Classification of Patterns on High Resolution SAR Images

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***Abstract*—Synthetic Aperture Radar being an all weather adaptive and deeply penetrating, forms an inevitable part of all processes of investigation. Classifying different patterns like rivers, buildings, land areas, farm land etc has got prominent role in remote sensing applications, military applications etc and hence has been actively researched in recent years. This paper presents a novel approach for classifying high resolution SAR images. Image denoising is the first step in certain applications like classification problem, pattern matching etc. Here a modified Non Local Means filter method is used for denoising and also explores the possibility of using Artificial Neural Networks (ANN) for classifying different patterns on high resolution SAR images based on a fusion method. The proposed method uses the features of Local Binary Patterns (LBP), features in RGB color space and features in HSV color space. The experiments on high resolution SAR images obtained from Quickbird and Ikonos satellites shows that the proposed method outperforms the other widely used feature extracting methods in SAR image classification.**

***Index Terms*- Artificial Neural Networks (ANN), Maximum Likelihood Estimation, Non Local Means filter, RGB color space, Synthetic Aperture Radar(SAR)**

I. Introduction

The significance of Synthetic Aperture Radar (SAR) images in remote sensing and tactical applications has had an exponential enhancement over the years. The SAR sensors are capable to operate in all types of weather conditions. Also they are capable to operate from very long ranges and also over wide areas of coverage. These features make them extremely attractive for monitoring the Earth's resources. We can analyze the presence of vegetation, mountains, oil sources, mineral resources etc. on a particular region even on other planets by pattern classification on SAR images. SAR images have achieved a prominent position in the field of remote sensing. Remote sensing is a means of acquiring information using airborne equipments and techniques to determine the characteristics of an area. Over the past few decades, SAR imaging has witnessed numerous advancements due to active research and development in it. These images will find many applications in resource management, agriculture, mineral exploration and environmental monitoring. But the effective use of SAR images requires an understanding of the nature and limitation of the data and of the various methods for processing the image and interpreting data from it.

The images obtained from radar contain noise, especially speckle noise. It adds to SAR images a granular aspect with random spatial variations. It degrades the quality of the image. The consequence with the speckle noise is that, the fine features of the SAR image could be lost while analyzing the image for certain purposes like pattern classification. Thus, the speckle noise present in SAR images hinders the proper interpretation of data and thereby makes the processes of segmentation, classification, and analysis of patterns in the image increasingly difficult and inaccurate. Thus we have to perform denoising prior to any processing in the SAR images. By denoising, the clarity of the data in the image gets enhanced and it helps in the proper interpretation of data.

Thus image denoising can be considered as a key preprocessing step in many cases, especially for pattern classification problems. An account of the varous denoising techniques is provided in the literature [1],[2]. The loss of resolution and fine details in an image are primarily taken care of by an image denoising technique. This can be achieved to a great extend by applying differentialy the smoothing over the image regions after checking whether they are homogenous or edge regions instead of just applying it equally over both. Mainly all denoising techniques aim at better preserving image structures while reducing the noise. Once the image is denoised, we can perform pattern classification on it. Patterns can be anything like rivers, vegetation, urban areas etc. Pattern classification can be done with the help of some features that is obtained from the region of interest. These features are mainly obtained using certain feature extraction methods. This improves the identification efficiency, reduces the time of recognition and lowers the resource utilization. Feature extraction process depends on the target pattern to be classified. Some methods extract pixel features while others extract local or global features.Some of them may make linear feature extraction while the rest of them may extract surface or areal features. SAR image features can be divided into features of detection, features of discrimination and features of classification. After extracting sufficient features from the image, we can perform pattern classification on it using efficient machine learning algorithm or the concept of neural networks. The extracted features play a vital role in the classification accuracy.

Many feature extraction and classification methods are proposed in image processing literature. In the case of existing thresholding methods, if the effect of inherent speckle is strong then it is difficult to gain an approximate threshold. To solve this, a sequential non-linear filtering based method is proposed. Here the actual target detection is performed on the basis of certain rules like area rule, brightness rule and histogram distribution rule. Some other works on image segmentation, image extraction and image mapping uses certain algorithms like wavelet transform, block-training and snake. Some recent works on classification of SAR images is based on some novel feature vector. This method uses Local Primitives (LPs) for the construction of feature vector for each pixel. The feature vector includes information about the size and contrast difference of LPs and finally classification is done by using SVM.

