SOM Based Segmentation Method to Identify Water Region in LANDSAT Images

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Abstract: The objective of this research is to identify the water region from LANDSAT satellite image. Water resources are sources of water that are useful or potentially useful to humans. Uses of water include agriculture, industrial, household, recreational, transportation and environmental activities. Surveying of water region and research on its feature is very basic step for many planning, especially for countries like Indonesia, where the rapid economic growth has caused increasing competition for water. Identifying water region from satellite images is one of the grand steps of water resources management for a country. In this paper, the segmentation algorithm based on SOM (self-organizing map) neural network with compression pre-processing by wavelet transform and image smoothing using Gaussian low-pass frequency domain filters is presented. Firstly, the input image is blurred using Gaussian low-pass frequency domain filter. Then wavelet decomposition is used for obtaining compressed image without affecting other features. Next, SOM neural network is trained with the approximation image, which can improve the representation of training. Finally, trained neural network classify pixels of original image by using K-mean algorithm.

Keywords – LANDSAT satellite image; SOM neural network; water region segmentation

I. INTRODUCTION

Remote sensing is one of the major areas of visual processing. Remote sensing is the observation of an object, surface or phenomenon from a distance without actually being in contact with it. It is based on the principle that objects reflect or emit radiations in different wavelengths and intensities depending on specific conditions. Thematic bands in NASA’s LANDSAT has been introduced Base on the consideration of different wavelength emitted. The primary function of LANDSAT is to obtain and transmit images of the Earth from space for purpose of monitoring environmental conditions on the planet.

Data collection using remote sensing offers a variety of advantages compared to other forms of data acquisition. Remote sensing makes it possible to measure energy at wavelengths that cannot be reached by human vision.

The main concern of this paper is to identify the water region from a LANDSAT image. The purpose is to ensure the planning and monitoring water resources. Water is essential to life and economic activity and its use and management cover almost spheres of human endeavor. In the food and agriculture sector, water is a prime factor in the production of adequate food. Beside, Water transport is a suitable and convenient made of transportation and has proved to be an important alternative to other forms of transportation such as road, air and rail.

Climate change is a phenomena which caused by global warming and its serious implications on human comfort, biodiversity and water resources. Observation of water region has become an important role in supervising the issue of climate change which has claim the attention of public. Climate change has become a very serious new reality in many countries, with affects changes in the rainfall, water cycling and seasonal cycle. It also lead to rise in sea level with its attendant consequences such as floods, droughts, poverty and series of health problems. Therefore, identifying the water regions can work as one of the way to analyze the related phenomenon problem.

At the present, there are many methods of water region extraction. One of the methods is using Automated Feature Extraction (AFE). It works at the pixel level and approaches to object recognition and feature extraction by using inductive learning algorithms and techniques to model the feature recognition process, rather than explicitly writing a software program (Maloof 1998; Burl 1998). The Feature Analyst analyzed the water surface pixels as the training set pixels to determine the overall characteristics of the feature class and to find the features that have characteristics that are similar to the training set pixels [9]. Although, AFE technique is not the best but it is considered as another approach for feature extraction.

In this paper, SOM (self organizing map) neural network based segmentation method is introduced to identify the water region from LANDSAT images. Firstly, the input image is blurred using Gaussian low-pass frequency domain filter. Then wavelet decomposition is used for obtaining compressed image without affecting other features. Next, SOM neural network is trained with the approximation image, which can improve the representation of training, then trained neural network classify pixels of original image by using K-mean algorithm.

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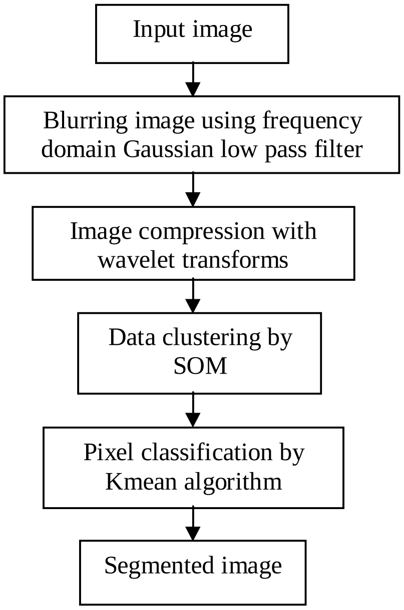

Figure 1. Design method to identify the water region from a LANDSAT image

The rest of this report discusses the methodology of the proposed system in section 2, and experimental results are discussed in section 3. Section 4 presents the future work and conclusion.

