International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 3 (2015) pp. 8043-8058
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Satellite Image Retrieval By Wavelet Based Marker Controlled Watershed Segmentation Technique

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Abstract

The method of image retrieval is to recover some features such as intensity, color, shape, texture and image segmentation is done prior to this. The literature survey shows most of the work for image segmentation based on the properties that is looking for complex land surfaces, particularly when sensed using multi-spectral high resolution satellite imagery, the image scene is usually not easily partitioned correctly using a single feature channel (property) due to the complicated nature of the image scene. From survey it is clear that integrated processing of the multiple features is essential to obtaining more reliable segmentation. For speedy processing of information an automatic segmentation of these high resolution images will be useful for getting more timely and accurate information. Benefits of the high resolution images are that it provides, through the use of a variety of analysis methods, extraction of more detailed information's. This paper strives to develop a methodological framework for automatically segmenting the images into different regions corresponding to various features such as texture, intensity, and color. A comparative study of survey shows that different segmentation techniques have to be studied in detail. One such method is watershed algorithm which is realized by comparing similarities between different features of sub-regions. Since it is not possible to apply the watershed algorithm on an image directly, the image must be preprocessed before the segmentation process.

Introduction

Basically, all satellite image-processing operations can be grouped into three categories: Image Refinement, Restoration, Enhancement and Information Extraction. The objective of the image retrieval operations is to replace visual analysis of the image data with quantitative techniques for automating the identification of features in a scene. This involves the analysis of multispectral image data and the application of statistically based decision rules for determining the land cover identity of each pixel in an image. Wavelet transform is mostly used in image retrieval technique. The main advantages of the wavelet transform, as a tool for analyzing signals, are (1) orthogonality, (2) good spatial and frequency localization, and (3) ability to perform multiresolution decomposition. This paper carries preprocessing as a first module & segmentation as a second module & image retrieval as a third & last module.

Segmentation

Segmentation refers to the process of screening a digital image into multiple fragments (sets of pixels, also known as super pixels).Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s) [18]. When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

All image processing operations generally aim at a better recognition of objects of interest, i. e., at finding suitable local features that can be renowned from other objects and from the background. The next step is to check each individual pixel to see whether it belongs to an object of interest or not. This operation is called segmentation and produces a binary image. A pixel has the value one if it belongs to the object; otherwise it is zero. Segmentation is the operation at the threshold between low-level image processing and image analysis. After segmentation, it is known that which pixel belongs to which object. The image is parted into regions by boundaries between the regions. The different types of segmentations [19] are

a. Pixel-Based Segmentation

Point-based or pixel-based segmentation is conceptually the simplest approach used for segmentation.

b. Edge-Based Segmentation

An edge based segmentation approach can be used to avoid a bias in the size of the segmented object without using a complex thresholding scheme. Edge-based segmentation is based on the fact that the position of an edge is given by an extreme of the first-order derivative or a zero crossing in the second-order derivative.

c. Region-based Segmentation

These methods focus attention on an important aspect of the segmentation process missed with point-based techniques. There a pixel is classified as an object pixel judging solely on its gray value independently of the context. This meant that isolated points or small areas could be classified as object pixels, disregarding the fact that an important characteristic of an object is its connectivity. If we use not the original image but a feature image for the segmentation process, the features represent not a single pixel but a small neighborhood, depending on the mask sizes of the operators used. At the edges of the objects, however, where the mask includes pixels from the object and the background, any feature that could be useful cannot be computed. The correct procedure would be to limit the mask size at the edge to points of either the object or the background. Obviously, this problem cannot be solved in one step, but only iteratively using a procedure in which feature computation and segmentation are performed alternately[31]. In the first step, the features are computed disregarding any object boundaries. Then a preliminary segmentation is performed and the features are computed again, now using the segmentation results to limit the masks of the neighborhood operations at the object edges to either the object or the background pixels, depending on the location of the center pixel [30]. To improve the results, feature computation and segmentation can be repeated until the procedure converges into a stable result.

