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Terrain Classification using Multiple Image Features

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ABSTRACT

A wide variety of image processing applications require segmentation and classification of images. The problem becomes complex when the images are obtained in an uncontrolled environment with a non-uniform illumination. The selection of suitable features is a critical part of an image segmentation and classification process, where the basic objective is to identify the image regions that are homogeneous but dissimilar to all spatially adjacent regions. This paper proposes an automatic method for the classification of a terrain using image features such as intensity, texture, and edge. The textural features are calculated using statistics of geometrical attributes of connected regions in a sequence of binary images obtained from a texture image. A pixel-wise image segmentation scheme using a multi-resolution pyramid is used to correct the segmentation process so as to get homogeneous image regions. Localisation of texture boundaries is done using a refined-edge map obtained by convolution, thinning, thresholding, and linking. The individual regions are classified using a database generated from the features extracted from known samples of the actual terrain. The algorithm is used to classify airborne images of a terrain obtained from the sensor mounted on an aerial reconnaissance platform and the results are presented.

Keywords: Image segmentation, multi-resolution, pyramid, texture, image classification, image processing, terrain classification

1. INTRODUCTION

Digital images are usually characterised by two main aspects–tone and texture[1]. The image tone consists of gray-level variation of the pixels throughout the entire image whereas image texture represents the intrinsic spatial variability of the neighbouring pixel values for each pixel within the image. Tone and texture are not independent of one another–results of processing using one could influence the other.

Image segmentation is a fundamental research area in image processing. Segmentation is considered as a pre-processing step for high-level vision tasks such as image interpretation and classification, colour image processing, medical image processing and object recognition. The problem of segmentation involves partitioning the image into classes of meaningful areas (regions) that are uniform and homogeneous and dissimilar to all spatially adjacent regions. Homogeneity may be measured in terms of colour, texture, motion, depth, etc.

An ideal segmented image should satisfy the following criteria:

- Region interiors should be simple.
- Adjacent regions should have significantly different

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value wrt the characteristics on which they are uniform.

- Boundaries of each segment should be simple and spatially accurate.

Although a large number of segmentation algorithms are proposed in the literature[2-5], a satisfactory solution which produces acceptable result for a variety of images obtained in actual environment is difficult to obtain.

In the present scenario, images are obtained from a reconnaissance aircraft where a camera is mounted on a gimbal. The environment is uncontrolled since neither the nature of the terrain nor the illumination characteristics of the environment are known *a priori*. Depending on the spatial resolution of airborne images, ground elements may be represented either by one pixel or by a group of pixels. The purpose of segmentation is basically to separate each of these ground elements to know the terrain. Therefore based on the requirements of the present problem, two different approaches of segmentation used are: (i) intensity-based approach, where segmentation is done based on the gray value of individual pixels and (ii) texture-based approach, where segmentation is done by computing gray-level relationship among the pixels of a neighborhood.

An image with a simple scene, composed of few types of regions having constant gray values, can be segmented into regions using intensity-based segmentation by simply slicing the gray values into intervals and classifying each pixel according to the interval in which its gray value belongs. In the presence of noise in the image, reliable segmentation results may be obtained by segmenting the image using a pixel-linking scheme in a multi-resolution pyramid of images.

Texture plays an important role in image processing, interpretation, and understanding of terrain obtained from airborne images. In a wide variety of applications, texture is considered to be an important image feature. Texture is viewed as a global pattern arising from a deterministic or random repetition of local sub-pattern or primitive. The structure resulting from this repetition is very useful for discriminating contents of the image in a complex scene. Task involved in texture analysis is to partition the image into a set of sub-regions each of which is homogeneously textured.

Following are the factors on which success in texture segmentation depends:

- Choice of highly discriminating textural features,
- Selection of appropriate window size for computing textural features, and
- Finding a reliable texture boundary.

A large number of texture features are available in the literature [6-8]. The quality of texture segmentation depends largely on the discriminating ability of these features used in the classification. The features that have promising discriminating performance for different textures are highly problem-specific. Usually texture features are extracted using a moving window i.e., for any point in the image, some property is estimated around its neighbourhood. A given texture property may not be reflected if the window size is very small. For a large window size, estimation of texture may be accurate and the noise content in the feature image may also be less. But a large window implies more averaging over different texture properties near region boundary. As a result, segmentation based on texture will not be able to determine the precise boundary of two adjacent regions of different textures[9].

