Improved Satellite Image Preprocessing and Segmentation using Wavelets and Enhanced Watershed Algorithms

K.M. Sharavana Raju, Dr. V. Karthikeyani

Abstract - Satellite imagery consists of photographs of earth or other planets made by means of artificial satellites. Satellite images have many applications in meteorology, agriculture, geology, forestry, biodiversity conservation, regional planning, education, intelligence and warfare. Segmentation is a process of partitioning a satellite image into non-intersection regions and is considered as a vital step in many satellite image processing applications. The performance of the segmentation algorithm is often degraded by the image quality and because of their huge size, is often slow. The current need is an algorithm which can solve both these drawbacks. In this paper, a solution that enhances the image quality through a simultaneous process that corrects intensity, adjusts contrast, enhances edges and removes unwanted noise is proposed. The enhanced image is then segmented using a modified watershed algorithm that uses mean-shift clustering. Experimental results prove that both the proposed enhancement procedure and segmentation algorithm show significant improvement when compared with existing solutions.

Index Terms - Satellite Image processing, Image Segmentation, Watershed algorithm, Clustering.

1. INTRODUCTION

Segmentation, a subtask in image processing, dates back over 40 years, with applications in many areas other than computer vision. Since the first Landsat Multispectral Scanner System (MSS) was launched in 1972, which began the modern era of land remote sensing from space, large volumes of satellite image data have been collected, which are invaluable to many applications including environmental assessment and monitoring, agriculture, renewable natural resources, and mapping. Recent advances in satellite imaging with significant contributions from electrical, computer engineering and computer science have witnessed a revolutionary growth in satellite imaging. Revolutionary improvements in engineering and computing technologies have made it possible to acquire high-resolution satellite images, to analyze structural and functional information for computer-assisted analysis, evaluation, and intervention.

Satellite image segmentation is defined as a task of image processing that partitions an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous and it can also be used to process of isolating objects of interest from the rest of the scene. These techniques play a vital role in many SAR processing systems, as they identify region of interest that lead to content understanding and visual object recognition [1].

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Image segmentation techniques work by locating objects and boundaries (lines, curves, etc.) and assigning labels to every pixel such that pixels with the same label share certain visual characteristics. In satellite imaging, the aim is to separate different parts of the image in a way that improves image understanding and analysis process.

Image segmentation has been an active topic for the past 30 years, but is still considered immature in the field of satellite image processing. The reason behind this is the huge variations in the quality of the image captured, increase in size and number of images along with increasing demands to understand satellite images by various applications. The number of visual patterns in an image is also increasing in an overwhelming fashion. These demands, in turn, have increased the use of computers in facilitating their processing and analysis. Segmentation of satellite images is considered challenging because these images contain different textured regions or varying background and are often subjected to illumination changes or environmental effects. All these stress the fact that there is an urgent need in satellite image processing system for a fast and reliable image segmentation model that requires minimum intervention from the user.

Existing solutions for segmentation of satellite images face three major drawbacks. They are performance degradation when supplied with large sized images, degradation of segmentation accuracy due to the quality of the acquired image and speed of segmentation is not meeting the standards of the modern equipments. To resolve these disadvantages, this paper considers the use of preprocessing techniques and two existing segmentation techniques, which are later combined to form a new segmentation technique. Preprocessing algorithms perform manipulations on the input image to enhance the quality so as to improve the segmentation process. Examples include histogram equivalization; image smoothening, image sharpening, contrast adjustment, intensity correction, edge

or boundary enhancement and denoising [2]. Out of these, intensity correction, edge enhancement and denoising have more impact on segmentation result.

According to [3], satellite images are more often affected by speckle noise, which are introduced due to imperfect acquisition or due to transmission errors. A speckle is a complex phenomenon, which significantly degrades image quality. Speckle appears interference of back-scattered wave and makes it more difficult to discriminate fine detail of the images. Presence of speckle noise prevents accurate segmentation and gives the image a grainy appearance. This paper proposes a novel amalgamation of techniques that automatically adjusts contrast, corrects intensity variation, enhances edges and removes noise simultaneously. This method is referred to as Automatic Enhancement Technique (AET) in this paper. The technique proposed uses CLAHE, anisotropic diffusion and wavelets for this purpose. The enhanced image is then segmented using two algorithms, namely, k-means and modified watershed algorithm using mean-shift algorithms. The affect of preprocessing on segmentation is also studied.