d. Model-Based Segmentation

All segmentation techniques discussed so far utilize only local information. The human vision system has the ability to recognize objects even if they are not completely represented. It is obvious that the information that can be gathered from local neighborhood operators is not sufficient to perform this task. Instead specific knowledge about the geometrical shape of the objects is required, which can then be compared with the local information. This train of thought leads to model-based segmentation. It can be applied if we know the exact shape of the objects contained in the image.

e. Color Image Segmentation algorithm

The human eyes have adjustability for the brightness, which we can only identified dozens of gray-scale at any point of complex image, but can identify thousands of colors. In many cases, only utilize gray-Level information cannot extract the target from background; we must by means of color information. Accordingly, with the rapidly improvement of computer processing capabilities, the color image processing is being more and more concerned by people. The color image segmentation is also widely used in many multimedia applications, for example; in order to effectively scan large numbers of images and video data in digital libraries, they all need to be compiled directory, sorting and storage, the color and texture are two most important features of information retrieval based on its content in the images and video. Therefore, the color and texture segmentation often used for indexing and management of data. This paper deals with the watershed segmentation algorithm. Good result of watershed segmentation entirely relay on the image contrast. Image contrast may be degraded during image acquisition. Watershed algorithm can generate over segmentation or under segmentation on badly contrast images. In order to reduce these deficiencies of watershed algorithm a preprocessing step is necessary.

The use of watersheds in image segmentation relies mostly on a good estimation of image gradients. However, background noise tends to produce spurious gradients, causing over-segmentation and degrading the result of the watershed transform. Also, low-contrast edges generate small magnitude gradients, causing distinct regions to be erroneously merged. A redundant wavelet transform is used to de-noise the image, enhance edges in multiple resolutions, and obtain an enhanced version of image gradients. Then, the watershed transform is applied to the obtained gradient image, and the segmented regions that do not satisfy specific criteria are removed or merged. Computing the watershed transform. Now the result is a de-noised image with enhanced edges.

Even after the pre-processing stage, some spurious gradients still remain in the image. To remove these undesired small magnitude gradients, a threshold T is applied to the gradient image, and coefficient values with M^{enh} smaller than T are set to zero. The threshold T selected as a standard value, such as T=k max (M^{enh}), where max (M^{enh}) is the maximum of the gradient magnitudes, and $0<k<1$ is constant (we used k=0.2 in this work). For example, consider the bacteria image shown in Fig. 1(a). It shall be noticed that background noise is intense, and some edges are fuzzy. Fig. 1(b) shows the denoising and edge enhancement of the bacteria image, using $J_{max}=3$. The enhanced magnitudes M^{enh} of the bacteria image (after thresholding) are shown in Fig. 1(c). The watersheds of M^{enh} are then computed, and the segmented image is obtained. Segmentation results for the bacteria image are shown in Fig. 1(d). It can be seen that all bacteria were segmented from the background.

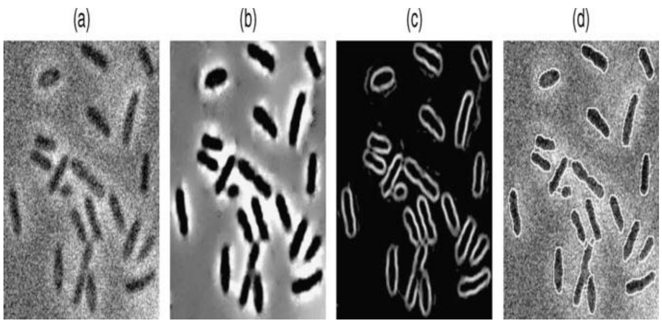


Figure 1: Watersheds on bacteria image (a) Noisy bacteria image. (b) De-noised/enhanced image. (c) Gradients of the de-noised/enhanced image. (d) Watersheds computed using gradient image.

