Infrared Image Segmentation by Combining Fractal Geometry with Wavelet Transformation

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Abstract: An infrared image is decomposed into three levels by discrete stationary wavelet transform (DSWT). Noise is reduced by wiener filter in the high resolution levels in the DSWT domain. Nonlinear gray transformation operation is used to enhance details in the low resolution levels in the DSWT domain. Enhanced infrared image is obtained by inverse DSWT. The enhanced infrared image is divided into many small blocks. The fractal dimensions of all the blocks are computed. Region of interest (ROI) is extracted by combining all the blocks, which have similar fractal dimensions. ROI is segmented by global threshold method. The man-made objects are efficiently separated from the infrared image by the proposed method.

Keywords: Infrared image, Segmentation, Wavelet transformation, Wiener filter, Fractal dimension, Global threshold.

1. Introduction

Recently, infrared technique has made great progress in many application domains, especially, in military, such as navigation, search and track, and so on. Compared with visible images, most of infrared images are fuzzy and noisy because of imaging principle and imaging system. This is disadvantageous to post-processing. Therefore, it is necessary to enhance and reduce noise for an infrared image. Having enhanced, some important information and details are extruded, and some trivial information is suppressed. Then the infrared image is segmented so as to extract the interested object from the background. In practical applications, usually people only care some specific regions or objects. Interested regions and objects can be extracted from an image by image segmentation technique. Image segmentation is usually used to extract the detected target from a complex image so as to provide data for classification, recognition and retrieval. Therefore, image segmentation is important to target detection and recognition.

Recently, many researchers are engaged in image segmentation algorithm and lots of new idea and methods are proposed. B. Bhanu and R. D. Holben proposed an infrared image segmentation algorithm based on model. The proposed algorithm solved the edge fuzzy problem which is resulted because of the low contrast between target and complex background [1]. Sun and Park developed an image segmentation algorithm for automatic target recognition by combining fuzzy threshold with edge detection operation. The proposed method can improve the segmentation accuracy and reduce the computation complexity [2]. Tsai used mathematical morphology method to extract the brain region from MRI [3]. Wavelet transform was proposed in the
1980s. Wavelet transform has good time-frequency property and has been widely applied to biological medical signal processing, sound and image coding, multi-scale edge detection and reconstruction [4, 5]. Recently, many new ideas, methods or improved algorithms have been developed. Generally, image segmentation methods are divided into four categories: threshold segmentation, edge detection, region extraction and segmentation method by special theory. Although many methods for image segmentation have been proposed, the progress is limited because image segmentation is a complex processing.

There are two main problems in image segmentation: 1) no common image segmentation method; 2) no good general evaluation metrics for image segmentation.

According to the history of image segmentation, image segmentation has some obvious trends: 1) Improvement is done to current existing algorithm; 2) New methods, concepts are introduced and many methods are used together. People have realized that any current image segmentation method cannot meet the requirement general images. Therefore, many researchers introduced some new methods and concepts into the image segmentation domain. Many methods are used together to obtain a good segmentation result. Wavelet transform is an efficient mathematic tool for image segmentation. 3) Interactive segmentation. Interactive segmentation has been widely applied in many domains, for example, interactive segmentation is suitable used to segment medical image. 4) The research for image segmentation assessment has become a hot point problem in image segmentation domain.

In this paper, fractal dimension is used to select the region of interest. Global threshold method is employed to segment the infrared image and extract the target from background. The flow chart of the proposed method is shown in Fig. 1.

2. Infrared Image Denoising and Detail Enhancement in Discrete Stationary Wavelet Domain

2.1. Denoising Principle of Discrete Stationary Wavelet

Discrete stationary wavelet transform (DSWT) has been proposed by many researchers as different names. It is mainly applied to image denoising, compression and fusion. However, most of existing image denoising algorithms based on DSWT used the noise variance to estimate the denoising threshold. Compared with classical discrete orthogonal wavelet transform, DSWT is redundant and shift invariant. DSWT can give a good approximation to continuous wavelet transform. It can obtain good visual quality for reconstruction image because the reconstruction image is smooth.

In this paper Daubechies wavelet is used as analysis wavelet. An infrared image, whose size is 256 by 256, is decomposed into three levels by using db1 as analysis wavelet in the discrete stationary wavelet domain. Wiener filter is chosen to reduce the noise in the horizontal, vertical and diagonal high frequency sub-images in the DSWT domain.