II. METHODOLOGY

A. Image smoothing using Gaussian low-pass frequency domain filters

Smoothing image is done to reduce the detail of the image. It is achieved in the frequency domain by high frequency attenuation. That is why low pass filtering has been chosen. The pixels of the original lake image consist of mixed pixels with both light pixels and dark pixels. It is very difficult to acquire the suitable segmentation threshold value directly from the original image to identify the water region [1]. Therefore, blurring the image is required. Some methods are proposed to reduce the details of the image. And Gaussian low pass filter smoothing is a good solution.

Gaussian smoothing makes no ringing effect. This is an important characteristic in practice, especially in situations in which any type of artifact is unacceptable. Besides that, blurring effect using frequency domain methods have a significant advantage over the spatial convolution approach. To achieve a significant blurring, a large size of mask needs to be used in spatial convolution method. Thus, long computational is needed and it would be even worse when the convolution is applied on a large image. In frequency domain, the blurring effect can be easily adjusted using cutoff frequency.

The form of these filters in two dimensions is given by

$$H(u,v) = e^{\frac{-D^2(u,v)}{2\sigma^2}} \tag{1}$$

Where, $D(u,v)$ is the distance from the center of the frequency rectangular [2]. σ is a measure of spread about the center. By letting σ=D_0, (1) become (2)

$$H(u,v) = e^{\frac{-D^2(u,v)}{2D_0^2}} \tag{2}$$

Where D_0 is the cutoff frequency [2]. The blurring effect can be changed by adjusting the cutoff frequency.

B. Image compression with wavelet transform

One of the important considerations for a process is time frame. The training time of the network is too long and the segmentation result and quality are much easily influenced by noise. R.Sudhakar, et al., [10] reports that have resulted in practical advances such as: superior low-bit rate performance, continuous–tone and bit-level compression, lossless and lossy compression, progressive transmission by pixel, accuracy and resolution, region of interest coding and others. Hence, wavelet transform and SOM (self organizing map) are coupled to reduce the training time. For this research purpose, wavelet transform is used for obtaining compressed LANDSAT image without affecting the water region structure.

Wavelet transform is introduced to obtain the image pyramidal structure, realize and down sample the image [4].

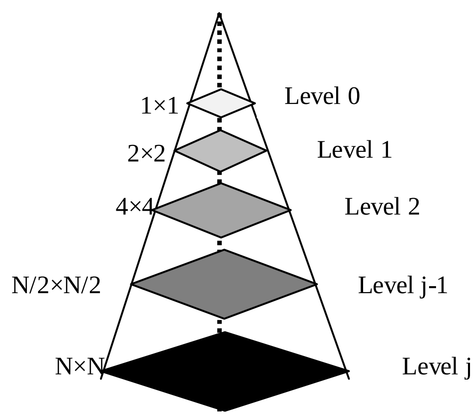

Figure 2. Pyramidal image structure

Figure 3. General structure of down sample an image

As can be seen in Fig.3, the original image contains a high resolution representation of the image being processed. The wavelet transform is performed discrete wavelet transform function, where the original image is decomposed into LL, HL, LH, HH frequency bands. The LL frequency band is selected for the subsequent processing. Here, the resolution of resultant image is reduced to half. For example, when the original image size is $N \times N$, and compressed size is $N/2 \times N/2$ which can be represented by $2^j \times 2^j$, where $0 \leq j \leq log_2{}^N$ [3]. The noise of approximation image at level j was notability depress. For this project purpose, only the LL part will be extracted to further process. This can be easily understood by studying the Figure 4.