Watershed Transformation

The watershed algorithm is an image segmentation algorithm that splits an image into areas of interests. It is described in the book of "digital image processing" by Gonzales and Woods as following:

"The concept of watershed is based on visualizing an image in three dimensions: two spatial coordinates versus gray levels. In such a "topographic" interpretation, we consider three types of points: (a) points belonging to a regional minimum; (b) points at which a drop of water, if placed at the location of any of those points, would fall with certainty to a single minimum; and (c) points at which water would be equally likely fall to more than one such minimum. The points satisfying condition (c) form crest lines on the topographic surface and are termed *divide lines* or *watershed lines*"

The goal of the algorithm is to find the watershed lines. The watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minimum (LIM). Pixels draining to a common minimum form a catch basin, which represents a segment.

a. Watershed Algorithm

Watershed transformation is a powerful technique that can be efficiently used for image segmentation. Watershed transformation is a powerful tool that demonstrates good performances in several applications like object based motion estimation, medical, multi-spectral satellite imagery, image processing and computer vision, etc. Image segmentation is an important pre-processing step for most image analysis tasks. The general segmentation problem involves the partitioning of a given image into a number of homogeneous regions. Therefore, segmentation can be considered as a pixel labeling process where pixels belonging to the same homogenous regions are assigned the same label. However, this definition hides a tremendous complexity which makes us facing many challenges in the implementation.

Several approaches have been proposed for the implementation of the watershed algorithm. In a watershed hardware implementation derived from Meyer's simulated flooding-based algorithm is described is based on ordered queues which add high complexity in the design.

But it can be a very hard and time consuming task facing hardware resources limitations on FPGA or complexity in the algorithm. Whereas, software based implementation offers simplicity and enables generality and flexibility. So here we are using MATLAB software to done this. In this, we have implemented an immersion based algorithm proposed by Vincent-Soille. Accordingly, during immersion process, water progresses in the relief, starting with valleys until adjacent lakes meet. The intercepting points constitute Watershed. Fig 2 illustrates the immersion principle.

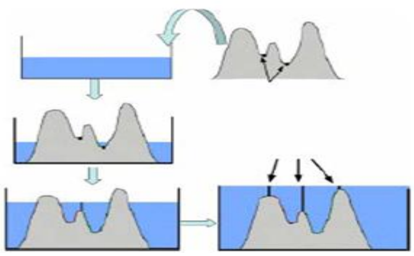


Figure 2: Immersion principle

Implementation of the Watershed algorithm includes the following steps:

- Sorting of the image grey levels.
- Extraction of the coordinates of all the pixels for each level.
- Processing of the image level by level in the following way:

For each pixel, if it has a labeled neighbor, it inherits this label, otherwise a new label is assigned and the pixel takes the new label. If two neighbors are labeled differently, then the pixel is considered as a watershed and so on until processing the entire image. Figure 3a presents an image of size 128*128 and figure 3b is its watershed transform. It is observed that the image obtained is over-segmented. To reduce this over segmentation we did quantification of the image. Figure 3c presents the image obtained after the application of the watershed algorithm on a quantified image.

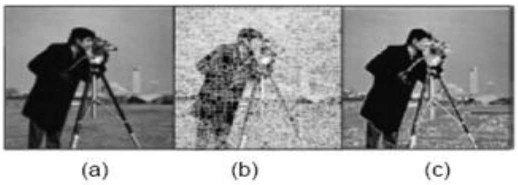


Figure 3: Application of watershed algorithm on a cameraman image a) Initial image b) Its watershed transform c) The same processing done on a quantified image

