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Hierarchical Segmentation Based Watershed for Mine detection

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Abstract: -A buried land mine is one of the most difficult problems faced during and after the war. The most serious problem in mine detection application is the ambiguity of target due to low contrast and background clutter. In this work, the mine detection problem is solved in the context of pre-processing and segmentation techniques for the data associated with infrared and infrared polarization sensors. Principle Component Analysis as a dynamic pr-processing is used to extract the whole dynamic information contained in a sequence of images. Also, the paper proposes a new hierarchical segmentation based on watershed for discriminating land mine from background clutter. The results indicate that the watershed is suitable to segment the outdoor images into noticeable texture region and gives good results for mine detection in IR polarization images. On contrary, the new hierarchy watershed encounters some difficulty in distinguishing buried mines from clutter in IR image.
Key Words: - mine detection, principle component analysis, and watershed transform.

1. Introduction

Anti-personal mines are still polluting many countries [1], preventing the land to agricultural use and many of civilians are injured from this dreadful pollution. The highest detection probability is tackled in context of using an efficient sensor and an intelligent image processing techniques for the data associated with this sensor. Among the different sensors that have been used: metal detector [2], Infrared (IR) sensor, and infrared polarization sensor. Metal detector is not optimal for detecting a non-metal object. IR sensor is a new approach based on IR radiation that is optimal for objects have different thermal properties from surrounding.

In this paper the mine detection by IR, and IR polarization sensors are implemented using pre-processing and texture segmentation.

The paper is organized as follow: Section2 describes the mine detection using the IR and IR polarization system and presents principle component analysis (PCA) to enhance the contrast. Section 3 introduces the watershed as a tool for handling image segmentation. Section 4 presents a new hierarchical segmentation based on a new immersion hills with convenient criterion to reduce the over segmentation before applying the watershed transform and studies it's applicability in mine detection tasks. Section 5 is the conclusion and evaluation to the performance of the proposed method.

2. Mine Detection by IR and IR Polarization Sensors

IR radiation is a portion of electromagnetic spectrum [3], all electromagnetic radiations when are absorbed by matter produce heat so, IR radiation can be more readily detected by the heat it produces. The signature of buried land mine in IR images varies significantly depending on external parameters such as temperature, solar radiation, and the sun position. The performance of IR system in mine detection is limited due to the existence of background clutter. Over the last few years, IR polarization filter was introduced into IR sensor for improving the low target to clutter ratio in infrared scene. Three IR intensity images taken for the same scene with three different orientation of a polarizing filter determine the stock images.

This paper studies the mine detection for two different sets of data: a sequence of IR, and a stock polarization images. The next paragraph introduces PCA method.

2.1 Principle Component Analysis in Landmine Domain

Principle components analysis (PCA) is a procedure for transforming a set of correlated variables into a new set of uncorrelated variables [4]. In land-mine application, PCA is used as a dynamic pre- processing for the change in temperature produced by time varying in a sequence of IR images, and also for a sequence of three stock polarization images. PCA is achieved by finding the deviation of each image from the mean, and the correlation matrix C_X of the data set as shown in Eqs. (1-2):

$$X_n : X_{nm} = f_{nm} - mean(f_{nm}) \quad (1)$$

$$C_x(i, j) = \frac{1}{M}\sum_{m=1}^{M} X_{im} X_{jm} \quad (2)$$

$$i = 1.......N,\ j = 1.........N.$$

Where: f_{nm} is a gray value of images in sequence, N is number of images in sequence, and M is the number of pixels in an image. The diagonalization of C_X gives the eigenvalues (λ_i) and eigenvectors (e_i). The transformed images for the population of all images (**X**) are calculated by Eq. (3):

$$y_i = e_i X \quad (3)$$

The eigenvalue describes the degree of information content for each of the transformed image. Table 1, and 2 show the eigenvalues for six IR and three polarization images.

Table 1.
Eigenvalues of covariance matrix for 6 IR images.

λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
24643	331	69	30	15	9

Table 2.
Eigenvalues of covariance matrix for 3 IR polarization images.