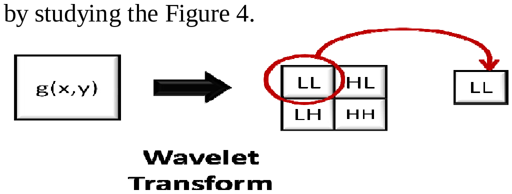

Figure 4. Overview of process compression

C. *Data clustering based on SOM*

SOM (Self organizing map) is a powerful technique for feature extraction. A SOM does not need a targeted output to be specified unlike many other types of networks. Further, when the node weights match the input vector, that area of the lattice is selectively optimized to more closely resemble the data for the classification of the input vector. From an initial distribution of random weights, and over much iteration, SOM eventually settles into a map of stable zones. Each zone is effectively a feature classifier. Thus, the graphical output is a type of feature map of the input space.

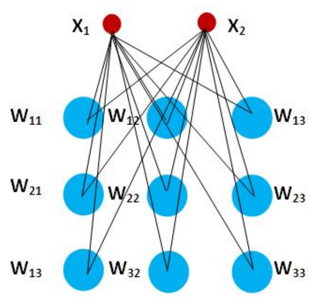

Figure 5. A very small Kohonen network of 3x3 nodes

For a given input LANDSAT lake image, SOM performed to cluster the data from the image based on the pixels value. The algorithm for the SOM training is the following:

1. Each node's weights are initialized.
2. A vector is chosen at random from the set of training data and presented to the lattice.
3. Every node is examined to calculate which one's weight are most like the input vector. The winning node is commonly known as "Best Matching Unit (BMU)".
4. The radius of the neighborhood of the BMU is now calculated. This is a value that starts large but reduces each time-step.
5. Each neighboring node's weights are adjusted to make them more like the input vector.
6. Repeat step 2-5 to get more accurate map.

The SOM method follows two basic equations: matching and finding the winner neuron determined by the minimum Euclidean distance to the inputs as (3), and the update of the position of neurons inside the cluster as (4).

$$d = \left[(x_x - w_{mnx})^2 + (x_y - w_{mny})^2\right]^{\frac{1}{2}} \quad (3)$$

$$w_i = w_i + \mu(t)\alpha(i,k)(x - w_i) \quad (4)$$

Where, for time t, with the network size $n \times m$,

x	is the input.
w_{mn}	is the weight vector of the corresponding coordinate.
μ and α	are the learning rate.
d	is the Euclidean distance.
w_i	is the updated weight.

D. *Pixel classification by K-mean*

Today several different unsupervised classification algorithms are commonly used in remote sensing. The most frequently used algorithm is the K-mean clustering algorithm. This algorithm is iterative procedure. In general, it assigns first an arbitrary initial cluster vector. Then, classify each pixel to the closest cluster. In the third step the new cluster mean vectors are calculated based on all the pixels in one cluster. The second and third steps are repeated until the "change" between the iteration is small. The "change" can be defined as the percentage of pixels that have changed between iterations [5].

The objective of the k-mean algorithm is to minimize the within cluster variability. The objective function is the sums of squares distances (D) between each pixel and its assigned cluster center. Minimizing the sum of square distances is equivalent to minimizing the Mean Squared Error (MSE). The MSE is a measure of the within cluster variability.

$$D = \sum_{\forall x} [x - c(x)]^2 \quad (5)$$

$$MSE = \frac{\sum_{\forall x}[x - c(x)]^2}{(N - c)b} \quad (6)$$

Where $C(x)$ is the mean of the cluster that pixel x is assigned to, N is the number of pixel, c indicates the number of clusters and b is the number of spectral bands.

III. EXPERIMENTAL RESULT

Two LANDSAT-7 ETM+ (Enhanced Thematic Mapper Plus) image of lake are selected for water region extraction experiment. The extraction results are shown as Figure 6 and Figure 7.

