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# IR Image Segmentation by Combining Genetic Algorithm and Multi-scale Edge Detection

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## 1. Introduction

The Canny operator applied in a multi-scale edge detection for images is the most optimal step edge detection operator. However the Canny edge detection operator is optimal only for the step edge detection influenced by white noises because the Canny operator utilizes the first order derivative of a Gauss function to get a better compromise between noises restraint and edges detection. The Canny operator based edge detection finishes the implementation per the three criteria, namely, detecting (no losing important edges and no false edges), locating (with the minimal deviation between the real edges and the edges detected) and responding singly (reduce multi-response into a single edge response).

Because the Canny operator is based on a derivative operator (the first order derivative) to seek for the derivatives in two directions and their directions about image grey scale, it determines the maximum gradient and local maximum by means of non-maximum restraint to the gradient. But the function with the maximum gradient and local maximum meeting with the above three standards limits is in fact the optimizing process of a multivariate function. Generally if an object function is continually differential, the space equation of a solution is simpler, and the general analysis is effective. However for the image segmentation with a complex configuration or sophisticated texture, it is very difficult to describe the multivariable object function satisfied with the above three standard limits by use of simple analysis functions because the image function itself is a multivariable nonlinear random function. So it has only an approximate and local sense to get the maximum gradient and local maximum of a function in traditional analysis methods. For multi-scale based Canny operator edge detection, Canny once presented the algorithm to get a multi-scale edge image based upon the above three standards for final edges composed, but it is related to the problem about the composition of different scale detections<sup>[1]</sup>. Jeong and Kim proposed a method for a single pixel to select local optimized scales by minimizing a scale-space energy function. Although this method is able to detect step edges exactly, delete false edges, restrain random noises relatively, and parry the problem mentioned above, the experiments showed that this method is not ideal compared with some fixed large scale methods. The reason is that the algorithm successive over relaxation (SOR) used for the solution of a minimizing energy function especially depends on initial given values resulting in not converging to the whole optimum solution<sup>[2,3]</sup>. Because there are some individual differences about homogenous properties and edges

vagueness between IR (infrared) images and general grey scale images, the former region segmentation mainly depends on the temperature field distribution of an equivalent black body for a target and the edge contour tends to blurring. It is more convenient to deal with the IR image edge detection by use of the individual fitness and mutation operation of the genetic algorithm. The individual fitness evaluation may be applied to the evaluation of a region segmentation with no segmentation reference. And the variation operation may be integrated with a kind of local contrast to design a dynamic variation operator as to measure the fuzziness of region edge information. This paper proposed a new multi-scale edge detection method based upon an optimized genetic searching algorithm, and put it into the image segmentation of IR target signature.

## 2. Optimized genetic searching algorithm

The genetic algorithm is introduced into an image segmentation based on edge detection. Firstly we determine the selection of a coding mode and a fitness function. Here according to the  $n$  cities' universal rank as a genetic coding, we take the inverse of Hamilton ring length,  $T_d$ , as a fitness function because there are always legal restraints of a hidden TSP problem in the initialization for possible solutions, crossover operation and mutation operation.

$$f = 1 / (T_d + \alpha \cdot N_t) \quad (1)$$

where  $N_t$  is the measurement for TSP route illegality,  $\alpha$  is a penalty coefficient.

The application of crossover strategy: based upon the above TSP rank coding, the OX [4] method proposed by Davis is used in order to reduce the space searched. Firstly select a region to be matched:

$$\begin{array}{l} A = 9 \quad 8 \quad 4 \quad | \quad 5 \quad 6 \quad 7 \quad | \quad 1 \quad 3 \quad 2 \quad 0 \\ B = 8 \quad 7 \quad 1 \quad | \quad 2 \quad 3 \quad 0 \quad | \quad 9 \quad 5 \quad 4 \quad 6 \end{array} \quad (2)$$

In accordance with the relation mapped of a region to be matched, H is signed at the relative position outside the region, thus

$$\begin{array}{l} A' = 9 \quad 8 \quad 4 \quad | \quad 5 \quad 6 \quad 7 \quad | \quad 1 \quad H \quad H \quad H \\ B' = 8 \quad H \quad 1 \quad | \quad 2 \quad 3 \quad 0 \quad | \quad 9 \quad H \quad 4 \quad H \end{array} \quad (3)$$