The rest of the paper is organized as follows. Section 2 discusses related works to image segmentation. Section 3 explains the proposed segmentation system and Section 4 presents the results of the various experiments conducted. The work is summarized along with future research directions in Section 5.

2. RELATED WORKS

Various techniques have been proposed for image segmentation. These are categorized according to the application, imaging modality, and other factors. This section provides an overview of current methods used for computer assisted or computer automated segmentation of satellite images. There are typically six general categories into which segmentation techniques can be divided [4]. They are (i) Thresholding approaches (ii) Region growing approaches (iii) Classification-based approaches (iv) Clustering-based approaches (v) Artificial neural networks and (vi) Watershed algorithm. Several general surveys on image segmentation exist in the literature [5] the following subsections provide a brief description of each of these categories in brief.

2.1 Thresholding

A thresholding procedure attempts to determine an intensity value, called the threshold, which separates the desired classes. The segmentation is then achieved by grouping all pixels with intensity greater than the threshold as one class, and all other pixels as another class. Thresholding is a simple yet often effective means for obtaining segmentation in images. The limitation of thresholding is that, in its simplest form only two classes are generated and it cannot be applied to multi-channel images. In addition, thresholding does not take into account the spatial characteristics of an image and therefore, are sensitive to noise. For these reasons,

variations on classical thresholding have been proposed that incorporates information based on local intensities and connectivity [6].

2.2. Region Growing

Region growing is a technique for extracting a region of the image that is connected based on some predefined criteria. These criteria can be based on intensity information and/or edges in the image. Region growing requires a seed point and extracts all pixels connected to the initial seed with the same intensity value. Its primary disadvantage is that it requires manual interaction to obtain the seed point. This problem can be solved by using split and merge algorithms which do not require a seed point [7]. Region growing are sensitive to noise, causing extracted regions to have holes or even become disconnected. Conversely, partial volume effects can cause separate regions to become connected. To help improve these problems, a hemitropic region growing algorithm has been proposed that preserves the topology between an initial region and an extracted region [8].

2.3. Classification-based Approaches

Classifier methods are pattern recognition techniques that seek to partition a feature space derived from the image using data with known labels. All pixels with similar features are grouped into one class. Classifiers are known as supervised methods since they require training data that are manually segmented. Classifier methods include nearest-neighbor classifier, K-nearest-neighbor (kNN) classifier, Parzen window classifier, Bayes classifier, etc. Being non-iterative, they are computationally efficient and can be applied to multi-channel images. However, they generally do not perform any spatial modeling. This weakness has been solved by including intensity inhomogeneities and neighborhood and geometric information [9]. Moreover, the requirement of manual interaction for obtaining training data is time consuming and laborious.

2.4. Clustering-based Approaches

Clustering algorithms essentially perform the same function as classifier methods without the use of training data and are termed unsupervised methods. In order to compensate for the lack of training data, clustering methods iterate between segmenting the image and characterizing the properties of each class. In short, clustering methods train themselves using the available data. Three commonly used clustering algorithms are: (1) k-means, the fuzzy means algorithm and the expectation-maximization (EM) algorithm. Although clustering algorithms do not require training data, they do require an initial segmentation (or equivalently, initial parameters). Like classifier methods, clustering algorithms do not directly incorporate spatial modeling and can therefore be sensitive to noise and intensity inhomogeneities. This lack of spatial modeling, however, provides significant

advantages for fast computation [10]. Work on improving the robustness of clustering algorithms to intensity inhomogeneities has demonstrated excellent success. Robustness to noise can be incorporated using Markov random field modeling [11].

