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Morphological-based Image Segmentation and Maximum Likelihood Classification for Landscape Assessment

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Abstract: **-- The rapid variation in the landscape due to agricultural, migration, exploration and expansion activities is a critical problem associated with the country. There are both positive and negative impacts on the social, economic and political development of the country due to these activities. The negative impact is the degradation of the ecosystem due to the pollution in the surface and ground water resources. This poses health hazards to the human being. The existing classification techniques suffer low accuracy due to the presence of complex land cover patterns and vague relationship between land cover and spectral signals. Thus, there is a need to develop an efficient and affordable technique to classify the land cover regions for monitoring the biological dynamics in those regions. This paper presents a combined approach of the morphological-based image segmentation and maximum likelihood classification to detect the land use/land cover (LULC) classes. This detects the change in the LULC to design an environmental decision making framework due to the continuous conflicts on the impacts of the oil activities in this area. The performance evaluation results demonstrated the overall better classification performance on the detecting the water and non-water regions in the satellite image.**

Index Terms: **-- Image Classification, Maximum Likelihood Classifier, Morphology, Remote sensing.**

1. INTRODUCTION

Remote sensing is used to analyze, infer and monitor the environmental changes using the optical and microwave imagery obtained from various kinds of sensors [1]. The satellite images are highly useful for the monitoring and management of the natural resources. Hence, usage of remote sensing images is required for the environmental studies[2]. Remote sensing is a significant part of the Geographic Information System (GIS). The GISis used for the collection, storage, retrieval, transformation and display of the spatial data from the real world. GIS offers an integrated tool for the generation and presentation of the relevant information. Image classification is a process of classifying all the pixels in a satellite image to obtain a definite set of labels or land cover themes [3]. Due to the various spectral reflectance and remittance properties for the types of features on the earth's surface, feature is recognized through the image classification process. Classification of the LULC features is one of the foremost applications in the remotesensing applications. As the images are high-dimensional and complex, image classification is a difficult task.The complexity of the classification process increases with the increase in the number of categories in the image. Thus, it becomes difficult to determine thecharacteristics of the categories and allocate a pixel to one ofthe categories.Fig.1 shows the satellite image of Aral sea. Yang and Lo [4] and Mundia and Aniya[5]performed land cover classification and land change detection using the ISODATA classification algorithm. Ojigi[6] applied the maximum likelihood classification method to classify the LULC regions. The remote sensing data is used for detecting the environmental variations in the delta regions of Nigeria [7, 8]. The decline in the mangrove and forest areas and increase in the agricultural land and built-up areas are reported.

Fig.1 Land cover map

This paper presents a combined approach of the morphological-based image segmentation and maximum likelihood classification to detect the LULC classes. Image enhancement is applied to the input satellite images and

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global thresholding is applied for labeling the images and morphological-based image segmentation is used for the segmentation of regions in the image. The maximum likelihood classifier is used for the classification of water and non-water in the satellite image. The performance evaluation results demonstrated the overall better classification performance on detecting the changes in the post-classification of landscape.

The sections in the paper are systematized as follows: Section II presents an overview of the hyperspectral image classification methods and Section III describes the morphological-based image segmentation and maximum likelihood classification of the satellite images. The performance evaluation analysis is illustrated in Section IV and conclusion of this work is given in Section V.

II. RELATED WORKS

Bulgin et al. [9] presented a Bayesian-based image classification scheme to identify the clear-sky areas over the ice-free ocean for the recovery of sea surface temperature. The proposed classification scheme achieved maximum classification accuracy with the better identification of ice scenes. Chen et al. [10] proposed a novel non-linear technique for the classification of hyperspectral image through the sparse representation of test sample. The test pixel is decomposed over a training dictionary to obtain a sparse representation vector and the class label of the text pixel is determined by using the vector. Higher image classification accuracy is achieved. Yu et al. [11] developed a Multiview Stochastic Learning method for the classification of images. Automatic learning of the combination coefficient is performed to apply the complementary information of the multiview data. The experimental analysis demonstrated the effective of the proposed method for image classification. Li et al. [12] proposed a non-local combined collaborative representation classification method and employed the locally adaptive dictionary for the classification of hyperspectral image. The proposed classification method achieved better performance than the Support Vector Machine (SVM) classifier. Song et al. [13] applied sparse representations of the morphological Extended Multi-Attribute Profiles by integrating the spatial and spectral information for the classification of remotely sensed image. Better classification results are achieved by exploiting the low-dimensional structure of the profiles.