Neither structural nor intensity information can be employed singly to efficiently solve the problem of feature extraction. Thus an attempt is made at developing a method that incorporates intensity information of pixels with spatial information and structural relationships along with texture and color features. Texture features vary according to shape and physical features. So, by using this multi-feature fusion method, we could achieve better feature extraction for SAR image classification. Finally, the classification is done using proper classification algorithm that is having better classification accuracy and less time complexity. In this project, we are focusing on detecting different patterns like water regions, buildings and land areas and finally the farmlands and vegetation.

The remaining part of the paper is organized as follows. Section 2 deals with the related works and Section 3 describes the solution approach. Experimental results and performance evaluation is discussed in Section 4 followed by conclusion.

II. Related Works

Over the years, various approaches have been proposed at classifying the different patterns on SAR images. The earlier stages of the works based on this problem , focuses on classifying a particular target pattern on SAR images. Ali El Zaart, Djemel Ziou, Shengrui Wang and Qingshan Jiang [3], proposes a new algorithm for segmentation of SAR images based on threshold estimation using the histogram. The maximum likelihood technique is used to estimate the histogram parameters. Thresholds are generated at the valleys of a multi-model histogram by minimizing the discrimination error between the classes of pixels in the image. The algorithm is applied to several RADARSAT SAR images with different number of looks. Even through the results are compromising, it fails in the specific pattern detection problems. Takako Sakurai-Amano, Shogo Onuki and Mikio Takagi [4], proposed a fully automated method for extracting narrow rivers. Here the method is implemented by using both the spectral and spatial information. Like the river detection, Guangzhen Cao and ya-Qiu Jin [5], proposed a two-step method for the extraction of road network from spaceborne SAR images. The two-steps are road candidates detection and connection. Possible road candidates are processed using the morphological thinning algorithm. Finally the main road network is traced out from the SAR image successfully. The experiments are done on ERS-2 SAR image datasets. Another road detection work was proposed by M. Mokhtarzade and M.J. Valadan Zoej [6], which utilizes the possibility of using artificial neural networks. Studies have been made in the direction of checking the contribution of different input parameters that the network devises to find out the optimum input vector for a problem.

Later several methods were developed to classify multiple patterns on a SAR image. Thus the feature extraction techniques has to be modified according to all the target patterns in the image. Dengxin Dai, Wen Yang and Hong Sun [7], propose a theoretically and computationally simple feature for SAR image classification which is known as Multilevel Local Pattern Histogram (MLPH). MLPH describes the size distributions of bright, dark and homogeneous patterns appearing in a moving window at various contrasts. MLPH is a very powerful descriptor of SAR images because it captures both local and global structural information. In a work by Debabrata Samanta and Goutam Sanyal [8], a novel method for classifying SAR images using statistical approach based on skewness is proposed. The statistical parameters contain high order image statistics which portray the outline and symmetry of the different image region. P. Vasuki and S. Mohamed Mansoor Roomi [9], proposed a method to recognize the SAR imagery by extracting the features from the segmented input image. Here, they first employed Statistical Region merging to segment the object from SAR Images. The extracted features are recognized by the distance measures using correlation metric. Orsan Aytekin, Mehmet Koc and Ilkay Ulusoy [10], proposes a new method for the classification of SAR images based on a novel feature vector. The method tries to incorporate intensity information of pixels and spatial information and structural relationships. The local primitives (LPs) proposed in this study provide us with an adaptive neighborhood for each pixel. LPs correspond to a certain number of layers of local homogeneous connected components.