Figure 6(a)

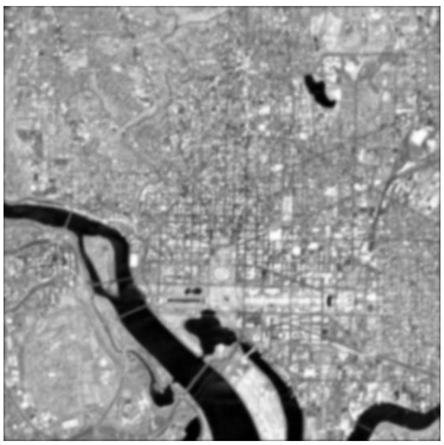

Figure 6(b)

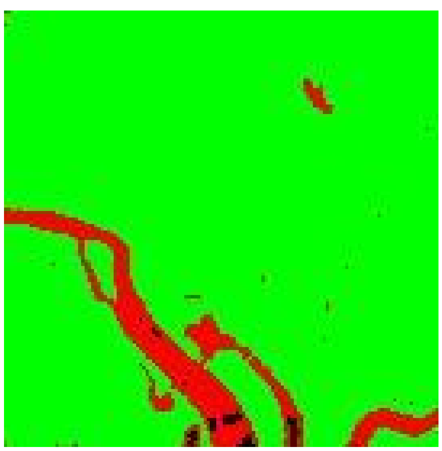

Figure 6(c)

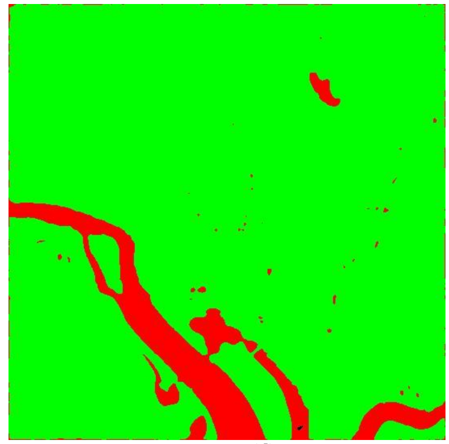

Figure 6(d)

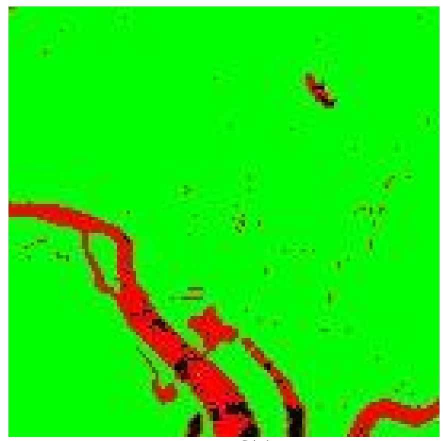

Figure 6(e)

Figure 6: LANDSAT-7 ETM+ image about Washington, D.C. (540 by 540 pixels). From top to bottom: (a) Input image, (b) Gaussian Blurred image with cutoff frequency 100, (c) Segmented image with wavelet transform, (d) Segmented image without wavelet transform, (e) Segmented image without Gaussian blurring effect.

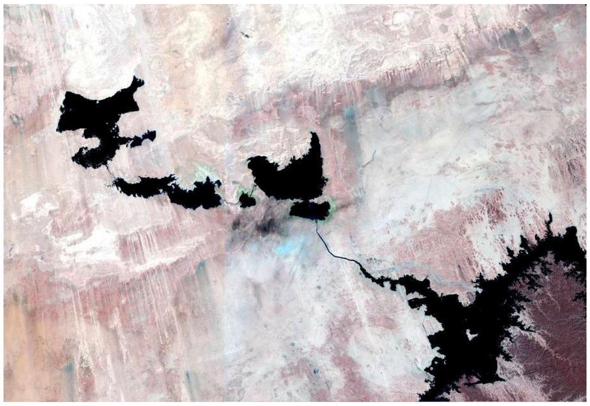

Figure 7(a)

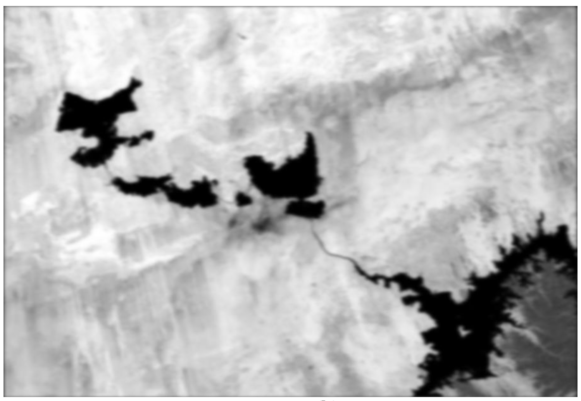

Figure 7(b)