Li et al. [14] developed a novel framework to manage with the linear and non-linear class data boundaries to classify the hyperspectral scenes through the combination of multiple features. Efficient classification is achieved without requiring high computational complexity. Li et al. [15] presented a novel image classification framework for the expansion of combined kernel machines. A new group of composite kernels is created while integrating the spatial and spectral information in the hyperspectral data. The proposed framework achieved better classification performance in the complex analysis scenarios. Kuo et al. [16]introduced an automatic feature selection method to select the Radial Basis Function (RBF) parameter for the SVM classifier. The separability of the feature space is measured using a criterion including the between and within-class information. The performance of the SVM classifier is improved. Li and Du [17] developed a combined within-class collaborative representation for the hyperspectral imageclassification. A combined collaborative model of the linear combinations of the labeled samples represented the neighboring pixels near the test pixel. The proposed representation outperformed the existing classification techniques. Pal et al. [18] evaluated the efficiency of a novel kernel-based extreme learning machine (ELM) algorithm for the classification of land cover using the multi-spectral and hyperspectral remote sensing data. Better classification accuracy is achieved without requiring more computational cost.

III. PROPOSED WORK

Initially, image enhancement is applied to the input images for improving the contrast of the images. Global thresholding is applied for labeling the images and morphological-based image segmentation is used for the segmentation of regions in the image. The maximum likelihood classifier is used for the classification of water and non-water in the satellite image. Fig.2 shows the overall flow diagram of the proposed work.

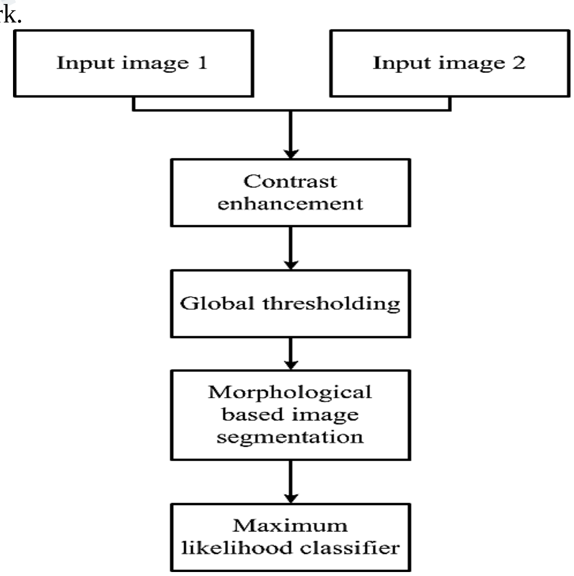

Fig.2 Overall flow diagram of the proposed work

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A. Contrast enhancement

Contrast is defined by the variation in the color and illumination of an object with respect to other objects. The visual system of the human is sensitive to the contrast. If the contrast is concentrated on a specific range, the information may be lost in those areas that are uniformly concentrated. The dynamic range of gray levels in the image is improved through the contrast enhancement. Image enhancement improves the quality of an image. It emphasizes or sharpens the features such as edges, boundaries, or contrast for efficient analysis of the image. This increases the dynamic range of the features for the easy detection of the features. Contrast enhancement increases the brightness values in an image for the efficient display of the image. It increases the visual contrast between two regions of different uniform densities. The areas with minimum density variations are discriminated easily.