Image Retrieval

Due to exponential increase of size of so called multimedia files in recent years because of the substantial increase of affordable memory storage on one hand and the wide spread of World Wide Web (www) on the other hand, the need for the efficient tool to retrieve the images from the large data base becomes crucial. This motivates the extensive research into image retrieval systems. From the historical perspective, the earlier image retrieval systems are rather text-based with the thrust from database management community since the images are required to be annotated and indexed accordingly [20]. However with the substantial increase of the size of images as well as size of image database, the task of user-based annotation becomes very cumbersome and at some extent subjective and thereby, incomplete as the text often fails to convey the rich structure of images. In the early 1990s, to overcome these difficulties this motivates the research into what is referred as content based image retrieval (CBIR) where retrieval is based on the automating matching of feature of query image with that of image database through some image-image similarity evaluation. Therefore images will be indexed according to their own visual content such as color, texture, shape or any other feature or a combination of set of visual features. The advances in this research direction are mainly contributed by the computer vision community.

a. Feature Extraction

Feature extraction is the basis of content based image retrieval. Typically two types of visual feature in CBIR:

1) Primitive features which include color, texture and shape.
2) Domain specific which are application specific and may include, for example human faces and finger prints.

There are following fundamental bases for content based image retrieval, i.e. visual feature extraction, multidimensional indexing, and retrieval system design.

1) Feature extraction and indexing of image database according to the chosen visual features, which from the perceptual feature space, for example color, shape, texture or any combination of above.
2) Feature extraction of query image.
3) Matching the query image to the most similar images in the database according to some image-image similarity measure. This forms the search part of CBIR systems.
4) User interface and feedback which governs the display of the outcomes, their ranking, the type of user interaction with possibility of refining the search through some automatic or manual preferences scheme etc.

b. Color

Color is the most extensively used visual content for image retrieval. First a color space is used to represent color images. Its three-dimensional values make its discrimination potentiality superior to the single dimensional gray values of images. Before selecting an appropriate color description, color space must be determined first. Typically, RGB space where the gray level intensity is represented as the sum of red, green and blue gray level intensities [21].

c. Color space

Each pixel of the image can be represented as a point in a 3D color space. Commonly used color space for image retrieval include RGB, Munsell, CIE L*a*b*, CIE L*u*v*, HSV (or HSL, HSB), and opponent color space. There is no agreement on which is the best. However, one of the desirable characteristics of an appropriate color space for image retrieval is its uniformity. Uniformity means that two color pairs that are equal in similarity distance in a color space are perceived as equal by viewers. In other words, the measured proximity among the colors must be directly related to the psychological similarity among them. RGB space is a widely used color space for image display. It is composed of three color components red, green, and blue. These components are called "additive primaries" since a color in RGB space is produced by adding them together. In contrast, CMY space is a color space primarily used for printing. The three color components are cyan, magenta, and yellow. These three components are called "subtractive primaries" since a color in CMY space is produced through light absorption. Both RGB and CMY space are device-dependent and perceptually non-uniform. The CIE L*a*b* and CIE L*u*v* spaces are device independent and considered to be perceptually uniform. They consist of a luminance or lightness component (L) and two chromatic components a and b or u and v. CIE

L*a*b* is designed to deal with subtractive colorant mixtures, while CIE L*u*v* is designed to deal with additive colorant mixtures. The transformation of RGB space to CIE L*u*v* or CIE L*a*b*space can be found in [24].In HSV (or HSL, or HSB) space is widely used in computer graphics and is a more intuitive way of describing color. The three color components are hue, saturation (lightness) and value (brightness). The hue is invariant to the changes in illumination and camera direction and hence more suited to object retrieval. RGB coordinates can be easily translated to the HSV (or HLS, or HSB) coordinates by a simple formula. The opponent color space uses the opponent color axes (R-G, 2B-R-G, R+G+B). This representation has the advantage of isolating the brightness information on the third axis. With this solution, the first two chromaticity axes, which are invariant to the changes in illumination intensity and shadows, can be down-sampled since humans are more sensitive to brightness than they are to chromatic information.

d. Color Moments

Color moments have been successfully used in many retrieval systems, pecially when the image contains just the object. The first order (mean), the second (variance) and the third order (skewness) color moments have been proved to be efficient and effective in representing color distributions of images.