λ_1	λ_2	λ_3
473	115	47

In both tables, the first transformed image has the highest contrast, while the other transformed images have low contrast due to the low eignvalues. Figs. 1a-1f are the sequence of six images taken during a period of time in gravel soil at 2 April 1998 at time from 11:18:24 to 21:44:30. The first three transformed images by PCA are shown in figs.1g-1i respectively. Figs. 2a-2d are the optical image for the scene, and the three stock polarization images for nine mines taken at 11 April 2001 at time 15:07:47 in grass. The three transformed images resulted from PCA are shown in figs. 2e-2g.

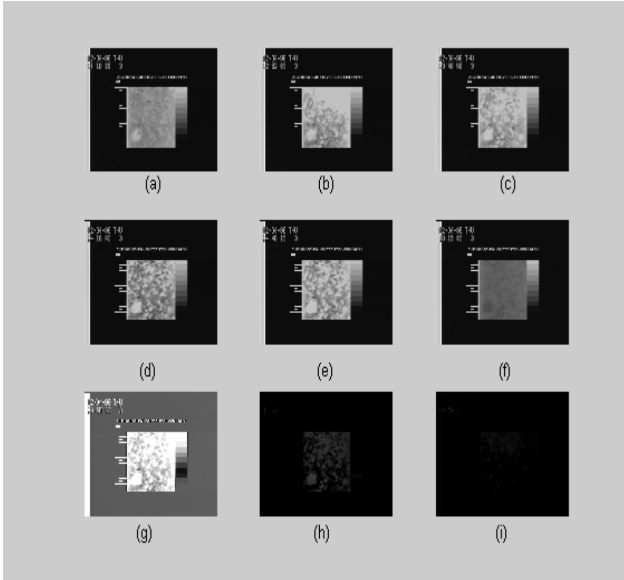

Fig.1. The results of PCA for a sequence of six IR images

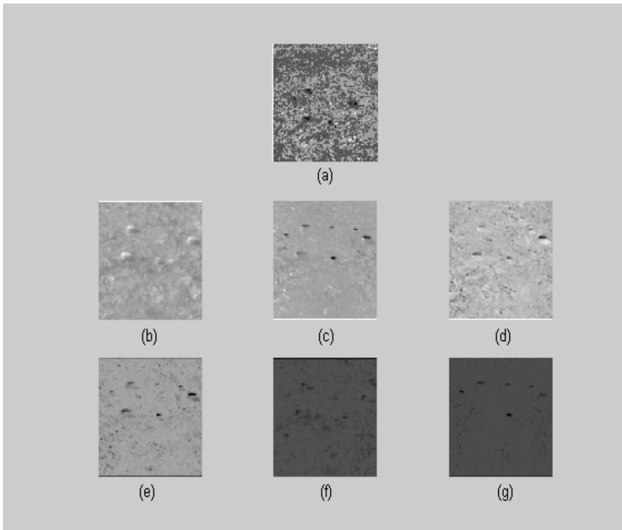

Fig. 2. The results of PCA for a sequence of three IR polarization images.

3. Segmentation Using Watershed

The watershed transform can be classified as a region- based segmentation. It is usual to consider that an image is a landscape; we begin by piercing hole in the regional minima of the surface, and then slowly immerse the landscape into a lake. The water progressively floods the catchment basins corresponding to the various minima. To prevent the merging of two different waters originating from two different minima, we erect a dam, and the process is stopped when the water level has reached the highest peak in the landscape. Then, the surface is partitioned into regions or basins separated by set of dams called watersheds lines [5]. Watersheds in their original form produce over segmentation that are many small basins are produced due to many local minima in the input image. In fact, all basins don't have the same importance; some of theme are induced by noise and produce over segmentation. There are many efforts to reduce the over segmentation by: marker based segmentation, and hierarchical based segmentation, which are introduced in the next paragraph.

3.1 Marker Based Segmentation

A marker is a region minimum involved in the watershed transform, each marker placed in the image will grow to generate a catchment basin in the final segmentation. The appropriate selection for a set of markers [6] depends on the additional knowledge about the specific segmentation problem e.g. (shape of the desired objects, darkness of the ground,.., etc.). Therefore, most of the time, and the complexity of the regions selection make the marking procedure a very difficult task.