As years passed, researches were focused on high resolution SAR data. The resolution of the images may change according to the resolution of the satellites. The methods adopted for low resolution satellites may not work for high resolution satellites. Corneliu Octavian Dumitru and Mihai Datcu [11], proposed to study the dependence of information extraction technique performance on SAR imaging parameters and the selected primitive features (PFs). This PFs include gray-level co-occurrence matrix, Gabor filters, quadrature mirror filters, and nonlinear short-time Fourier transform. One of the main contribution of this work is the evaluation of the dependence on the patch size, orbit direction, and incidence angle of the TerraSAR-X. With the advent of very high resolution (VHR) synthetic aperture radar (SAR) images, local content description is becoming a critical issue for indexing. Traditional SAR image analysis techniques, like segmentation and pixel-level classification, are prone to failure as high- level semantic description should be addressed properly for better discrimination. Shiyong Cui, Corneliu Octavian Dumitru, and Mihai Dat[12], proposes to use image-patch-based analysis method for SAR image interpretation. Driven by the idea of ratio edge detector, in this letter, a new feature extraction method represented by the mean ratios in different directions is proposed for VHR SAR image content characterization. Proposed feature evaluation is done by image patch indexing based on active learning using a SAR image database made up of high-resolution TerraSAR-X patches is performed. While comparing with the state-of-the-art features, particularly texture features, the proposed method had shown improved performance for SAR image categorization.

III. Solution Approach

Our problem of classifying different patterns on high resolution SAR images is mainly focused on a fusion method based on different features extracted from different planes. This classification problem has got various applications in different fields like remote sensing, military, environmental studies etc. The whole work can be divided into three phases namely the denoising phase, the feature extraction phase and finally the classification phase. Fig:1 shows the block diagram of the entire work.

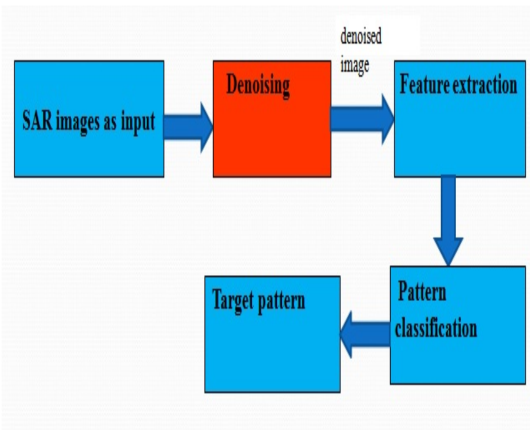

Fig. 1. Block diagram for classification of SAR images.

A. Denoising

Denoising is done prior to feature extraction in the classification problem to remove the unwanted speckle noise present in the high resolution SAR images. The speckle noise adds to SAR images a granular aspect with random spatial variations. It degrades the quality of the image. The consequence with the speckle noise is that,the fine features of the SAR image could be lost while analyzing the image for certain purposes like pattern classification. This is because the presence of speckle noise reduces the possibilities of visual interpretation. Here, the denoising process is based on Maximum Likelihood estimation method using a robust m-estimator known as Geman-McClure estimator[1]. This method denoises the image without any loss in fine features or edge structures. Also, this method increases the accuracy of further processing on the SAR images.

Among the existing denoising technologies, NL means algorithm can be adaptively extended to get better results in denoising. This technology is based on the redundancy of neighboring patches in the image. In this technology, the noise free estimated value of a pixel is defined as a weighted mean of pixels in a certain region. The local and Non local ML estimation methods have some drawbacks. The local ML estimation causes blurring of edges and the distortion of fine structures in the image while the Non local ML estimation causes either under or over-smoothing. For denoising, maximum likelihood estimation along with the Geman-McClure estimator is used. Fig:3 shows the block diagram for the denoising process of SAR image. First of all estimate the noise standard deviation of the noisy input image. Here, data masking technique is used for noise estimation. Noise standard deviations of images are performed facilitating suitable filtration and noise removal. Then create a reference image using NL Means method.

After creating the reference image, calculate threshold values from it. From the noisy image, create a list for each pixel values based on the neighborhood values of each input noisy pixel. Actually, by this process we are selecting certain pixels that may go to final noise free image and this process utilizes the threshold value which is obtained from the reference image. Finally, we can estimate the values by applying maximum likelihood estimation method by using the noise free image obtained using NL Means method and the pixels in the list. In the literature, maximum likelihood estimation is applied on exponential distributions like Gaussian distribution, reduces noise at the cost of blurring the edges. Hence in the proposed method, Geman-McClure estimator is used instead of exponential distribution.

