is considered as the initial scale layer, to which we will refer as scale s=1.2 (corresponding to Gaussian derivatives with σ=1.2). The following layers are obtained by filtering the image with gradually bigger masks, taking into account the discrete nature of integral images and the specific structure of filters. Specifically, this results in filters of size 9×9, 15×15, 21×21, 27×27, etc.

In order to localize interest points in the image and over scales, non-maximum suppression in a 3×3×3 neighborhood is applied. The maxima of the determinant of the Hessian matrix are then interpolated in scale and image space with the method proposed by Brown, et al. Scale space interpolation is especially important in this case, as the difference in scale between the first layers of every octave is relatively large.

Local neighborhood descriptor

The goal of a descriptor is to provide a unique and robust description of an image feature, e.g., by describing the intensity distribution of the pixels within the neighbourhood of the point of interest. Most descriptors are thus computed in a local manner, hence a description is obtained for every point of interest identified previously.The dimensionality of the descriptor has direct impact on both its computational complexity and point-matching robustness/accuracy. A short descriptor may be more robust against appearance variations, but may not offer sufficient discrimination and thus give too many false positives

The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. Then we construct a square region aligned to the selected orientation, and extract the SURF descriptor from it. Furtherrmore, there is also an upright version of SURF (called U-SURF) that is not invariant to image rotation and therefore faster to compute and better suited for application where the camera remains more or less horizontal.

Orientation assignment

In order to achieve rotational invariance, the orientation of the point of interest needs to be found. The Haar wavelet responses in both x- and y-directions within a circular neighbourhood of radius $6s$ around the point of interest are computed, where s is the scale at which the point of interest was detected. The obtained responses are weighed by a Gaussian function centered at the point of interest, then plotted as points in a two-dimensional space, with the horizontal response in the abscissa and the vertical response in the ordinate. The dominant orientation is estimated by calculating the sum of all responses within a sliding orientation window of size $\pi/3$.

The horizontal and vertical responses within the window are summed. The two summed responses then yield a local orientation vector. The longest such vector overall defines the orientation of the point of interest. The size of the sliding window is a parameter that has to be chosen carefully to achieve a desired balance between robustness and angular resolution.

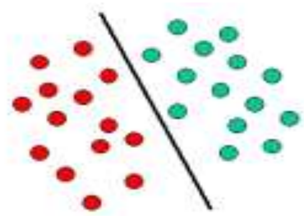
Descriptor based on the sum of Haar wavelet responses

To describe the region around the point, a square region is extracted centered on the interest point and oriented along the orientation as selected in the previous section. The size of this window is 20s. The interest region is split up into smaller 4x4 square sub-regions, and for each one, the Haar wavelet responses are extracted at 5x5 regularly spaced sample points. The responses are weighted with a Gaussian (to offer more robustness for deformations, noise and translation).

3. Recognition of object using SVM

Support vector machine (SVM) is based on the principle of structural risk minimization, support vector machines can be used for pattern classification and nonlinear regression. SVM constructs a linear model to estimate the decision function using non-linear class boundaries based on support vectors. If the data are linearly separated, SVM trains linear machines for an optimal hyper plane that separates the data without error and into the maximum distance between the hyper plane and the closest training points.

SVM are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. Let us denote a feature vector (termed as pattern) ‘ $x'=(x_1, x_2, \cdots, x_n)$ and its class label by y such that ‘y’ = $\{+1, -1\}$. Therefore, consider the problem of separating the set of n-training patterns belonging to two classes.



The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. The illustration above shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped

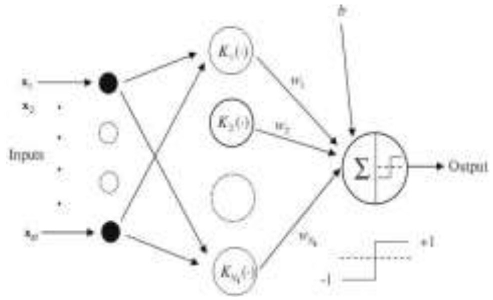


Fig 3. Architecture of SVM

V.EXPERIMENTAL RESULTS

In this chapter the experimental result of five class of image can be calculated. performance evaluation of each class can be explained as follows. In this project for training 40 samples from each class that means 200 images are to be taken and the features are extracted using SURF from that we can get 128 features for each image then we can classify the image using SVM.
For testing part we can take 10 images from each class that means 50 sample images are to be tested and categorize the regarding class of the image for the final output. For that the performance calculation are to be calculated.