3.2 Hierarchical based segmentation

There are many efforts to overcome the over-segmentation problem by using the hierarchical segmentation that is originally developed by Beucher [7]. The published literatures in hierarchical segmentation approaches [8-9] still offer no satisfactory acceptable results. Most of them suffer from the statistical stopping criterion that gets early termination, so the final number of segments is difficult to get it, and each segmented region has no noticeable texture. A new hierarchical segmentation using immersion hills is proposed to overcome the watershed drawbacks, and is illustrated in the next paragraph

4. Immersion hills with constrained dynamics of regions

The basic concept of the immersion hills depends on the analogy of Grimaud's dynamics [10] that is based on Vincient watershed algorithm [11]. Imagine a landscape has many hills with different heights, and there is a water source at each hill. If all the water sources are opened at the same time and the water is falling down from higher to lower hills, then the water heights will be immersed by the water and the process is stopped when the water levels reached highest hill in the landscape. To prevent the landscape from full immersion, we use the analogy of Grimaud's dynamics with some modification as a constrained dynamics of regions. The dynamics of regions are determined with respect to its neighbouring regions, and the saddle point(meeting point two basins) is considered here as one of its neighbouring, where the gray value of the region is lower than the gray value of its neighbouring.

dynamic-region= gray-value of (saddle-region) – gray-value of (dynamic-region).

To immerese the homogenous dynamic regions and their saddle regions, we choose a range from one to a certain number of dynamic, that is so called **dynamic range**. Also the dynamic regions and their saddle regions that satisfying the dynamic range is called **working region**. Fig. 3 illustrate the constrained dynamics of regions.

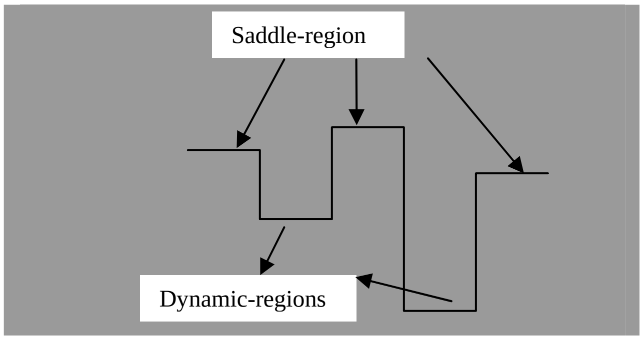

Fig.3. The constrained dynamics of regions

4.1 Algorithm of immersion hills with constrained dynamics of regions

The procedure for the algorithm of immersion hills with constrained dynamics of regions is illustrated as follows:

- Choose the convenient dynamic range of the gray scale image.
- Replace each gray value of the working regions that corresponding to the dynamic range with its negative value which represent the height of the hills. And the other gray values remain as it is.
- Imagine that there is a water source at each saddle region, that floods its corresponding dynamic region, and open all sources of the working regions. The flooding operation is stopped, if there isn't any dynamic region withen the dynamic range.
- some regions are merrged together and there gray values are replaced by other lower values, and the other are still as they were without any variations thus acting as natural dams. Then, again get the negative gray values of the working regions positive value. With the appropriate selection of dynamic range, the number of irrelevant minima is reduced before applying the watershed transform on image.

The next paragraph presents a new hierarchical segmentation using the immersion hills with dynamic range.

4.2 New hierarchical segmentation based watershed transform

The proposed hierarchical segmentation is diveded into two main stages: pr-processing stage, and watershed transform [12].

4.2.1 Preprocessing stage

In this stage the image is prepared to be ready for applying the second stage(watershed transform) to get homogenous regions. This phase includes four step in the next paragraph.

4.2.1.1 Gradient

A morphological gradient is mentioned in [13] as:

$$g(i,j) = \max\{f(x,y),(x,y)\in N(i,j)\} - \min\{f(x,y),(x,y)\in N(i,j)\}$$

Where, f is a gray scale image with $s \times s$ neighborhood for each point p(i,j). It is noted that the gradient step may result zero gray value pixels, which increases the number of minima.

4.2.1.2 Smoothing

This step is applied only to the non zero gray value pixels of the gradient image, where the gray value of each pixel is replaced by the intger value of the average of its value and the value of its 8-neighbors.