Mathematically, the first three moments are defined as:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} (f_{ij}$$

$$\sigma_i = (\frac{1}{N}\sum_{j=1}^{N} (f_{ij} - \mu_i)^2)^{\frac{1}{2}}$$

$$s_i = (\frac{1}{N}\sum_{j=1}^{N} (f_{ij} - \mu_i)^3)^{\frac{1}{3}}$$

where *fij* is the value of the *i*-th color component of the image pixel *j*, and *N* is the number of pixels in the image. Usually the color moment performs better if it is defined by both the L*u*v* and L*a*b* color spaces as opposed to solely by the HSV space Using the additional third-order moment improves the overall retrieval performance compared to using only the first and second order moments. However, this third-order moment sometimes makes the feature representation more sensitive to scene changes and thus may decrease the performance. Since only 9 (three moments for each of the three color components) numbers are used to represent the color content of each image, color moments are a very compact representation compared to other color features. Due to this compactness, it may also lower the discrimination power. Usually, color moments can be used as the first pass to narrow down the search space before other sophisticated color features are used for retrieval.

e. Color histogram

In image retrieval a histogram is employed to represent the distribution of colors in image [22]. The number of bins of histogram determines the color quantization.

Therefore the histogram shows the number of pixels whose gray level falls within the range indicated by corresponding bin. The comparison between query image and image in database is accomplished through the use of some metric which determines the distance or similarity between the two histograms. The color histogram serves as an effective representation of the color content of an image if the color pattern is unique compared with the rest of the data set. The color histogram is easy to compute and effective in characterizing both the global and local distribution of colors in an image. In addition, it is robust to translation and rotation about the view axis and changes only slowly with the scale, occlusion and viewing angle. Since any pixel in the image can be described by three components in a certain color space (for instance, red, green, and blue components in RGB space, or hue, saturation, and value in HSV space), a histogram, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component. Clearly, the more bins a color histogram contains, the more discrimination power it has. However, a histogram with a large number of bins will not only increase the computational cost, but will also be inappropriate for building efficient indexes for image databases. Furthermore, a very fine bin quantization does not necessarily improve the retrieval performance in many applications. One way to reduce the number of bins is to use the opponent color space which enables the brightness of the histogram to be down sampled. Another way is to use clustering methods to determine the *K* best colors in a given space for a given set of images. Each of these best colors will be taken as a histogram bin. Since that clustering process takes the color distribution of images over the entire database into consideration, the likelihood of histogram bins in which no or very few pixels fall will be minimized. Another option is to use the bins that have the largest pixel numbers since a small number of histogram bins capture the majority of pixels of an image. Such a reduction does not degrade the performance of histogram matching, but may even enhance it since small histogram bins are likely to be noisy. When an image database contains a large number of images, histogram comparison will saturate the discrimination. To solve this problem, the *joint histogram* technique is introduced. In addition, color histogram does not take the spatial information of pixels into consideration, thus very different images can have similar color distributions. This problem becomes especially acute for large scale databases. To increase discrimination power, several improvements have been proposed to incorporate spatial information. A simple approach is to divide an image into sub-areas and calculate a histogram for each of those sub-areas. As introduced above, the division can be as simple as a rectangular partition, or as complex as a region or even object segmentation. Increasing the number of sub-areas increases the information about location, but also increases the memory and computational time.

f. Shapes

In image retrieval, depending on the applications, some require the shape representation to be invariant to translation, rotation and scaling, whiles others do not. Shape is the most obvious requirement at the primitive level. Unlike texture, shape is a fairly well-defined concept – and there is considerable evidence that natural objects are primarily recognized by their shape In general shape representation can be divided into two categories:

1) Boundary based which uses only the outer boundary of the shape.
2) Region-based which uses the entire shape regions.

The most successful representative for these two categories are Fourier descriptor and Moment invariants. The main idea of a Fourier descriptor is to use the Fourier transformed boundary as the shape feature. Rui et al. proposed a modified Fourier descriptor which is robust to noise and invariant to geometric transformation [23].