1) Estimation of noise standard deviation: From the noisy input image, estimation of noise standard deviation is performed by data masking technique. Spatial filtering is done in the conventional manner

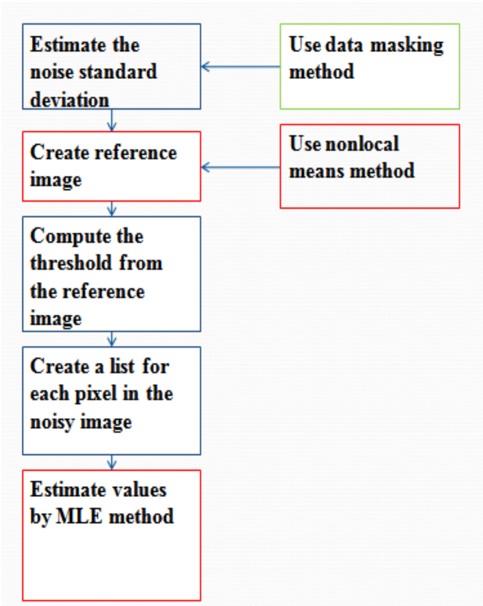

Fig. 2. Block diagram for denoising

of convolving the image with a moving window called mask. In order to apply data masking on SAR image first we have to convert the image into log domain. Then only we can apply the data masking procedure similar to additive noise. In data masking, one method to estimate the noise standard deviation is to first filter the image to remove the image structure. By this, we get the image with only noise. Here a Laplacian mask is used for image structure suppression. In remote sensing images like SAR image, there exist a high degree of correlation between a pixel and the surrounding neighborhood. Laplacian mask essentially computes the difference of adjacent pixels in an image. Even though applying the Laplacian mask, there exists some edge structure information in the image. For detecting edge structures Sobel edge detector is applied. Now to form an edge/no-edge binary decision map from the Sobel filtered image, we require a threshold value. To find this optimum threshold value, we define certain threshold values and find the variance of the corresponding images obtained by using that particular threshold value. Pick that threshold as the optimum threshold which gives the highest variance. Edge structure is detected. Then the given image is subtracted from the Laplacian filtered image which results in the suppression of the image details.

Now divide the noisy image into blocks of pixel size 9x9. On each block apply function to find standard deviation. Based on the results obtained, plot a histogram of estimated noise standard deviations. The histogram of the standard deviation of small blocks from the image can be used to make a final estimation of noise standard deviations. In the case of multiplicative noise the final estimation is different from that of in additive noise. Here, find the median of the histogram as well as the variance of the histogram. Final noise standard deviation is obtained by subtracting the median value of histogram from the variance of the histogram.

2) Creating reference image: For creating reference image, Restricted Non Local Means method [1] is used. Mainly the NL Means method was based on the Markovian hypothesis which states that pixels with a similar neighborhood have a similar gray level value. Here the filtered value at noisy pixel at a particular location is calculated using the NL Means method as a weighted average of all the pixels in the image.

$$v_i = \frac{1}{C_i} \Sigma_{j\varepsilon\Omega_s} w_{i,j} m_j \tag{1}$$

where

$$C_i = \Sigma_{j\varepsilon\Omega_s} w_{i,j} \tag{2}$$

This indicates normalization constant and the weight is given by the similarity of the Gaussian neighborhood between pixels and is expressed as

$$w_{i,j} = exp(-\frac{||N_i - N_j||^2_{2,a}}{h^2}) \tag{3}$$

Here h acts as degree of filtering and a is the standard deviation.

Because of the fact that exponential function degrades edge preserving in denoised image, our method uses Robust M-estimator function for weight calculation. Here we use Geman-McClure estimator function for calculating weight for Non Local Means method.

$$w(x,y) = \vartheta_{\sigma_s}(\Sigma_{t\in\Xi} GM_{\sigma_c}(t)(s(x+t)-(s(y+t))^2) \tag{4}$$

$$:= \vartheta_{\sigma_s}(||s(x)-s(y)||_2, \sigma^2) \tag{5}$$

GM_σ is the Geman-McClure kernel with closeness parameter that is calculated from Geman-McClure weighting function.

We calculate the weight function on each 3x3 block neighborhoods. Here restricted local neighborhoods are obtained by taking the pixel values that are closer to target pixel.

After creating reference image, next we have to find the threshold value from it. This threshold value is used for further denoising process. On each 3X3 block of the reference image, we find the range value. Actually range value indicates the difference of largest value and smallest value in that particular block. Then, find the mode value of the range values obtained from the block. From this, we obtain the thresholds.