2.2. Detail Enhancement

Image enhancement methods employ some ways to add some information or transform data. Some interested features are extruded or some trivial features are suppressed so that image can be matched with visual response properties. During image enhancement, the reasons for image degrading are not cared and the enhanced image need not approximate the original image. Usually, a nonlinear transform function is used to enhance the details and edge information in the wavelet domain. Because the wavelet coefficients reflect the details of different scales, the nonlinear transform function can enhance the contrast of the details and the enhancement
degree can be controlled by adjusting the wavelet coefficients. Original image is decomposed into three levels and nonlinear transform function is used to enhance the details of level 2 and 3 in the wavelet domain. Here inverse normalization should not be ignored. Low frequency sub-image is kept its original components unchanged. It is very important to choose a good nonlinear function in order to obtain good enhancement result. In this paper, following nonlinear function is designed in order to efficiently enhance the details of an infrared image:

$$y = \frac{\tan(kx)}{\tan(k)}$$  \hspace{1cm} (1)

where $\tan(k)$ is the arc tangent function, $k$ is the constant and can be used to control the shape of nonlinear function curve.

Further it can control the visual quality of an enhanced image. Different nonlinear function curves can be obtained when $k$ is set as different values as shown in Fig. 2.

![Nonlinear curves when k is set as different values.](image)

It is very important that the gray levels of an input image should be mapped to $[-1,+1]$ when above nonlinear function is used to enhance the details of an infrared image.

Inverse normalization should be done after having implemented nonlinear enhancement. Low resolution wavelet coefficients are enhanced by the designed nonlinear function and high resolution wavelet coefficients are denoised by wiener filter. The modified wavelet coefficients and low frequency wavelet coefficients are used to reconstruct the infrared image. Fig. 3(b) and Fig. 3(c) respectively the original infrared image and enhanced infrared image, where $k=3$.

![Original infrared image and enhanced infrared image.](image)

3. Region of Interesting Extraction with Fractal Dimension

3.1. Calculation for Fractal Dimension

Fractal geometry and fractal dimension were proposed by American mathematician Mandelbrot in 1975 [6]. The fractal dimension can be used to identify different textures. Natural textures have fractal feature, however, artificial targets have not fractal features because they have not self-similarity [7]. Therefore, the fractal dimension can be used to detect the infrared target from natural background. In this paper, Differential Box Counting is used to calculate the fractal dimension in order to extract the infrared target from natural background [8]. According to the theory of Sarkar and Chaudhuri, the fractal dimension of an image window should be calculated as follows: an image can be considered as a three dimension space $(x,y,z)$, where $(x,y)$ shows the two dimension coordinates, and $z$ represents the gray level of an
image. The space $(x, y)$ is divided into many small grids whose size is $s \times s (M/2 \geq s > 1, \ s$ is an integer). Let $r = s/M$.

Many boxes whose bottom size is $s \times s$ are stacked on the each square grid. The height (h) of the box can be obtained by calculating the all the gray level $G$, i.e., $[G/h] = [M/s]$. Each box is labeled from bottom to top. The maximum and minimum of the image in the $(i, j)^{th}$ square grid are checked which box they are respectively put into. Supposed that the maximum is put into the $I^{th}$ box and the minimum is put into the $K^{th}$ box, then following equation can be obtained:

$$n_{i,j}(i, j) = I - K + 1,$$

(2)

Each grid is calculated in return, following equation can be obtained:

$$N_r = \sum_{i,j} n_{i,j}(i, j),$$

(3)

The least square method is used to fit $\log(N_r)$ and $\log(1/r)$, the fractal dimension $D$ of a window image can be written as

$$D = \lim_{r \to \infty} \frac{\log(N_r)}{\log(1/r)},$$

(4)

It is important to choose proper image window and the scale of fractal dimension. Some important textures will be lost if the window size is too small. The edge pixels and other pixels in the image region will be mixed together if the window size is too big. This will affect to choose the texture features. In order to choose proper size for a texture sub-image, let $M = 16, 32, 64$, an optimal $M$ is chosen to calculate the fractal dimension for an infrared image. According to lots of tests, we found $M=32$ is the best. When $M=32$, the scale is set from 3 to 15 (3, 5, 7, 9, 11, 13, 15).

Thus the fitting accuracy can be improved. The infrared image in Fig. 2(b) is divided into blocks whose size is 8 by 8 and the fractal dimensions of the blocks are calculated. Table 1 shows the fractal dimensions of the blocks.