B. Global thresholding

Global thresholdingis a method that uses a single global threshold value for separating an image into the separate regions. The local thresholding algorithms require more computational power than the global thresholding algorithms. Otsu [19] and Kapur methods [20] are the popular global thresholding algorithms used for the histogram-based segmentation of image into two classes. In the global thresholding algorithm, the new threshold value 'T' is computed during each iteration. The new threshold is computed as

$$T = 1/2\,(m_1 + m_2) \qquad (2)$$

Where m_1and m_2 represents the average of all pixels whose intensities are smallerand larger than the previous threshold.

Global thresholding algorithm

Step 1: Select an initial estimate for the global threshold 'T'

Step 2: Segment the image using 'T'. The two groups of pixels are

$G_1 \Leftarrow f(x,y) > T and G_2 \Leftarrow f(x,y) \leq T$

Step 3: Calculate the mean of intensity values $m_1, m_2\ of\ G_1, G_2$

Step 4: Calculate new threshold value using eqn (1)

Step 5: Go to step 2 until the difference in the global threshold values is small enough

C. Morphological-based image segmentation

Morphology is a tool to extractthe components that are suitable in the illustration and depiction of the shape of regions in the image. It modifies the images based on the shapes. The morphological operations eliminate the flaws and preserve the structure of image. The morphological techniques check the image with a structuring elementapplied to the probable locations of the input satellite image. It generates the output image of same size. The pixel values of the output image are based on the similar pixels of input image. Fig.3 shows the morphological operations.

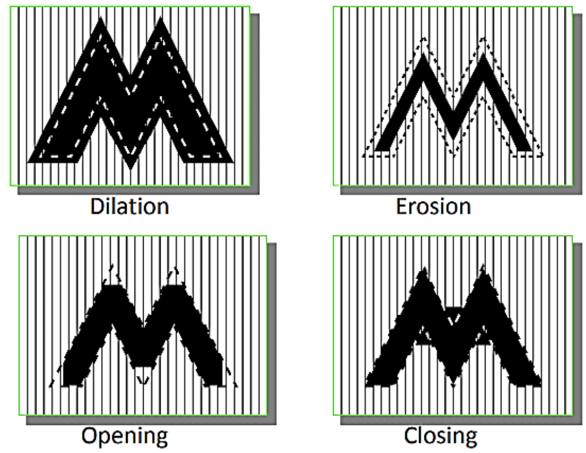

Fig.3 Morphological operations

D. Maximum Likelihood classifier

The maximum likelihood classifier is a statistical-based classifier, which depends on the normal data distribution in the class. An ellipsoid represents the geometrical shape of a number of pixels that belongs to a class. The location, shape and size of the ellipsoid are resultant from the variance-covariance matrices of the classes. The ellipses denote the outlines of probability of membership and values of decrease in the distance from the mean center. This distance value can be applied as a criterion to ascertain whether a pixel in the image belongs to a single class. The shape of the probability outlines depends on the relative dimensions of the axes and direction of the ellipse. It results in the accurate classification than the statistical-based classification techniques, as the training sample data is used for providing estimates of the membership distribution of each class in the n-dimensional feature space and location of the center point [21].The ML classifier provides better classification results if the frequency distribution of data lies in the multivariate normal distribution. After computing the probabilities of each pixel being a member of the class, the most likely class with the maximum probability is allocated to the pixel with a class label. The pixel is labeled as an unclassified one, if the maximum probability is lower than the threshold value.