3) Maximum likelihood estimation: Before performing maximum likelihood estimation [13], we need to create list of pixels from the noisy image. Here we compare the pixel values in the noisy input image and pixel values in the noise free reference image. Then take the difference between the corresponding pixels in both the images using 3x3 block neighborhoods. Then the difference is compared with that of the threshold values obtained from reference image. Now those pixels in the noisy images with values less than the threshold will be used for denoising of the image using maximum likelihood estimation. These list values are given by

$$l_i = m_j, (j\varepsilon\Omega_m)|abs(f(m_j) - f(m_i)) < t \quad (6)$$

Here each i location indicates pixels in the noisy image and j location indicates pixels in noise free reference image.

where

$$f(m_j) = v_j \ and \ f(m_i) = v_i \quad (7)$$

These values indicate the absolute pixel vales in noisy image and noise free reference image. Here we can use 3x3 neighborhoods or 5x5 neighborhoods. But efficiency is more for 3x3 neighborhoods.

Now we have to perform signal estimation using maximum likelihood estimation. The probability density function of the m observations of the image can be given as

$$p(m_i|A, \sigma_g) = \Pi_{i=1}^{n} \frac{m_i}{\sigma_g^2} e^{-\frac{m_i^2 + A^2}{2\sigma_g^2}} I_0(\frac{Am_i}{\sigma_g^2}) \quad (8)$$

where $I_0(.)$ is the 0th order modified Bessel function. The ML estimate of A can now be computed by maximizing the likelihood function L(A) or equivalently ln L(A), with respect to A.

$$\ln L = \Sigma_{i=1}^{n} \ln(\frac{m_i}{\sigma_g^2}) - \Sigma_{i=1}^{n} \frac{m_i^2 + A^2}{2\sigma_g^2} + \Sigma_{i=1}^{n} \ln I_0(\frac{Am_i}{\sigma_g^2}) \quad (9)$$

Here A denotes the noise free image obtained from non local means method. By maximizing the above equation with respect to A gives the noise free output image.

$$A_{ML} = arg \ max_A(lnL) \quad (10)$$

Algorithm 1 DENOISING ALGORITHM

Input: Noisy SAR image.
Output: Denoised image.

1. Estimate the noise standard deviation from the input
magnitude using data masking technique
2 .Create the reference image using non local means method.
3. Compute the threshold t from the reference image by
applying
t=mode(range($v_f)_w$)
for every pixel m of M (input image) do **do**
create the list,

$$l_i = m_j, (j\varepsilon\Omega_m)|abs(f(m_j) - f(m_i)) < t \quad (11)$$

4. Using l_i values, estimate intensity values by maximum
likelihood method
end for

The Fig.3 shows the input image, the reference image obtained using Robust m-estimator and the output image obtained after applying maximum likelihood estimation.

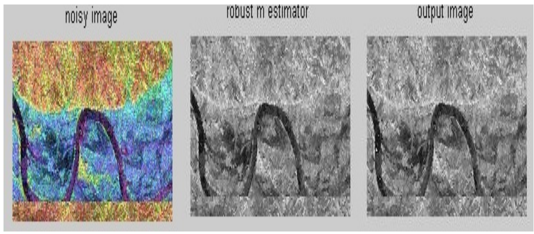

Fig. 3. (a) Input image (b) Reference image obtained by using Robust m-estimator (c) Output image obtained after applying maximum likelihood estimation.

B. Feature extraction

On the denoised high resolution SAR images, we could apply our fusion based method for the classification of target patterns. Here, we are considering pixel intensity difference by using Local Binary patterns (LBP). LBP is the particular case of the Texture Spectrum model. It has been found that Local Binary Pattern is a powerful feature for texture classification. By using LBP, we could distinguish homogeneous as well as heterogeneous areas in SAR images. The Local Binary pattern is based on the local relationships of pixel intensities. Image quanitization is done, matrix splitting is done to facilitate the movement of the window and connected components are traced out within the window.

In the quantization stage, all pixel intensities within the window are compared to the intensity of the central pixel. Here, we are considering a moving window of size 5X5. Let g_c denote the intensity of the central pixel. Then, all intensities in the range $g_c \pm t$ are replaced with 0, intensities above this range are quantized to +1, and all others are replaced with -1, where t is the threshold. The quantized image obtained is known as the " pattern matrix". Fig:4 shows the pattern matrix for an input SAR image.