2.5. Artificial Neural Networks

ANNs represent a paradigm for machine learning and can be used in a variety of ways for image segmentation. The most widely applied use in satellite imaging is as a classifier [11], where the weights are determined using training data, and the ANN is then used to segment new data. ANNs can also be used in an unsupervised fashion as a clustering method [12], as well as for deformable models. Because of the many interconnections used in a neural network, spatial information can easily be incorporated into its classification procedures. Although ANNs are inherently parallel, their processing is usually simulated on a standard serial computer, thus reducing this potential computational advantage.

2.6. Watershed Algorithm

Watershed segmentation, a very predominant segmentation scheme has many advantages. It ensures the closed region boundaries and gives solid results. Watershed segmentation is a way of automatically separating or cutting apart particles that touch. The watershed algorithm uses concepts from mathematical morphology to partition images into homogeneous regions. This method can suffer from over-segmentation, which occurs when the image is segmented into an unnecessarily large number of regions. Thus, watershed algorithms are usually followed by a post-processing step to merge separate regions that belong to the same structure [13].

3. PROPOSED SYSTEM

The main aim of the proposed system is to develop methods that are fast, handle noise efficiently and perform accurate segmentation. For this purpose, the proposed methodology uses two steps. The first step enhances the image in such a way that it improves the segmentation process, while the second step performs the actual segmentation. The working of the enhancement and the segmentation procedures is explained in this section.

3.1. Image enhancement techniques

This section explains the proposed enhancement method that performs simultaneous contrast adjustment, edge enhancement and denoising. The AET algorithm used for enhancing the input satellite image starts with applying a 2D-DWT to obtain four sub-bands, namely, LL, LH, HL and HH. It is known that the LH, HL and HH sub-bands has the edge details while the LL sub-band has the detailed information of an image. The AET algorithm works in two stages as given below. Stage 1 uses Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm [14] to enhance LH, HL and HH sub-bands. Stage 2 performs

Intensity correction and removes noise using edge-preserving directional anisotropic diffusion method. Finally, an inverse DWT (IDWT) is performed to obtain the enhanced image.

Stage 1: Contrast Adjustment

The CLAHE algorithm originally written by Karel Zuiderveld is a special class of adaptive histogram equalization. Adaptive histogram equalization maximizes the contrast throughout an image by adaptively enhancing the contrast of each pixel relative to its local neighborhood. This process produces improved contrast for all levels of contrast (small and large) in the original image. For adaptive histogram equalization to enhance local contrast, histograms are calculated for small regional areas of pixels, producing local histograms. These local histograms are then equalized or remapped from the often narrow range of intensity values indicative of a central pixel and its closest neighbors to the full range of intensity values available in the display. Further, to enhance the edges, a sigmoid function (Equation 1) is used.

$$y(x) = \frac{M}{1 + e^{-\left(\frac{x - m - \Delta x}{a}\right)}} + \Delta x \qquad (1)$$

where M is 255, m = 128 (for 8 bit image), x is the edge pixel, $-127 \Delta \leq x \leq +128$, parameter 'a' refers to the speed of the change around the center. This process is repeated for detailed coefficients. Finally an inverse wavelet transformation is performed to obtain an edge enhanced image.

Stage 2: Intensity Correction and Despeckling

This section explains the method used for intensity correction and despeckling.

- **Intensity Correction**

Intensity non-uniformity in satellite images is due to a number of causes during the acquisition of the image data. In principle, they occur due to the non-uniformity of the acquisition devices and relate to artifacts caused by slow, non-anatomic intensity variations. In this paper, an Expectation-Maximization (EM) algorithm is employed to correct the spatial variations of intensity. The EM methods do not make any assumption of the sequences type or texture intensity and therefore can be applied to all kind of image sequences. In general, the EM algorithm consists of two steps: (i) E-Step (or) Expectation Step and (ii) M-Step (or) Maximization step. The algorithm is similar to the K-means procedure in the sense that a set of parameters are re-computed until a desired convergence value is achieved. These two steps are repeated alternatively in an iterative fashion till convergence is reached. The algorithm used is given in Figure 1.