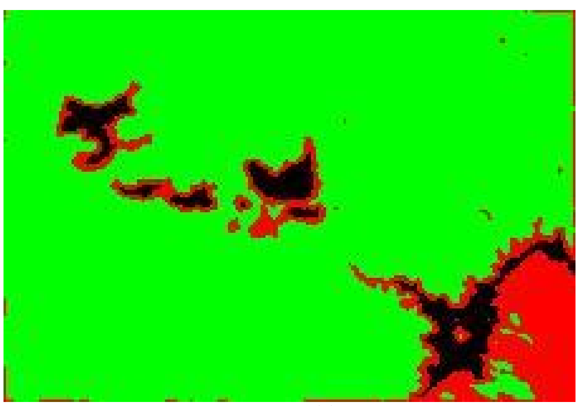

Figure 7(c)

Figure 7(d)

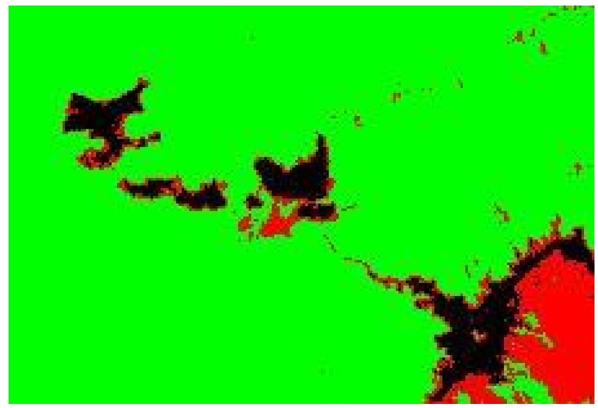

Figure 7(e)

Figure 7: LANDSAT-7 ETM+ image about West of Lake Nasser Southern Egypt (618 by 2721 pixels). From top to bottom: (a) Input image, (b) Gaussian Blurred image with cutoff frequency 100, (c) Segmented image with wavelet transform, (d) Segmented image without wavelet transform, (e) Segmented image without Gaussian blurring effect.

Based on the results shown in Fig. 6 and 7, segmentation using SOM with K-means alone shows a clear border of the water region. With the combination of the wavelet method, the water region was indentified correctly but contour of the water region is corrupted by blockiness effect due to down sampling of the corresponding image. This problem will lead to wrong estimation of water area when the area is calculated based on the number of pixels. When the blurring effect is not utilized in the segmentation process, fine details in an image will enhanced, which gives false representation of the water area or spot. The time taken for the computation of segmentation is given in the Table 1 for the images in Fig 6 and 7.

Table 1: Time taken for the segmentation tasks

	Figure 6(a) (Size: 540 by 540)	Figure 7(a) (Size: 618 by 2721)
Frequency based image blurring ($D_0=100$)	2.61s	9.56s
Image compression by wavelet (factor of 4)	Resized image: 135 by 135 0.59s	Resized image: 155 by 227 0.97s
SOM Clustering (with 100000 iterations)	95.02s	81.02s
Total timing	98.23s	91.55s

If the time frame is considered as one of the factor of identification, then the implementation of wavelet transform is important. Experimental results show that the duration of the process will be halved when implemented using wavelet transform. For example time taken to process the image without wavelet transform is 54.86s, while with wavelet transform is 26.34s. The method chosen depends on this consideration.

IV. Conclusions and Future Work

The first part of this paper introduced the important of water region information. The SOM based segmentation method has been used to identify the water region from a LANDSAT lake image. And the water region extracted by this method is available to provide information for some application such as planning and monitoring. In future, the improvement in the water region extraction algorithm is expected. Extractions of the exact information about the water region still remain challenging. The current method has to be integrated with other algorithm for further enhancement to provide more accurate information. The proposed method can be implemented in other problems such as segmentation of forest and land.

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