This paper proposes an automatic method for the classification of a terrain using intensity, texture, and edge. The textural features are calculated using statistics of geometrical attributes of connected regions in a sequence of binary images obtained from a texture image. A pixel-wise image segmentation scheme using a multi-resolution pyramid and an edge map is used to improve the texture classification result and localisation of texture boundaries.

2. METHOD

The steps which need to be performed in the image are:

- Intensity-based segmentation,
- Texture-based segmentation,

- Edge detection,
- Texture classification, and
- Correcting the texture boundary.

Step 1. Intensity-based Segmentation using Pyramid Node Linking

In intensity segmentation, homogeneity of the region is measured by gray-level similarity. Since structures may be present in an image at different scales, computation is done using a multi-resolution pyramid with linked structure. The approach differs from the conventional classification techniques as follows:

- All processing is performed using a pyramid of image of reduced resolution. For the present image of size (512 x 512), computation is performed in 4 levels of pyramid, viz., images of size (256 x 256), (128 x 128) and (64 x 64). This ensures that processing is performed at a resolution appropriate for any given portion of any given image.
- Property used for image segmentation is average gray level.
- Segmentation and image property computation are performed in a cooperative iterative fashion. The results of one pass are used to improve the performance of the next pass.

The pyramid data structure is defined by linked arrangement of levels of arrays. The elements in the array at each level are obtained by averaging property values of 4 x 4 blocks of elements in the array at the level immediately below, where these blocks overlap by 50 per cent both horizontally and vertically. The sizes of the arrays at the various levels thus shrink by power of 2. An element at level k has sixteen sons at level k-1. An element at level k-1 has four fathers at level k. Links are defined between elements at successive levels based on similarity of their property values. Each element at level k-1 is linked to one of its four fathers at level k. The element property values are then recomputed as the average of the property values of only those of its sons linked to it. This causes the similarities to change and the links are changed accordingly. This process is repeated until the links stabilise. The links are then traced from the bottom-most level upto the top to define trees of linked image blocks. The set of pixels at the leaves of the tree constitute a homogeneous segment in the image. The intensity segmented image is post-processed using K-means clustering algorithm to identify the homogeneous regions present in the image. K-means clustering algorithm starts by selecting K Nearest Neighbours to each point and then group the clusters based on their similarity and closeness.

Step 2. Texture-based Segmentation

Texture features are extracted based on the statistics of geometrical properties of connected regions in a sequence of binary images[12]. The first step of the approach is to decompose a texture image into a set of binary images. For each binary image, geometrical attributes such as the number of connected regions and their irregularity are statistically considered.

- *Construction of a Stack of Binary Images*

Consider a digital image (n_x x n_y) where n_x is the image length and n_y is the image width. Let the number of gray levels in the image be n_l. This image can be modelled by a 2-D function $f(x,y)$, where $(x,y) \in \{0,1,2, n_x-1\} \times \{0,1,2, \ldots .n_y-1\}$ and $f(x,y) \in \{0,1,2,3 \ \ldots n_l-1\}$. $f(x,y)$ is termed as the intensity of the image at (x,y).

When an image $f(x,y)$ is thresholded with a threshold value α, $\alpha \in \{1,2,3 \ldots n_l-1\}$, a corresponding binary image is obtained, i.e.,

$$f_b(x,y;\ \alpha) = \begin{cases} 1 & \text{if } f(x,y) \geq \alpha \\ 0 & \text{otherwise} \end{cases}$$

where $f_b(x,y;\ \alpha)$ denotes the binary image obtained with a threshold value α. From a given original image there are n_l-1 different binary images i.e., $f_b(x,y;\ 1)$, $f_b(x,y;\ 2)$, $f_b(x,y;\ 3)$, $f_b(x,y;\ 4) \ldots f_b(x,y;\ n_l-1)$. This set of binary images can be termed as binary stack.