The second step is the splitting of the pattern matrix into three matrices: a 'positive matrix'(PM), a 'negative matrix'(NM) and an 'equal matrix'(EM) according to the values in the pattern matrix. Fig:5 shows the three matrices for a pattern matrix of an input SAR image. The three matrices play different roles in the image representation. The positive matrix captures brilliant patterns. That means points or regions which are significantly brighter than the central pixel. The negative matrix describes dark patterns, and the equal matrix captures a homogeneous regions. We already knows that the water areas comes under homogeneous regions and buildings and farm lands comes under the other regions.

After splitting the pattern matrix, we could segment each region, that means water regions, farm

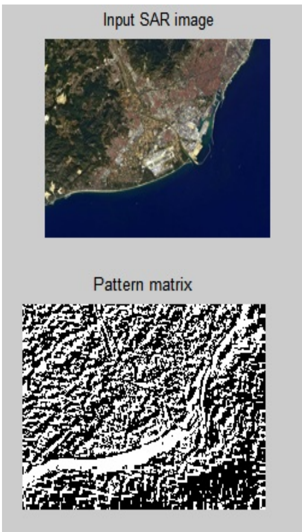

Fig. 4. Input SAR image and its pattern matrix.

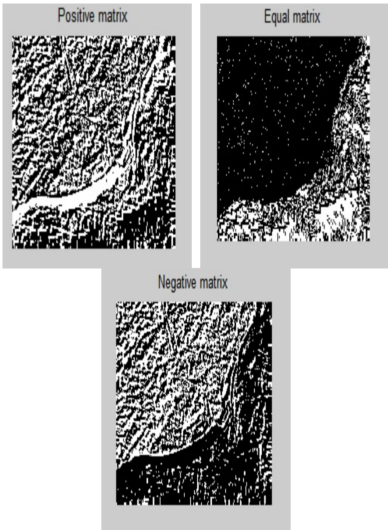

Fig. 5. Pattern matrix of the input SAR image, positive matrix, equal matrix and negative matrix.

lands ,buildings etc. based on the connected components. So, next step is to find the connected components for each matrices. In each matrix, elements with the value one form the foreground, while those with the value zero form the background. The local pattern counted is the continuous fragments of the foregrounds. This is marked as the connected components. After finding the connected components, we could filter those connected components that belongs to each region, according to the length of the connected components. Fig:6 shows the filtered water regions (one of our target pattern) based on connected components.

But certain patterns within homogeneous or within heterogeneous areas cannot be distinguished by using Local Binary Patterns. For example, rivers and roads appear as same pattern in homogeneous region. So, in order to solve this problem, we are going for another important and vital feature called color. Here we are using the features of color in RGB color space as well as in HSV color space.

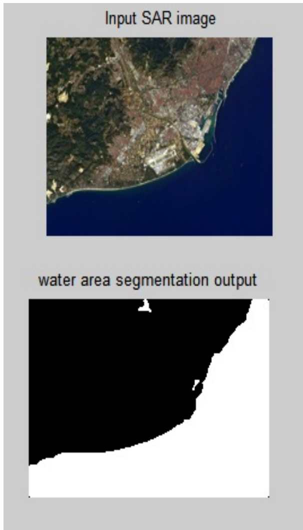

Fig. 6. Input SAR image and segmented water region.

The most known way of representing color spectrum is in RGB color space where R stands for the color ’Red’, G stands for the color ’Green’ and B stands for the color ’Blue’. The perception of color and our way of talking about it in everyday life is not well served by the RGB color space. HSV and HSB are the two most common cylindrical coordinate representation of points in an RGB color model. The definition for HSV color model can be given as- Hue, Saturation, Value or HSV is a color model that describes colors (hue or tint) in terms of their shade (saturation or amount of gray) and their brightness (value or luminance).Thus hue, saturation and value are like an alternative colorspace. Any color can be decomposed into three components and like for RGB, it is possible to represent this space as a cube.