- **Despeckling Algorithm**

The despeckling procedure is illustrated in Figure 2. After correcting intensity, an enhanced version of anisotropic diffusion is applied to remove speckle noise in a fast and efficient manner. Anisotropic diffusion, also called Perona–Malik diffusion, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image [15].

Anisotropic diffusion filter is a frequently used filtering technique in digital images. In spite of its popularity, the traditional anisotropic diffusion algorithm introduces blocking effects and destroys structural and spatial neighborhood information. Further they are slow in reaching a convergence stage. To solve these problems, the algorithm was combined with an edge-sensitive Partial Differential Equation (PDE) during despeckling and was termed as SRAD (Speckle Reducing Anisotropic Diffusion) [16]. The anisotropic filtering in SRAD simplifies image features to improve image segmentation by smoothening the image in homogeneous area while preserving and enhances the edges. It reduces blocking artifacts by deleting small edges amplified by homomorphic filtering.

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1. Initialize bias field to mean variance of the image (x) and weight field to the Gaussian value (c) and estimate initial probability as P = x | c.

2. E-Step: Estimate Expected-value of the hidden intensity value for the current value

$$P_{new}(x_i) = P(x_i|c_i)$$

3. M-Step: Re-estimate the model parameters by taking the maximum likelihood estimate according to the current estimate of the complete data.

    (i) $P_{old}(x_i) = P_{new}(x_i)$

    (ii) $P_{new}(c_i) = \dfrac{1}{N} \sum\limits_{i=1}^{N} P_{new}(c_i \mid x_i)$

4. If $\dfrac{P_{new}}{P_{old}} < 1 + \in$ then convergence is reached, stop process,
    else go to Step 2.

Figure 1: EM Algorithm

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1. Read intensity corrected image
2. Divide into 8 x 8 blocks and for each subblock, perform steps 2a and 2c
    a)   Calculate Bayesian shrinkage threshold for each iteration of anisotropic diffusion

$$T = max\ (r(T))$$

        where $r(T) = E(X' - X)$, where X is the image and X' is the generalized Guassian Distribution (GCD)
    b)   Perform directional anisotropic diffusion
    c)   If convergence reached, then goto step 3, else step 2a
3. Output denoised image

Figure 2: Proposed Algorithm

SRAD is an effective despeckling algorithm but the convergence time still needs to be improved. In this paper, the SRAD algorithm is further improved by using the numerical characteristics for the flux diffusion. The concept is to add to the SRAD filter a nonscalar component which can perform directional filtering of the image along the structures and is therefore termed as directional SRAD. The directional SRAD when combined with Baye's shrink thresholding, produce faster denoising operation. The working of directional SRAD is given below.

- **Directional SRAD**

The directional SRAD technique analyzes the numerical characteristics of the SRAD algorithm to improve its efficiency. For this purpose, the image is represented in discrete form as

$$\begin{cases} \forall_k \in [0,+\infty], & u^o = f \\ & u^{k+1} = Q(u^k)u^k \end{cases} \qquad (2)$$

where u^k is the image represented as a vector of size the total number of pixels of the image, denoted n and $Q(u^k)$ is a n x n matrix. Six criteria are derived for the matrix to ensure good properties like maximum-minimum principle and convergence to a constant steady state. These properties are D1 (continuity in its arguments), D2 (symmetry), D3 (unit row sum), D4 (non-negativity), D5 (positive diagonal), D6 (irreducibility).

To increase the speed and accuracy of noise removal the Jacobi method, which satisfies the above properties, is combined. The Jacobi method is a method of solving a matrix equation on a matrix that has no zeros along its main diagonal. Each diagonal element is solved for, and an approximate value plugged in. The process is then iterated until it converges. The Jacobi approach has the advantage of being straightforward to parallelize using a multithreading approach while the Gauss–Seidel scheme, being recursive, does not allow straightforward parallelization.