The main idea of moment invariant is to use region based moments which are invariant to transformation, as the shape feature. Polynomial filtering is done to represent local geometric information, from which geometric invariants are used in object matching and recognition. Some recent work in the shape representation includes the finite element method (FEM), the turning function and wavelet transform..A number of features characteristic of object shape (but independent of size or orientation) are computed for every object identified within each stored image. Queries are then answered by computing the same set of features for the query image, and retrieving those stored images whose features most closely match those of the query. Two main types of shape feature are commonly used – *global* features such as aspect ratio, circularity and moment invariants [Niblack et al, 1993] and *local* features such as sets of consecutive boundary segments [Mehrotra and Gary, 1995]. Alternative methods proposed for shape matching have included elastic deformation of templates (Pentland et al [1996], del Bimbo et al [1996]), comparison of directional histograms of edges extracted from the image and *shocks*, skeletal representations of object shape that can be compared using graph matching techniques.

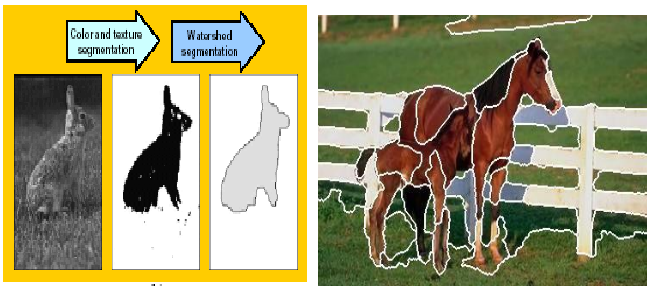


Fig: 4: shape retrieval

g. Texture

Texture is another important property of images. It refers to the visual patterns that have property of homogeneity or arrangement that do not result from the presence of only a single color or intensity. Various texture representations have been investigated in both pattern recognition and computer vision. The co- occurrence matrix approach explored the gray level spatial dependence of structure. Tamura developed computational approximation to the visual texture properties found to be important in psychology studies. The six visual texture properties were coarseness, contrast, directionality, line likeness, regularity and roughness. One major distinction between

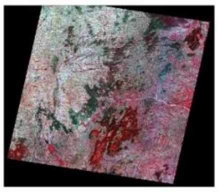
Tamura texture representation and the co- occurrence matrix is that all the texture properties in Tamura Representation are visually meaningful, whereas some of texture properties used in co-occurrence matrix may not be. Two classes of texture representation method can be distinguished: 1) Structural methods including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. They deal with the arrangement of image primitives, presence of parallel or regularly spaced objects.

2) Statistical methods which include the popular co-occurrence matrix, Fourier power spectra, Shift invariant principal component analysis (SPCA), Tamura feature, Multi-resolution filtering technique such as Gabor and wavelet transform, characterize the texture by statistical distribution of the image intensity.

What if the images are of same color? This will be answered by textures. The ability to retrieve images on the basis of texture similarity may not seem very useful- But the ability to match on texture similarity can often be useful in distinguishing between areas of images with similar color (such as sky and sea, or leaves and grass). A variety of techniques has been used for measuring texture similarity; the best-established rely on comparing values of what are known as *second-order statistics* calculated from query and stored images. Essentially, these calculate the relative brightness of selected *pairs* of pixels from each image. From these it is possible to calculate measures of image texture such as the degree of *contrast*, *coarseness*, hom*ogeneity* and *regularity* or periodicity, correlation and entropy. A recent technique is the texture thesaurus, which retrieves textured regions in images on the basis of similarity to automatically-derived codeword's representing important classes of texture within the collection. **Contrast** is the dissimilarity or difference between things (color, brightness etc). **Homogeneity** means "being similar throughout"(like same color can be said to one part segmentation can also be done through this). **Entropy** is a measure of the uncertainty associated with a random variable.