4.2.1.3 Removing zero-irrelevant minim

This step is applied only on the zero gray value pixels of the gradient image. Each connected zero gray value pixels represent minima, so these zeros are replaced by the minimum gray value of its neighbors.

4.2.1.4 Hierarchy of immersion hills

The hierarchical levels is producesd using the dynamic range as a threshold at each level. The dynamic range is zero at the first level, and maximum at the last level, and each level of hierarchy, represent a homogenous texture image. Fig. 4 illustrates the hierarchy of homogeneity of regions. A convient criterion is introduced to select the appropriate hierarchy level

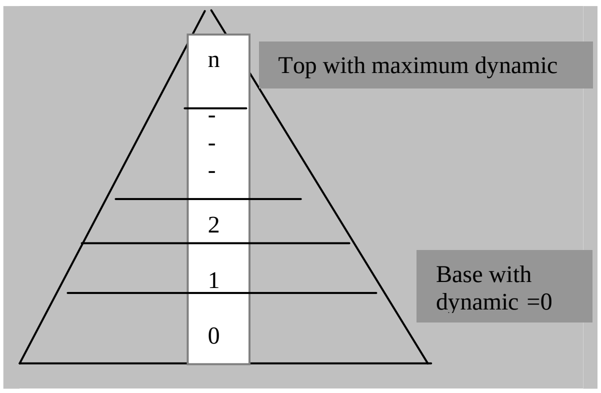

Fig.4. The hierarchy of homogeneity of regions

- **Selection Criterion for the Produced Image**

The image at the first level of the hierarchy (dynamic rane=0) is a preprocessed image and the image at any level of the hierarchy is called a produced image. Each produced image is segmented into a number of regions, then the auto correlation that measure the homogenity value of each region is determined by using the co-occurrence matrix. The value of autocorrelation of each segmented region of the produced image is assigned to its corresponding regions of the preprocessed image by using the simple regression analysis [14]. At each hierarchical level, the linest value of auto-correlation values of regions of the preprocessed image is determined. At the first hierarchical, the linest value is zero because no merging is done, and increases to its maximum value. Then it decreases until it reaches to zero at the last hierarchical level, due to merging of all regions of the produced image. We choose the produced image that is corresponding to the maximum linest value. Figs. 5-7 show the preprocessing phase for the tested out-door, IR polarization, and IR images respectively with the convenient dynamic range. Figs. 5a-7a are the tested images. The gradient of the tested images are shown in figs. 5b-7b. Figs. 5c-7c depict the smoothing of the tested images, and the removing of zero-irrelevent for the tested images are shown in figs. 5d-7d. The immersion hills for images are depicted in figs 5f-7f.

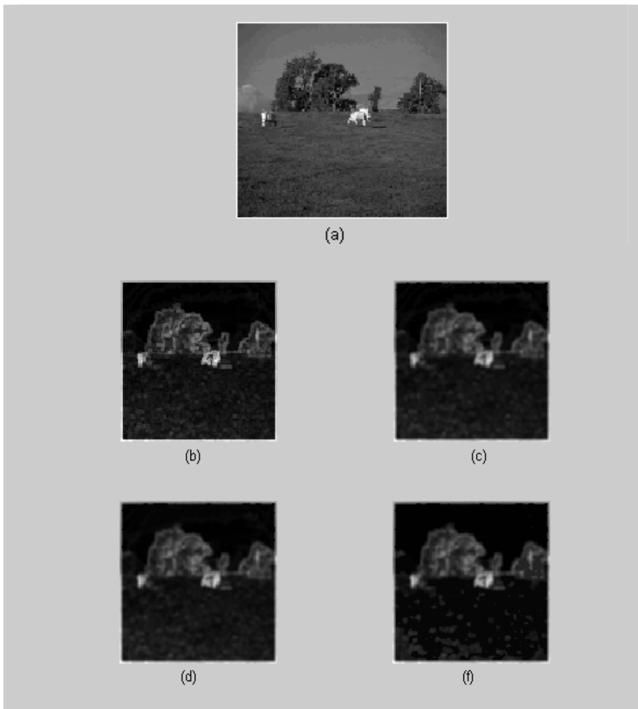

Fig.5. The results of pr-processing phase for outdoor image.