Given a square system of *n* linear equations: Ax = b where,

$$A = \begin{bmatrix} a_{11} & a_{12} & ... & a_{1n} \\ a_{12} & a_{22} & ... & a_{2n} \\ ... & ... & ... & ... \\ a_{n1} & a_{n2} & ... & a_{nn} \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \\ ... \\ x_n \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ ... \\ b_n \end{bmatrix} \quad (3)$$

Then A can be decomposed into a diagonal component D, and the remainder R:

$$A = D + R \qquad\qquad (4)$$

where

$$D = \begin{bmatrix} a_{11} & 0 & ... & 0 \\ 0 & a_{22} & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & a_{nn} \end{bmatrix}$$

$$R = \begin{bmatrix} 0 & a_{12} & ... & a_{1n} \\ a_{12} & 0 & ... & a_{2n} \\ ... & ... & ... & ... \\ a_{n1} & a_{n2} & ... & 0 \end{bmatrix}$$

The system of linear equations may be rewritten as, $(D + R)x = b$, $(D+R)x = b$, $Dx + Rx = b$ and finally, $Dx = b - Rx$. The Jacobi method is an iterative technique that solves the left hand side of this expression for x, using previous value for x on the right hand side. From this the new diffusion matrix is calculated as

$$D = \begin{bmatrix} 1-k & ... & ... \\ ... & c_{max} & ... \\ ... & ... & c_{min} \end{bmatrix} \qquad (5)$$

where c_{max} is the amount of smoothing along the direction of maximal curvature and is the amount of smoothing along the direction of minimal curvature. In the case of the flux diffusion, $c_{min} = 1$ and $c_{max} = 0$. This is called the directional SRAD. Usage of directional SRAD reduces the time taken to converge while denoising an image and produces an accurate denoised image.

3.2. Segmentation Process

The enhanced image is segmented using a segmentation algorithm that combines watershed algorithm with mean-shift clustering algorithm and is explained in this section. Watershed Transform (WT), which through the flooding of the valleys, is capable of recognizing similar topographical areas, surrounded by mountain ridges. The WT is a segmentation method based on regions, which classifies pixels according to their spatial proximity, the gradient of their gray levels and the homogeneity of their textures [17]. Watershed segmentation is a predominant segmentation scheme with several advantages. It ensures the closed region boundaries and gives solid results. It is a way of automatically separating or cutting apart particles that touch. The watershed algorithm uses concepts from mathematical morphology to partition images into homogeneous regions. Careful analysis of this system

identified two major drawbacks, (i) Sensitivity to noise and (ii) Over and under segmentation. The first problem can be solved by using the preprocessing step which removes noise and at the same time, preserve the features that represent the image boundaries. The over segmentation problem can be solved by using an appropriate clustering algorithm to group similar pixel values together.
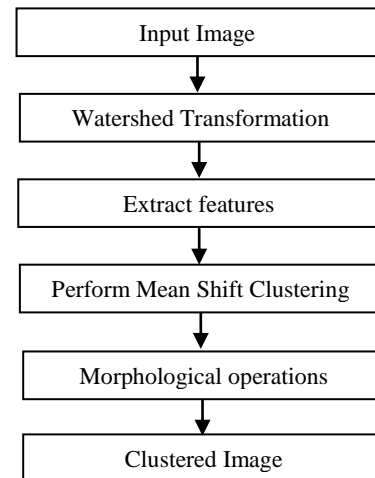

Figure 3: Proposed Clustering Algorithm

Normally to handle the over-segmentation problem of watershed algorithm, the over-segmented regions will be clustered using k-means algorithm [17]. The result while reducing the over-segmentation problem requires the correct selection of 'k' in the k-means algorithm. In this paper, this problem is solved by using a non-parametric clustering algorithm, namely, mean-shift clustering algorithm. The proposed algorithm is shown in Figure 3.
The algorithm starts by applying the traditional watershed transformation that uses the regional minima as starting markers. This step results with an image where each pixel is identified to belong to regional minima. The second step analyzes the texture of the labeled image and creates a feature vector based on the mean and standard deviation of each region. The mean-shift clustering algorithm is applied to group regions with similar features, thus reducing the number of regions. These regions are now used as optimal markers and the morphological operations were applied to obtain the internal markers. Open and close operators were used to join adjacent regions corresponding to adjacent regions belonging to same objects. The results are then used as internal markers during final WT. The erosion operator was then applied to compliment the internal markers and to obtain the external or background markers. The obtained internal and external markers are then used to obtain the final segmented image. The mean shift clustering algorithm is used to merge regions.
The mean shift estimate of gradient of a density function and the associated iterative procedures of mode seeking has been developed by Fukunaga and Hostetler [18]. The property of data compaction of the mean shift has been exploited in image segmentation. Based on the idea of