For segmenting different patterns, first of all convert the input RGB into HSV color space. Then split the Hue, Saturation and Value separately. For our convenience we could normalize the value to 0 and 255. Then we could fix thresholds for different patterns based on the hue, saturation and value. Fig:7 shows the input SAR image and its corresponding Image in HSV color space. In order to segment any pattern from the image, we should combine both the segments obtained from thresholding based on hue and saturation. Then the morphological operations-dilation and erosion are applied resulting in noise removal of the filtered image leading us to the proper segmented output. Fig:8 shows segmentation of water region from the SAR image. It shows the segmented images based on thresholding on hue and saturation and finally combining these two images to get the proper segmented water region.

For the third feature, we are using color as a feature vector that is fed as input to the Artificial Neural

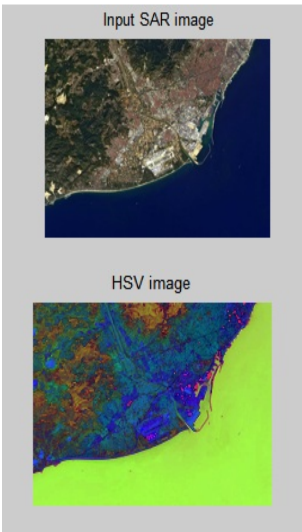

Fig. 7. Input SAR Image and its corresponding image in HSV space

Fig. 8. Input SAR image and segmented water region.

Networks for classifying different patterns on SAR images. For that the neural network is trained using some known input-output samples based on color feature. That means we are training the ANN with the RGB values of different patterns on the SAR image. That means, the RGB combination of a particular pattern say,river has some uniqueness while comparing with other patterns. The values of R, G and B varies according to different patterns. We use this feature as input and provides output accordingly to the RGB value of the patterns.

Here, a feed forward neural network is ued for training. Dataset consist of input-output pattern pair is created for training the network based on color as the input parameter. The input contains the matrix namely 'pattern' that contains the value of R, G and B components of different patterns like water, farmlands and urban areas for about 150 images collected from the Quickbird and Ikonos satellites. The target matrix contains the threshold values that determine the target patterns as water region or farm lands or urban areas accordingly. After training, When a new input high resolution SAR image is given to get classify, first of all the red, green and blue components are extracted.Using these parameters the trained network is simulated and the results are obtained accordingly.

These three features together provides a proper patterns for the segmentation of different patterns like water regions, farm lands, buildings land areas etc from the high resolution SAR images.

C. *Classification*

Classification is the final stage by which different patterns like water region, farm lands and vegetation, buildings and urban areas etc get segmented. Here a fusion method is proposed for classifying these patterns on high resolution SAR images. We get segmented images of these patterns by using the three features LBP, HSV and RGB. Fig:9 shows the segmented images of water regions obtained by using LBP and HSV and the final segmented water region. The results obtained from these methods are

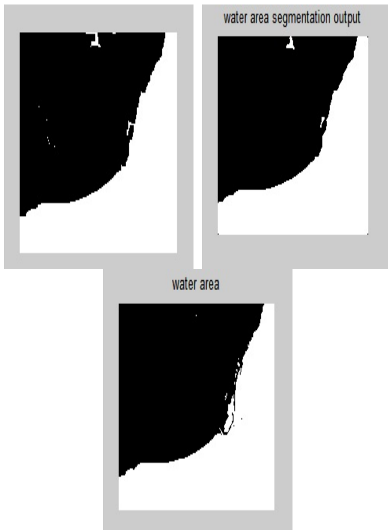

Fig. 9. Segmented images obtained by using LBP, HSV and the final segmented water region.

finally combined with the result obtained from RGB method together gives the final classification output. The output obtained from ANN classifier is again thresholded according to the target pattern. Here we fix the thresholds for water region, farm lands and buildings using histogram threholding. During the training time, we fix the target threshold for water region as 50,building threshold as 150 and farm land threshold as 250. So while recalling the values in the range 30 to 70 will be marked as water area. Like that for farm lands and buildings. So, we need to find the proper values there to get the final target patterns more accurately. So again we filter the values by thresholding and combine those segments with the result of previous methods. Finally, we get the output image with patterns classified according to different colors where red indicates buildings and land areas, Green indicates vegetation and farm lands and blue indicates water regions. Fig:10 shows the final result of classification

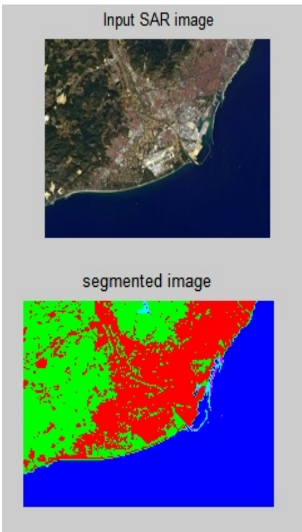

Fig. 10. Input SAR image and its corresponding output image with patterns classified according to color.