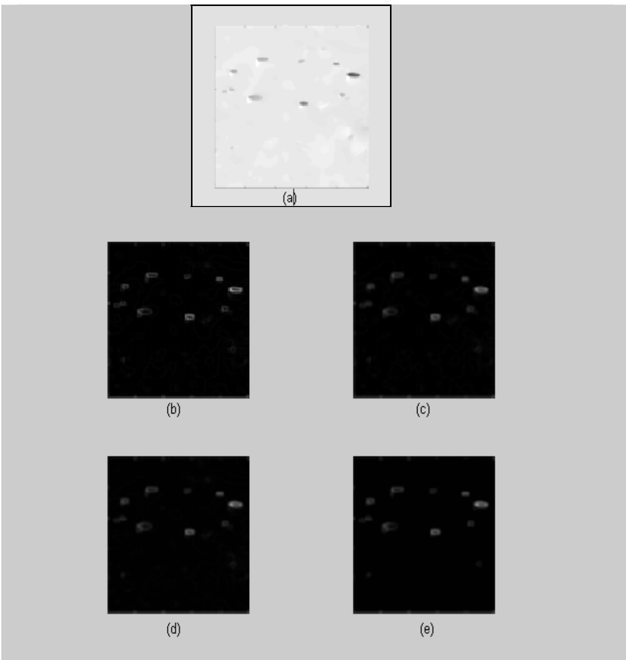

Fig.6. The results of pr-processing phase for enhanced IR polarization image by PCA

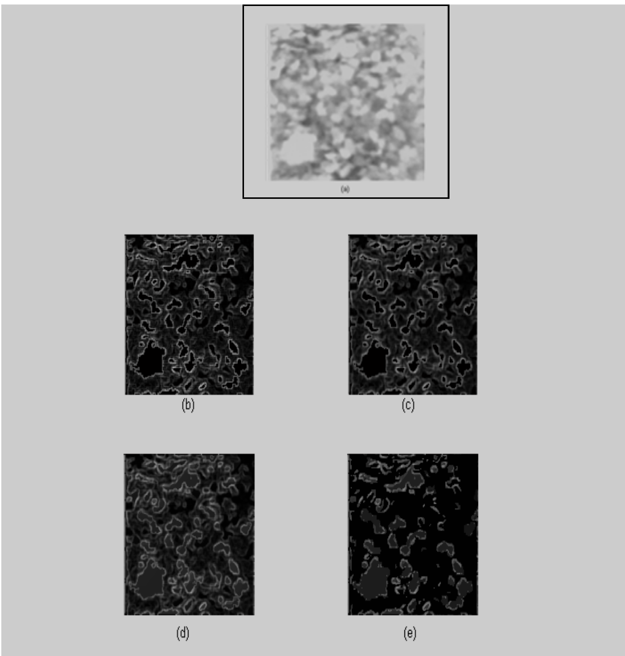

Fig7. The results of pr-processing phase for enhanced IR image by PCA.

4.2.2 Watershed transform stage

After the pr-processing stage, the images are ready to apply the watershed transform that follow up the border of each texture region. Figs. 8a-10a show the tested images that are the original outdoor image, enhanced IR polarization, and the enhanced IR images by PCA. Figs. 8b-10b show the over-segmented images after applying watershed on the tested images. Figs. 8c-10c show the over-segmented images after applying watershed on the gradient of the tested images. Figs. 8d-10d depict the result of watershed on the smoothing of the tested images. Figs. 8e-10e show the watershed transform on the removing zero irrelevant minimas of the tested images. Figs. 8f-10f are the final segmentation of watershed transform after applying the immersion hills technique with dynamic range 1:2, 1:1, and 1:3 on the tested images respectively.

As shown in the figures, the new hierarchical segmentation by the immersion hills with conevient dynamic range introduces a relaible methode to solve the watershed over segmentation problem.