- *Geometrical Attributes*

For each binary image, all 1-valued pixels are grouped into a set of connected pixel groups termed as connected region and the same is done for 0-valued pixels. The number of connected regions of 1-valued pixels in the binary image $f_b(x,y;\ \alpha)$, denoted by $NOC_1(\alpha)$ and the number of connected regions of 0-valued pixels in the same binary image, denoted by $NOC_0(\alpha)$ are computed. These $NOC_1(\alpha)$ and $NOC_0(\alpha)$ are functions of α, $\alpha \in \{1,2,3\ldots\ n_1\text{-}1\}$.

The two geometrical attributes $NOC_1\ (\alpha)$ and $NOC_0\ (\alpha)$ are characterised using the following formula:

$$\text{Maximum value} = \max_{1\le\alpha\le n_{l-1}} g(\alpha)$$

$$\text{Average value} = \frac{1}{n_l - 1}\sum_{\alpha=1}^{n_l-1} g(\alpha)$$

$$\text{Sample mean} = \frac{1}{\sum_{\alpha=1}^{n_l-1} g(\alpha)}\sum_{\alpha=1}^{n_l-1} \alpha.g(\alpha)$$

Sample variance =

$$\frac{1}{\sum_{\alpha=1}^{n_l-1} g(\alpha)}\sum_{\alpha=1}^{n_l-1} (\alpha - sample\_mean)^2 .g(\alpha)$$

where $g(\alpha)$ is one of the two functions $NOC_1(\alpha)$ and $NOC_0(\alpha)$. Texture feature images were generated using all these parameters and it was found that texture image generated from sample mean of $NOC_1(\alpha)$ was capable of capturing the fine details of the image compared to others. The texture segmented image is post-processed using K-means clustering algorithm to further segment the image into homogeneous regions.

Step 3. Edge Detection

Edges are detected using Nevatia-Babu operator[13]. The method consists of the following steps:

(a) Convolution

The convolution masks corresponding to ideal step edges in a selected number of directions are applied to the image. Each pixel is convolved with six masks with directions 30° apart. The output from this stage is stored in two arrays, viz., magnitude array and direction array for further processing.

(b) Thinning and Thresholding

For each pixel, presence of an edge at that point is decided by comparing the edge data with some of the eight neighboring pixels. An edge element is said to be present in a pixel if the edge magnitude of the central pixel exceeds a specified threshold, the output edge magnitude at the pixel is larger than the edge magnitudes of its two neighbours in a direction normal to the direction of the edge and the edge directions of the two neighboring pixels are within one unit (± 30°) of that of the central pixel. Also if the later two conditions are satisfied, the two neighbouring pixels are disqualified from being candidates for edges. The result from this stage is stored in an array having binary values with '1' representing the presence of edge and '0' representing no edge.

(c) Linking and Noise Removal

In the first step, all the pixels are given one successor and one predecessor based on the direction and edge information and in the second step features are joined by filling the gaps. Finally, all the clusters of edges which are not connected, and hence, size less than a predefined threshold are removed.

Step 4. Texture Classification

The objective of this study is to classify an unknown terrain on which a flight mission has just taken place[14-16]. To generate the database required to classify the terrain and validate the algorithm, sample images are collected from flight trials conducted at various time on various parts of a terrain covering an area of (50 km x 50 km). From these large number of samples, study of ground truth shows that the terrain consists of mainly four kinds of ground elements, viz., waterbody, bareland, grassy region, and forest area.

Database of these four regions are generated by arbitrarily selecting sub windows from known images and textural features are extracted from them. Each feature is normalized using the following equation

$$f_i^1 = \frac{f_i - f_i^{\min}}{f_i^{\max} - f_i^{\min}} \quad i = 1,2,3...8$$

where $f_i^{\max}$, $f_i^{\max}$ are the maximum and minimum values of the feature and i is the total number of sample points.

Step 5. Correcting the Texture Boundary

The intensity segmented image is first generated from the input image using pyramid node linking process. Since the appropriate window size needed for texture computation is not known, the texture segmentation is initially done from the input image on windows of sizes starting from (32 x 32) to (4 x 4). In each step, the difference between intensity and texture segmented images are computed and the window size, which gives minimum number of erroneous pixels, are selected. This gives an approximate idea of the window size needed for texture computation for these classes of images. One now has three images, first image obtained after intensity segmentation, second after texture segmentation, and the third is the difference image indicating the number of erroneously segmented pixels. Total number of erroneous pixels has two components: (i) error in intensity segmentation, which occurs due to averaging, and (ii) error in texture segmentation, which occurs due to error in texture calculation near the region boundary. The difference image is scanned and regions of erroneous pixels of size (3 x 3) and above are identified. Texture computation of these regions is performed and the pixels are assigned the appropriate value of the texture class it belongs using the database. This process is repeated for the erroneous pixels obtained from both intensity and texture segmentations. The boundary between two adjacent regions is now made one pixel width after superimposing the edge image on this final segmented image.