### 3.2. Region of Interesting

The infrared image which is enhanced is divided into blocks whose size is 8 by 8. The fractal dimensions of the blocks are used to extract the region of interesting (ROI). The different regions which have the same fractal properties should have the same fractal dimension. If the fractal dimension of some images is less than topology dimension, this shows that the fractal model is not fit for the images. Generally the region belongs to the boundary between different textures. In this paper, the fractal dimensions of different image blocks should be correctly calculated and different regions are extracted by the fractal dimensions. The fractal dimensions are different for different targets. Fig. 4(a)-Fig. 4(h) shows the sub-images of the 6th row in the original infrared image.

<table>
<thead>
<tr>
<th>Table 1. Fractal dimensions of blocks.</th>
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<tr>
<td>2.1757</td>
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<td>2.2381</td>
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<td>2.2818</td>
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<td>2.2547</td>
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<td>2.1323</td>
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</table>

![Fig. 4. Sub-images of the 6th row in the original infrared image.](image)
Fig. 5 (a)-Fig. 5 (h) respectively indicates the sub-images of the 7th row in the original infrared image. Fig. 6 (a)-Fig. 6 (h) respectively represents the sub-images of the 8th row in the original infrared image.

Fig. 7 indicates the region of interesting which is extracted from the original infrared image based on the fractal dimension.

4. Threshold Segmentation for ROI

In this paper, Bezier curve is used to smooth the histogram of ROI so that the noise and small disturbance can be reduced. Let the gray levels of the ROI is quantified into L gray levels. The control points' position is written as \( P_k = (x_k, y_k) \), \( k = 0, 1, 2, ..., L-1 \). A position vector \( P(t) \) is determined by the L control points:

\[
P(t) = \sum_{k=0}^{L-1} P_k B_{k,L-1}(t),
\]

where \( 0 < t < 1 \). The harmonic function \( B_{k,L-1}(t) \) on the Bezier curve is Bernstein basis function:
Beziers curve has two important properties: convex hull and variation shrinkage. This will make all the points on the curve are contained in the convex hull which is constructed by Bezier polygon. In addition, the disturbance of Bezier curve is less than that of the feature polygon. That is to say, Bezier curve is smoother than the polyline. The two important features of Bezier curve can make the smoothed histogram not to contain big disturbance. The burr which is resulted in because of noise will be efficiently reduced. Therefore, the smoothed histogram can accurately reflect the gray level distribution of the ROI.

The vector equation in the equation (5) shows two parameter equations for position coordinates of Bezier curve:

\[ x(t) = \sum_{k=0}^{L-1} x_k B_{k,L-1}(t) \]
\[ y(t) = \sum_{k=0}^{L-1} y_k B_{k,L-1}(t) \]

The curvature \( \text{Cur}(t) \) of each control point on the Bezier histogram can be calculated by following equation:

\[ \text{Cur}(t) = \frac{x'(t)y''(t) - y'(t)x''(t)}{(x'(t)^2 + y'(t)^2)^{3/2}} \]

where \( x'(t), y'(t) \) are the first-order derivatives, and \( x''(t), y''(t) \) are the second-order derivatives.

The gray level which is on the valley of the Bezier histogram is chosen as the segmentation thresholds. Generally, the histogram of ROI has two peaks because most of background is filled with zero when extracting ROI. Therefore, the final segmentation threshold is obtained by following equation:

\[ T = (T_1 + T_2)/2 \]

where \( T_1, T_2 \) are the gray levels which are on the two peaks of the Bezier histogram.

A global threshold is obtained by equation (11) and it is used to segment the ROI. The binary image can contain some broken edges and holes. Mathematically, morphology operations are used to reduce the broken edges and fill the holes so that final segmentation image is obtained. Fig. 8(a) and Fig. 8(b) respectively shows the binary image which is reduced broken edges and final segmentation image.

5. Conclusion

In this paper, discrete stationary wavelet transform is combined with fractal dimension to extract infrared targets from background. In order to reduce the noise and enhance the details of the infrared image, an efficient image enhancement method is proposed by designing a nonlinear function in the discrete stationary wavelet domain. ROI which contains person and vehicle is extracted by using fractal dimension. A global threshold is used to extract the person and vehicle from the ROI. In this paper, Db1 wavelet is chosen as the analysis wavelet because it can reduce computing time. ROI can improve the accuracy of extracting targets. Further work is to analysis the fractal dimension features for different targets in an infrared image so that they can be extracted from a complex background.

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