IV. PERFORMANCE ANALYSIS

The performance of the proposed work is analyzed using the WorldView-2 Satellite Image gallery [22]. The satellite can collect images of areas nearly 1 million km2 every day. In this work, two images of area 101703.75000 and 287952.75000 km2 are considered. The input images are

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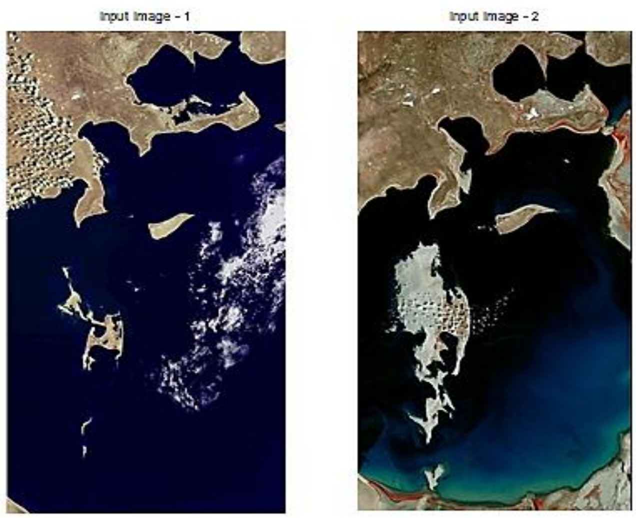
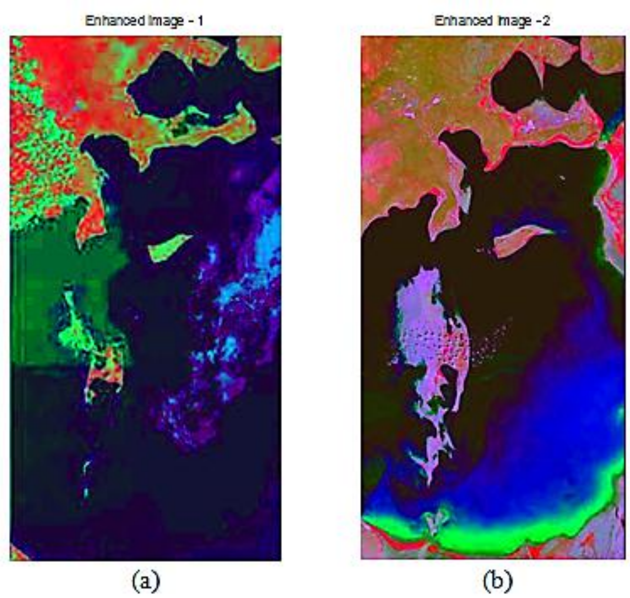
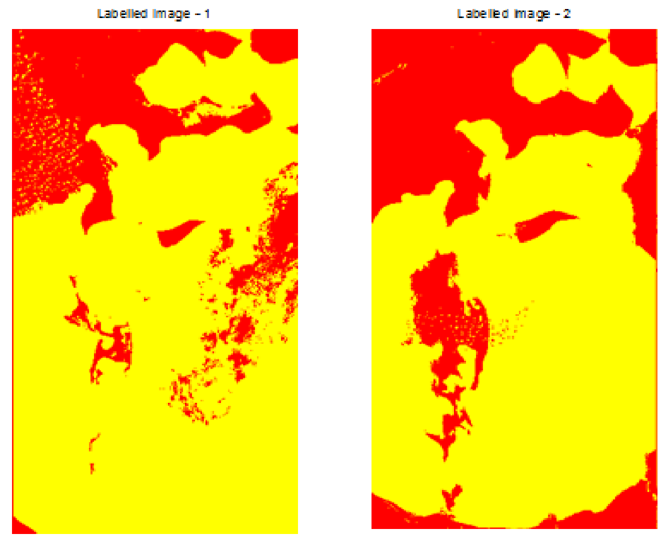
enhanced and labeled. Morphological-based image segmentation is applied and maximum likelihood based classification is performed to find the land cover and water regions in the images. Fig.4 shows the input images and Fig.5 illustrates the enhanced images. Fig.6 depicts the labelled images and Fig.7 presents the segmented images. The likelihood images are shown in Fig.8. Table I shows the water area and non-water area. Fig.9 depicts the water area analysis and Fig.10 shows the non-water area analysis.