3. RESULTS

The proposed method of terrain classification using intensity, texture, and edge as image features is implemented on a Pentium PC using Visual C++ in Windows environment. The algorithm is tested for airborne images obtained from UAV and results presented. Figure 1 shows a sample database of the ground features used in this paper for classification

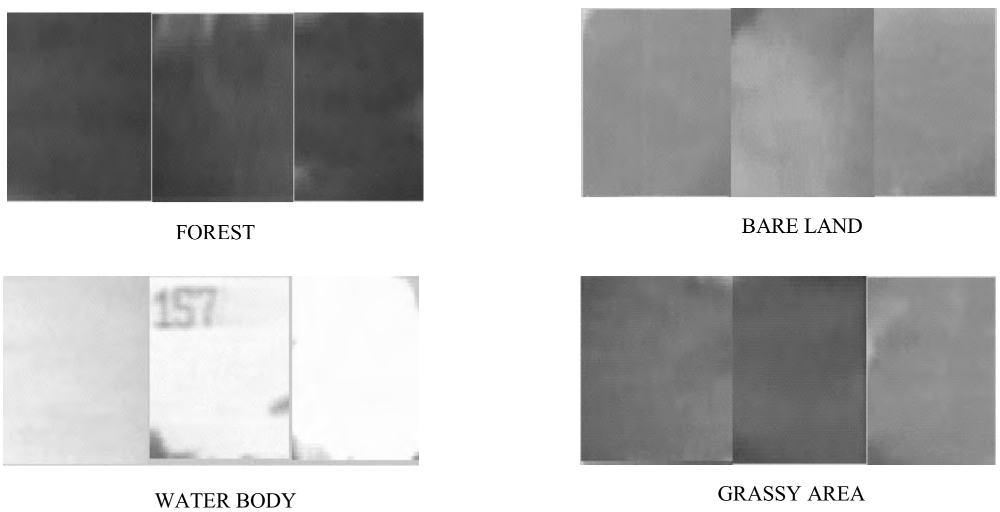


Figure 1. Sample database.

Figure 2. Input image 1.

of terrain. Figure 2 shows the input image of size (512 x 512) and Fig. 3 shows the result obtained after pyramid segmentation, where 4 levels of the pyramid were used for segmentation. Figures 4 (a) to 4(d) show the result of texture-based segmentation using window sizes of (32 x 32), (16 x 16), (8 x 8), and (4 x 4). Figure 5 shows the difference between the texture and intensity segmented image. The difference between the intensity segmented and texture segmented image indicates the total number of pixels which could not be assigned as belonging to a given class by both intensity and texture segmentations. Total number of such pixels are 93060 and these are shown in black colour.