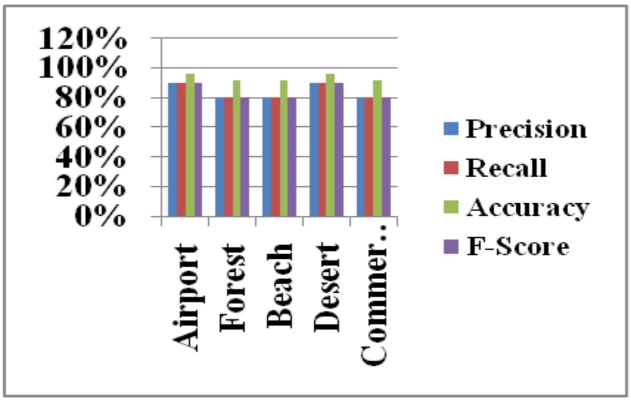


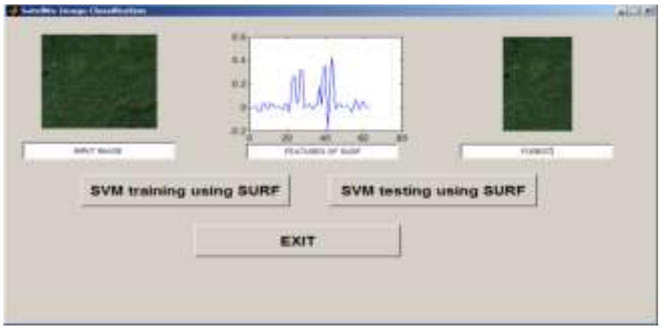
Fig 4.Performace Measures of Overall Classification

VI .CONCLUSION

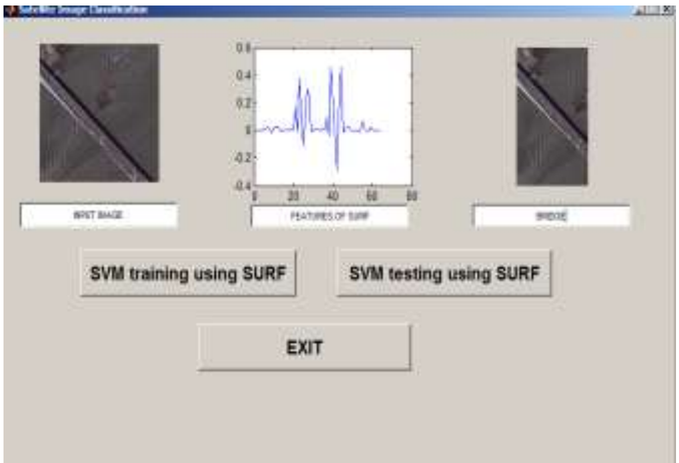
The proposed TSC model is an effective tool for the satellite image classification. A method for satellite image classification from real-time Environment was presented. An approach for image classification, feature extraction from object and recognition of class have been proposed and implemented. To extract the feature from filtered image SURF features used. Ten features were extracted from each point using SURF features. Finally class recognition was performed through SVM. The performance of the system for images of classes achieves an accuracy rate about 93.63 % using SURF and SVM**.**

VII SCREEN SHOTS OF SATELLITE IMAGE CLASSIFICATION

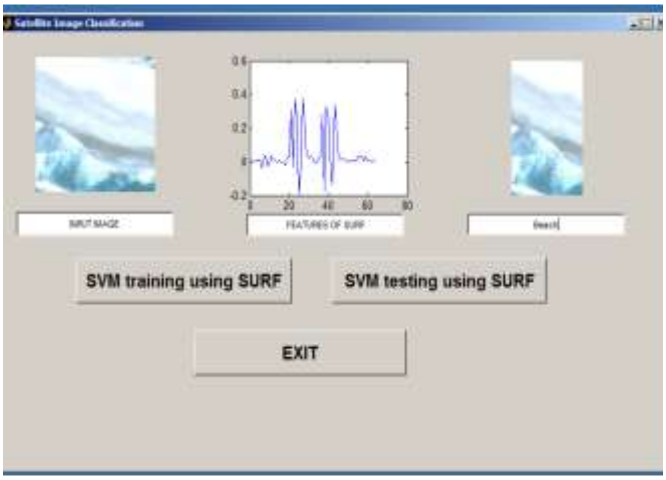
FOREST



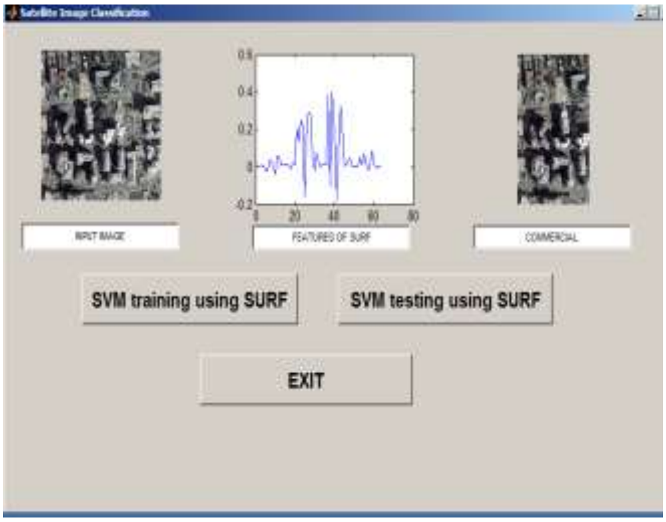
BRIDGE



SEA



COMMERCIAL AREA



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