Figure 5: Texture Retrieval

Experimental Results & Outputs



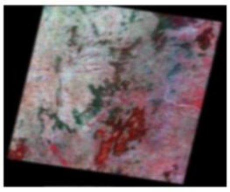


Figure 6: Input Image **Figure 7:** FFT Shift

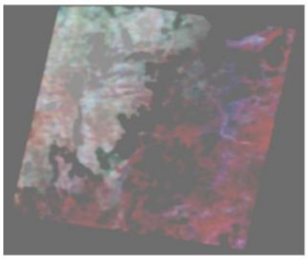


Figure 8: IFFT Shift

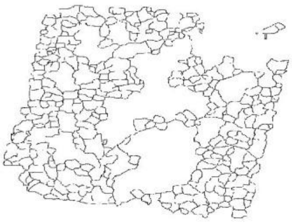


Figure 9: Watershed ridge lines

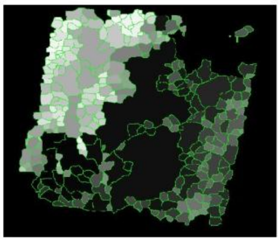


Figure 10: Colored Watershed On color image

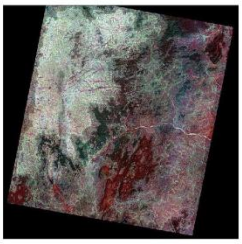


Figure 11: watershed Superimposed on input image

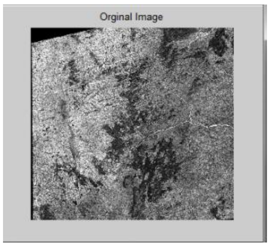


Figure 12: Original image in gray scale

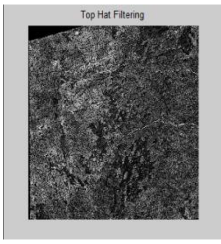


Figure 13: Top Hat filtering

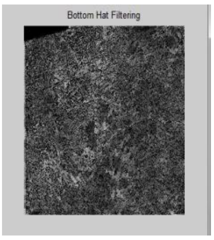


Figure 14: Bottom Hat filtering

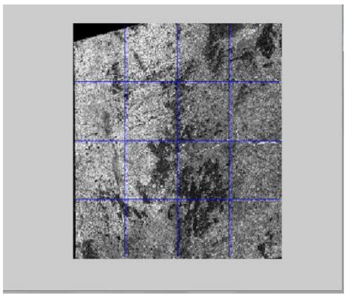


Figure 14: Block segmentation

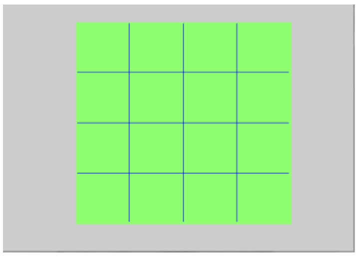


Figure 15: Block segmentation

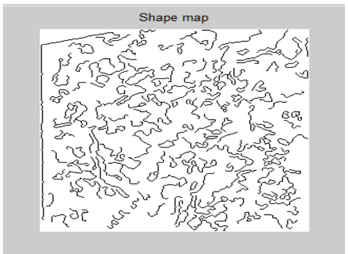


Figure 16: shape map

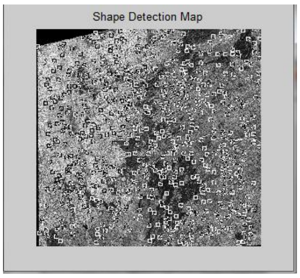


Figure 17: Shape Detection Map

Conclusion & Future Work

Satellite image is used to test the algorithm selected. For retrieval purpose watershed algorithm for segmentation and the implementation of feature extraction from the segmented image includes color, shape, intensity, and texture. The result shows that watershed algorithm is better than existing algorithm. This paper gives efficient result in terms of over segmentation in watershed algorithm. In this paper, we consider in our work only color, shape & texture extractions. In future work, many other features also will be retrieved.

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