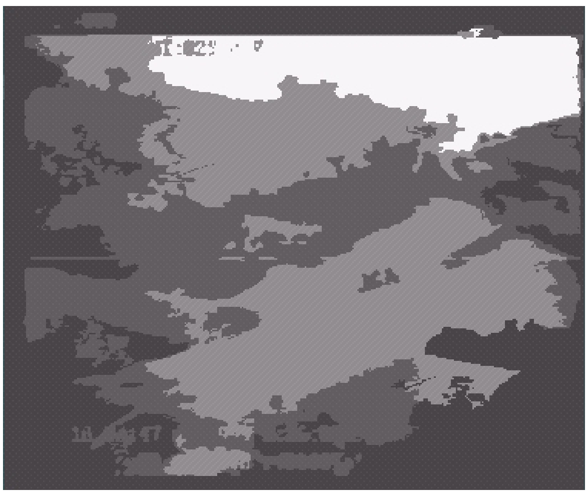
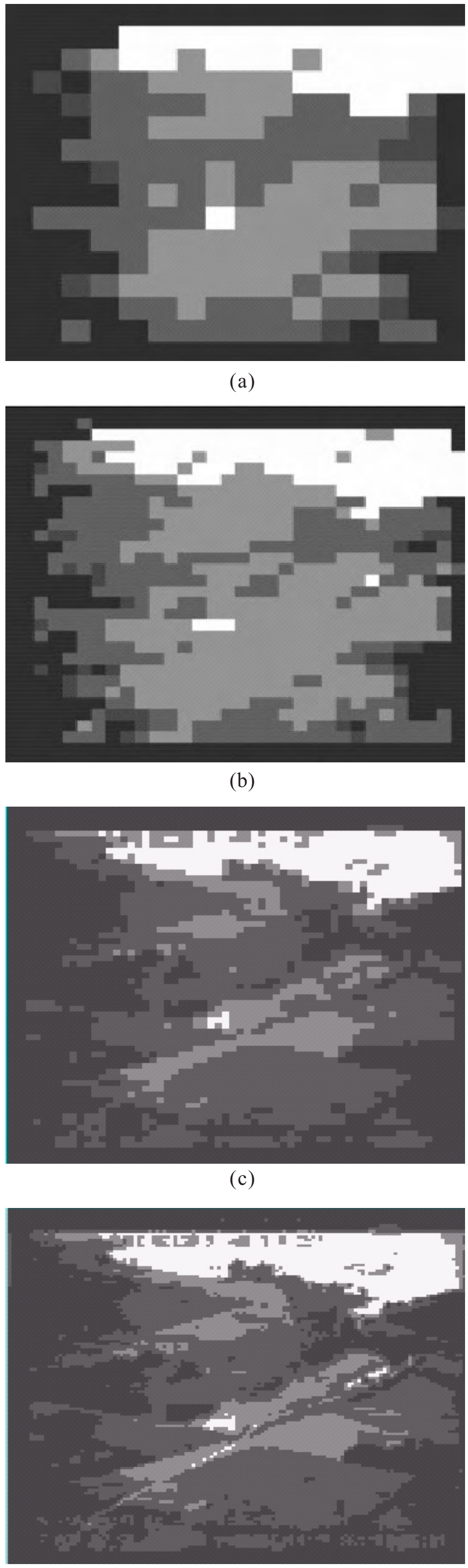


Figure 3. Intensity segmentation using pyramid node linking.



(a)

(b)

(c)

(d)

Figure 4. Texture segmentation window size: (a) 32 × 32, (b) 16 × 16, (c) 8 × 8, and (d) 4 × 4.

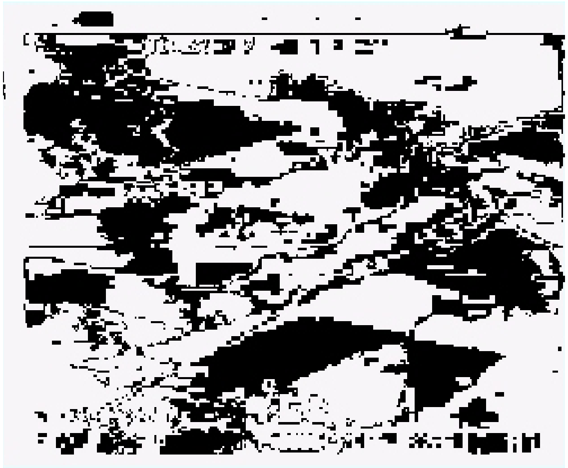


Figure 5. Difference between intensity segmented and texture segmented image (without correction in the texture and intensity segmented image). Total no. of mismatch pixels : 93060.

Figure 6 shows the results of classification with these erroneous pixels. A (3 x 3) window is now scanned over the difference image in Fig. 5 and the windows for which intensities of all the 9 pixels are black are identified as active windows. Texture features of the active windows are now calculated after replacing their intensity values to the intensity value of the input image from the respective location. The 9 pixels are assigned the class depending on their texture values, and accordingly a new modified texture segmented image is obtained. A similar correction is made in the intensity segmented image also.