iteratively shifting a fixed size window to the average of the data points was taken. The mean shift procedure can be obtained by successive compute the mean shift vector $M_h(x)$, and translate the window $S_h(x)$ by $M_h(x)$.

$$M_h(x) = \frac{1}{nx} \sum_{x_i \in S_h(x)} x - x_i \qquad (6)$$

The mean shift vector always points towards the direction of the maximum increase in the density f(x), so it can define a path leading to a local density maximum.

$$f(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad (7)$$

Let $\{x_i\}_{i=1..n}$ be an arbitrary set of n points in the d-dimensional Euclidean space R^d. f(x) is the multivariate kernel density estimate with the kernel K(x) and the window $S_h(x)$ radius h. The mean shift filtering procedure is:

- For each j = 1..n

  Initialize k = 1 and $y_k = x_j$

  Compute

  $$y_{k+1} = \frac{1}{n_k} \sum x_i \in S_i(y_k)x_i, k \leftarrow k+1$$

  Assign $\quad Z_j = (x_j^s, y_{conv}^r)$

- Let $\{z_j\}_{j=1..n}$ be the *d*-dimensional original and filtered image in the spatial-range domain. The *s* and *r* denote the spatial and range parts of the vectors, respectively. The last assignment specifies that the filtered data at the spatial location of x_j will have the range components of the points of convergence y_{conv}.

4. EXPERIMENTAL RESULTS

The proposed system was tested using an experimental set consisting of satellite images of 512 x 512 sizes. The system was developed using MATLAB 7.3 and was tested on Pentium IV system with 2GB RAM. Several test images were used during experimentation and the result of four sample images (Figure 4) are projected in this section.

Image1　　**Image2**　　**Image3**　　**Image4**
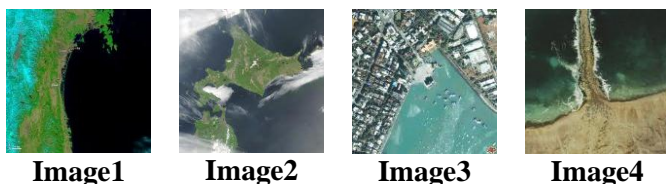
Figure 4: Sample Test Images

A. Enhancement Algorithm Results

To analyze the performance of image enhancement algorithm on segmentation, experiments were conducted by with 0.4% speckle noise added images. Moreover, contrast was randomly adjusted on all the noisy images. To evaluate the image enhancement algorithm three metrics, namely, Peak Signal to Noise Ratio (PSNR), enhancement time and segmentation time were considered.

The PSNR values obtained during experimentation are presented in Table I.

TABLE I: PEAK SIGNAL TO NOISE RATIO (dB)

Images	Anisotropic Diffusion	Wavelets	Proposed
Image1	27.32	29.46.n	33.48
Image2	29.10	31.89	36.46
Image3	24.67	28.14	31.08
Image4	29.55	32.47	39.51

It can be observed that the proposed system produce an enhanced version that is indicated by the high PSNR values obtained. According to [19] an improved denoising algorithm is recognized by a high PSNR or a lower MSE. In agreement with this, the results of the proposed systems with high PSNR prove that they are an improved version over existing methods.

Table II shows the time taken by the proposed and conventional filters to perform the enhancement operation.