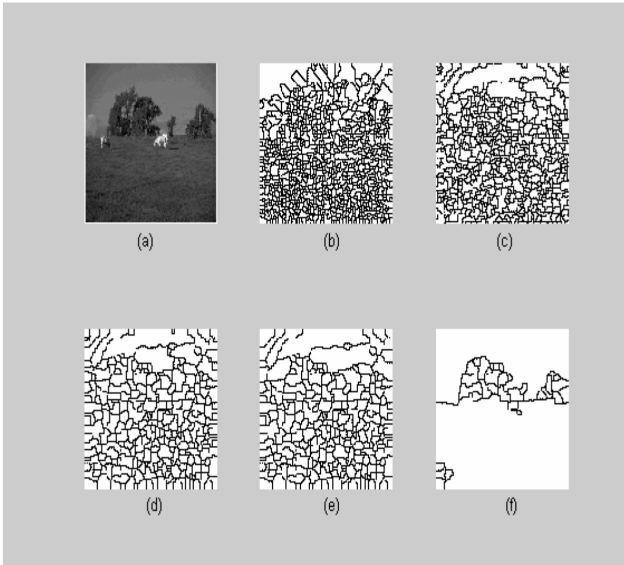

Fig.8. The results of segmentation on outdoor image by watershed transform.

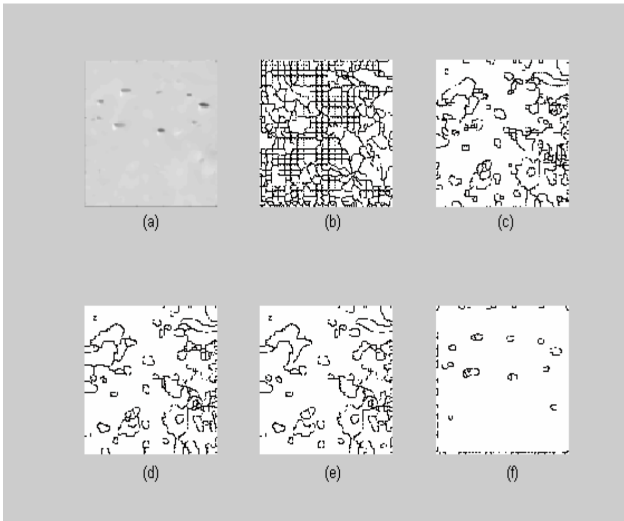

Fig9. The results of segmentation by watershed for the enhanced IR polarization image.

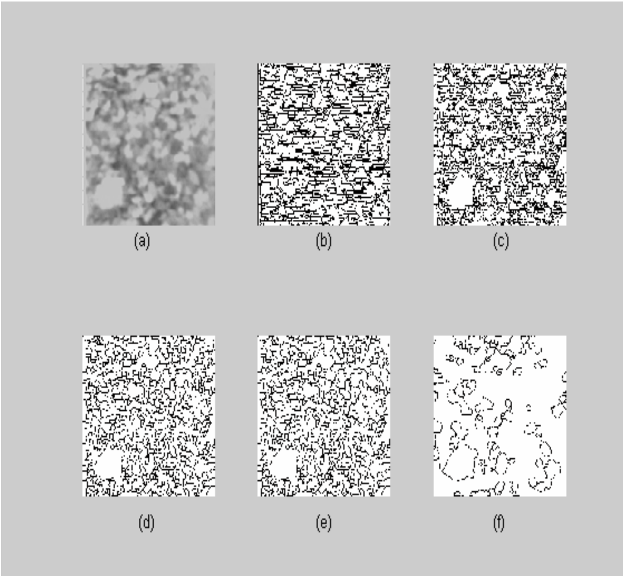

Fig 10. The results of segmentation by watershed transform for the enhanced IR image.

5. Conclusion

This paper has presented mine detection by means of general context of image-processing techniques for data related with IR polarization, and IR sensors. The proposed PCA method for reducing the redundancy has the ability to discriminate the different thermal properties for the mine signature through the day and enhance the contrast for the first transformed image. The paper introduces a new hierarchical segmentation using immersion hills to reduce the over segmentation problem in classical watershed segmentation. The technique was tested on a variety of outdoor, IR and IR polarization images. The result for outdoor images was noticable texture regions with reduction for the over segmentation. But in mine detection application, it faced severity in distingushing the land mines from clutter specially in IR images due to low contrast of objects and produced some over-segmentation. The future work will be a post processing step for resullt.

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