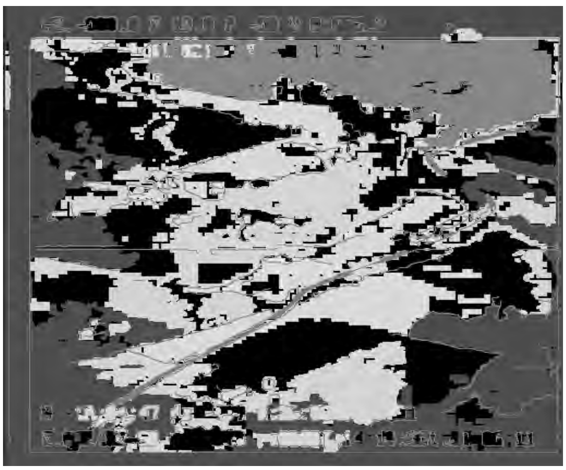


Figure 6. Classified image without correction.

Figure 7. Modified texture-segmented image.

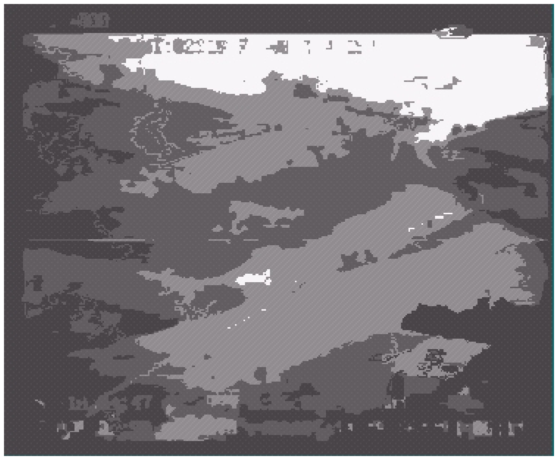


Figure 8. Modified intensity-segmented image.

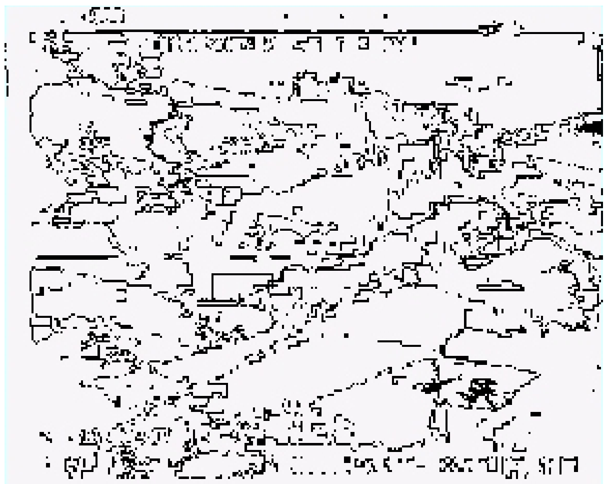


Figure 9. Difference between intensity and texture segmented image (with corrections in the texture and intensity segmented image). Total no. of mismatch pixels: 30531.

Figures 7 and 8 show the modified texture and intensity segmented image. The new difference image shown in Fig. 9 has only a total number of 30531 erroneous pixels. At this stage the error is only due to error in texture segmentation near the region boundary. To get a precise region boundary so that both the sides of the boundary is differently textured, edge information is used. Figure 10 shows the result of edge detection, linking, and merging using Nevatia-Babu operator. Figure 11 shows the edge image superimposed on the texture segmented image. Texture values of pixels on both sides of the edge are assigned their respective classes accordingly. Figure 12 shows the final classification result.

Figure 10. Edge detected image.

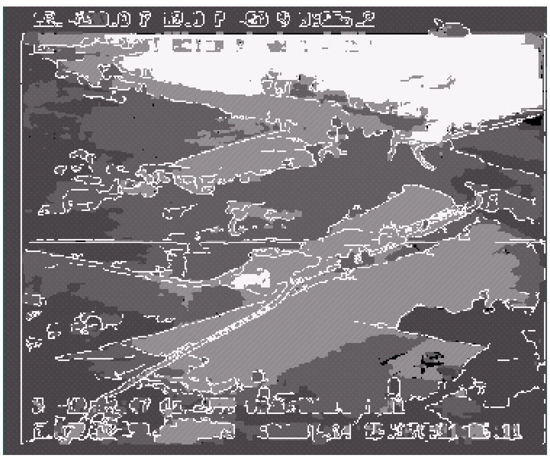


Figure 11. Edge image superimposed and corrected near boundary.