IV. Results and Analysis

The proposed algorithm based on the fusion of three features for SAR image classification is applied for various high resolution SAR images obtained from Quickbird and Ikonos. The three feature extraction method is applied on the input SAR image and they are fused together to get the final results of classification. The output image contains mainly three different patterns- water area, buildings and rock area, farm lands. Fig:11 shows the different patterns classified for an input image. Since the input image contains different patterns, output image clearly shows the three different patterns. The red color shows buildings and rock lands, green color shows farm lands and forest areas and the blue color shows water regions. The input image in fig:12 contains mostly bare land. It is very clear from the output image.

A. Evaluation

The experimental results show some positive effect of increasing the number of training samples. Although these results underline the positive impact of the number of training samples on the accuracy and the stability of the classification result, the use of 200 training samples is adequate in terms of accuracy and computation time. Thus, 200 training samples were chosen for all further experiments. Besides the impact of the number of training samples, the influence of a features used on the classification accuracy was analyzed. Here, as the number of features increased, we get classification with better accuracy. Note that Fig:11 includes three classes: Buildings marked with red, water area with blue and

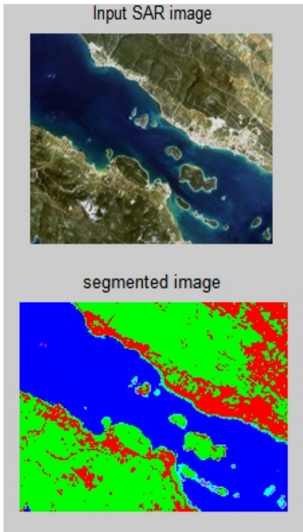

Fig. 11. Input image and the final segmented water region.

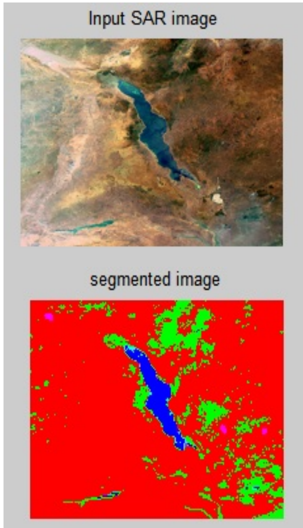

Fig. 12. Input image and the final segmented water region.

farmlands with green. The PSNR values of GLCM, Gabor filter, LPP and the proposed method for the same dataset are indicated in Table 1 so that the performance can be compared.
From the table, it is concluded that the proposed

TABLE I. PSNR Values of Robust M-Estimator and NLM Method for the image shown in Fig.3.a

Methods	GLCM	Gabor	LPP	New method
Buildings	779.03	66.91	88.37	92.48
Farm lands	89.97	95.48	94.42	98.62
Water	53.63	72.85	80.55	96.15
Overall accuracy	84.89	82.18	92.03	97.56
Average accuracy	74.21	78.41	87.78	95.76

method outperforms the existing methods in terms of accuracy. The proposed algorithm expects the following: (i) Directly exploits the local patterns (ii) shape invariant, rotation invariant and scale invariant (iii)Properly classifies the different patterns according to the features.

V. Conclusion

A new method to classify different patterns on high dimensional SAR images applying a fusion method, based on feature extraction is proposed. Here the features from different planes such as pixel level, HSV color space and RGB color space is extracted and combined together to form a basis for segmentation of different patterns from the SAR image. The main advantage of this fusion method comes in the proper differentiation of patterns within homogeneous and heterogeneous areas where the existing methods fails. Also by using block-wise estimation, computational complexity gets reduced. The method was applied to various original images on the data set available on the site http://www.jpl.nasa.gov/radar/ as well as on the images obtained from Quickbird and Ikonos ,which are high resolution satellites. The results from this proposed method reveal improvements in terms of accuracy in classifying different patterns in SAR images.

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