TABLE II: ENHANCEMENT TIME (seconds)

Images	Anisotropic Diffusion	Wavelets	Proposed
Image1	0.36	0.27	0.21
Image2	0.29	0.22	0.17
Image3	0.42	0.31	0.26
Image4	0.39	0.29	0.20

While considering the execution time, it is evident that the proposed model is the quickest in enhancing the input satellite image.

PSNR and speed are the two most important performance factors of any denoising algorithm. From the results, it is evident that the speed of the proposed denoising algorithm is faster when compared to the standard algorithms and therefore makes it an attractive option for segmentation.

It is clear from the various projected results that the proposed algorithm produces improved results and therefore is used during further experimentation.

B. Segmentation Results

The performance of the segmentation algorithm was analyzed using the segmentation results before and after incorporating enhancement algorithm. The results were also compared with the traditional k-means algorithm. The

time taken to segmentation an image was also considered to analyze the speed of segmentation.

(i) Segmentation results

The segmentation results along with the effect of enhancement techniques on preprocessing are shown in Figure 5.

(ii) Speed of Segmentation

Segmentation speed is the time taken by the algorithm to segment or divide the input image into regions. The time taken by the two algorithms is shown in Table III.

TABLE III: SEGMENTATION TIME (Seconds)

Images	K Means	Watershed
Image1	0.82	0.936
Image2	0.62	0.84
Image3	0.67	1.23
Image4	0.97	1.13

All these results stress the fact that the watershed segmentation algorithm is an improved version when compared to the result of traditional k-means algorithm. Further, the introduction of enhancement algorithm before segmentation improves the segmentation results.

5. CONCLUSION

This paper presented satellite image segmentation system. The segmentation system consists of two steps, namely, image enhancement and segmentation. The image enhancement technique, treated as a preprocessing step, performs intensity correction, contrast adjustment, edge enhancement and noise removal. The noise considered is the speckle noise. The enhancement technique proposed a hybrid version that combined wavelets, improved anisotropic diffusion and CLAHE to improve the input satellite image. The result of the proposed preprocessing algorithm was compared with conventional anisotropic diffusion and wavelet based method and it was found the proposed method is an improved method. Therefore, the results after preprocessing using proposed enhancement method was used during segmentation. Three algorithms were used during segmentation. They were conventional mean-shift algorithm, clustering based k-means algorithm and modified watershed algorithm. Various experiments proved that modified watershed algorithm produce better segmentation results when compared with other two algorithms. The performance of the k-means algorithm depends on the correct assumption of the initial parameters. In future, algorithms that can automatically select these initial parameters are to be considered. Moreover, the proposed watershed algorithm, takes care of the over segmentation process efficiently, but the under segmentation process is not considered. In future research, this problem will also be considered.

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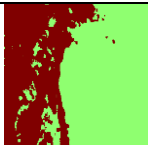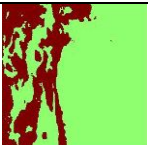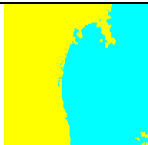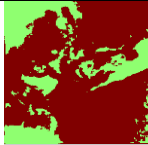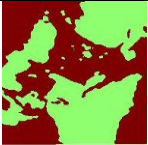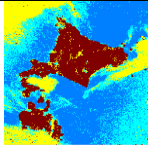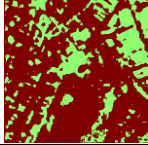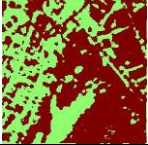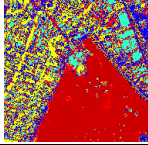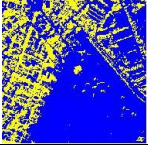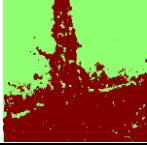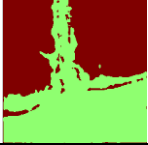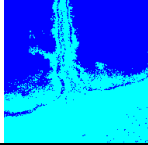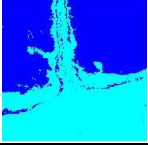
Figure 5: Segmentation results and its effect on preprocessing