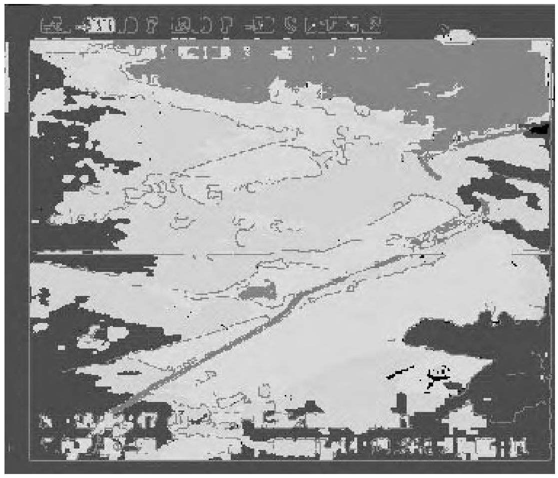
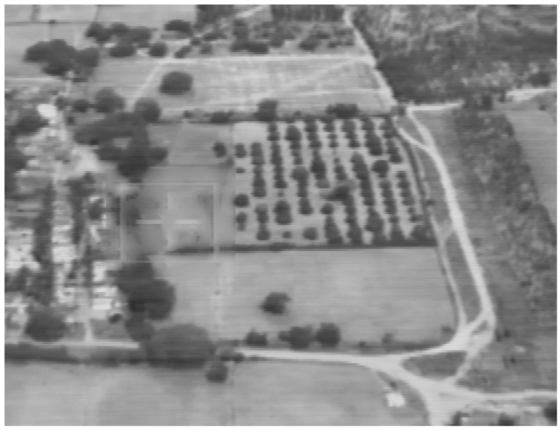
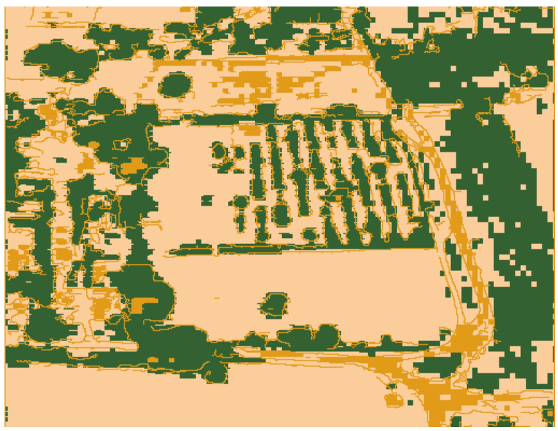


Figure 12. Final classified image.

Figures 13 and 14 show some more examples of input images with classified outputs.



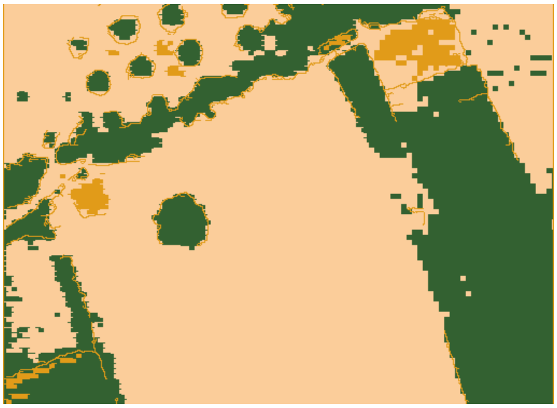
(a)



(b)

Figure 13. (a) Input image 2 and (b) final classified image 2.

(a)



(b)

Figure 14. (a) Input image 3 and (b) final classified image 3.

4. CONCLUSIONS

This paper proposes an automatic method for the classification of a terrain by combining image features and texture features. The intensity- and texture-segmented images are further divided into homogeneous regions using k-means clustering algorithm. An iterative procedure corrects the texture boundaries for the erroneous pixels obtained from intensity and texture-segmentation output. This is followed by the superimposition of the edge image on the final segmented image. The individual regions are then classified using a database generated from the features extracted from known samples of actual terrain.

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