(a) (b)
Fig.4(a) and (b) Input images

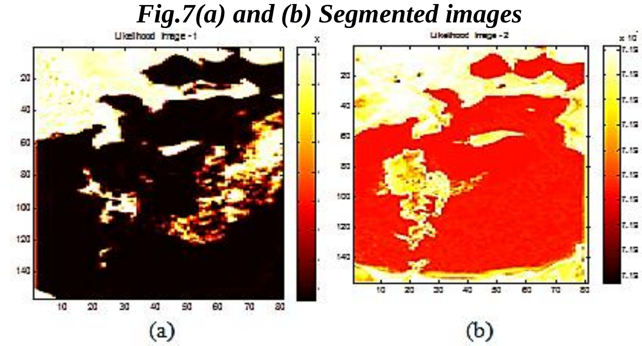


(a) (b)
Fig.5(a) and (b) Enhanced images



(a) (b)
Fig.6(a) and (b) Labelled images

(a) (b)
Fig.7(a) and (b) Segmented images



(a) (b)
Fig.8(a) and (b) Likelihood images

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Table I Water area and non-water area

Images	Water Area	Non Water Area
Aral Sea(1977)	101626	35896
Aral Sea(1989)	87868	50438
Pangong Lake(1998)	45260	214480
Pangong Lake(2013)	51485	211655
Lake Ayakkum(1992)	24764	186706
Lake Ayakkum(2012)	38659	170957

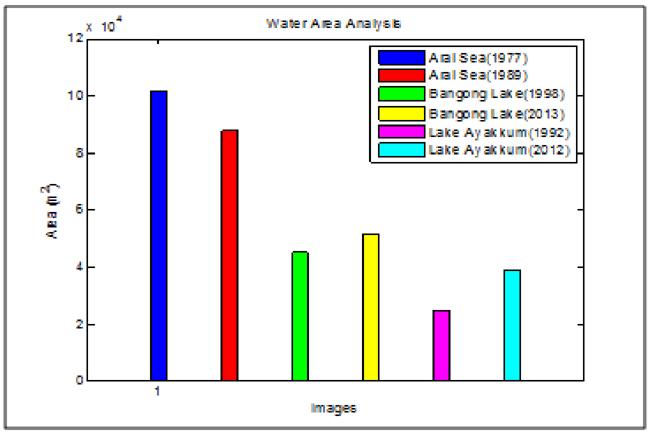

Fig.9 Water area analysis

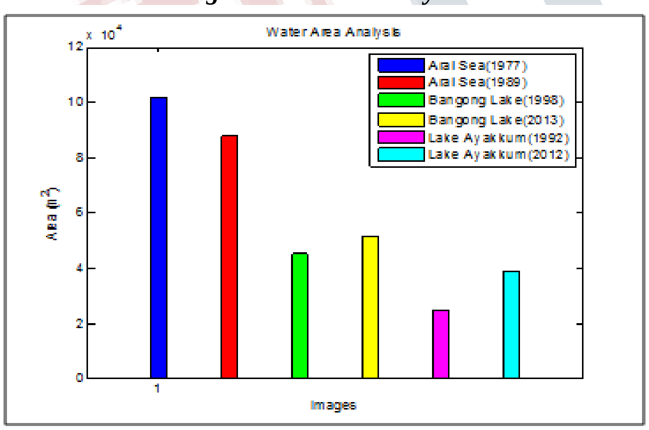

Fig.10 Non-water area analysis

V. CONCLUSION

The maximum likelihood classification algorithm depends on the visual interpretation of the different types of land cover on the satellite image and the ISODATA is an iterative procedure that groups the pixels based on a certain threshold. The ML classifier ensured better classification performance. The importance of the spatial and temporal remote sensing data and GIS tools in detecting the environmental degradation due to the migration and urbanization activities is realized. The reduction of the forest and mangroves can be attributed due to the increase in the urbanization. The ML classifier ensured better classification of water and non-water regions in the satellite image.

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