Move the region matched to the initial position, pre-leave the space (H number) equal to the region matched afterwards, and then range other codes behind the region pre-left in accordance with their relative rank, thus

$$\begin{array}{l} A'' = 5 \quad 6 \quad 7 \quad H \quad H \quad H \quad 1 \quad 9 \quad 8 \quad 4 \\ B'' = 2 \quad 3 \quad 0 \quad H \quad H \quad H \quad 9 \quad 4 \quad 8 \quad 1 \end{array} \quad (4)$$

Finally interchange the father's A, B regions, put them into  $A''$ ,  $B''$  regions pre-left, and then get two descendant generations:

$$\begin{array}{l} A''' = 5 \quad 6 \quad 7 \quad | \quad 2 \quad 3 \quad 0 \quad | \quad 1 \quad 9 \quad 8 \quad 4 \\ B''' = 2 \quad 3 \quad 0 \quad | \quad 5 \quad 6 \quad 7 \quad | \quad 9 \quad 4 \quad 8 \quad 1 \end{array} \quad (5)$$

The mutation is an operation on backgrounds in the whole sense of genetic algorithms. For the TSP problem, the "Inverse mutation" operation is used in order to keep the individual of population varied so that there is a great change in possible solutions rank. Randomly select two points and inversely insert the subset between the points into the original positions.

Because the above mutation operation for the TSP problem made the TSP ring length changed around adjustments and this change led to the finest adjustments, the local accuracy arrive at a better level.

From the optimization of genetic algorithms the individual with a superior fitness has more opportunities to breed in a limited scale of population. The another feature of the genetic algorithm is not good enough to optimize locally. In practical applications GA generally converges to some possible solution which is not surely a optimized point as a whole or even not a local optimized point.

To improve the deficiency of a basic genetic algorithm in local optimization and upgrade the quality of a solution as a whole, this paper proposed an improved hybridized algorithm SGA (Simple genetic algorithm)+SA (Simulated anneal)+TABU, in which SGA is integrated with a heuristic searching algorithm. The alternative optimization strategy applied is as follows,

1. Utilize a stochastic method to produce many different possible solutions for an initial possible solution population.
2. For one half of the individuals of possible solutions, execute TABU searching to get a local optimization solution.
3. For the other half of the individuals of possible solutions, execute SA searching to get a local optimization solution.
4. For the local solution from 2) and 3) steps, execute genetic selection and crossover operations.
5. Repeat 2), 3) and 4) steps until the objective condition of an algorithm is finally satisfied.

Fig.1 shows the comparison between SGA+SA+TABU and SGA performances. Where the SGA optimization as a whole is better but poor at local. Relatively the SGA+SA+TABU algorithm intensifies the local ability of the simplex SGA. And compared with the simplex SA and simplex TABU, the SGA+SA+TABU algorithm extends the local optimization range of SA and TABU, and strengthens the whole optimization ability of simplex SA and simplex TABU.

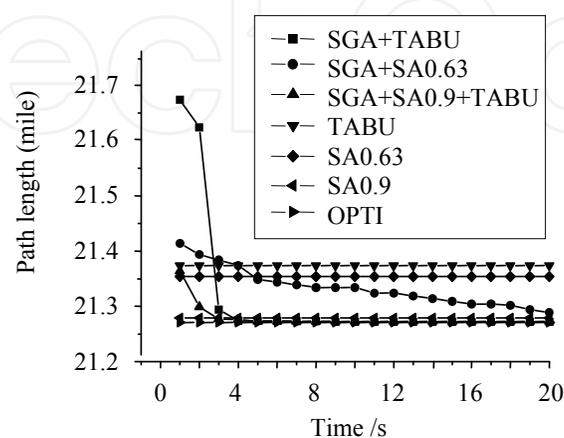


Fig. 1. Performances comparison of optimization algorithms

### 3. Genetic algorithm + Canny multi-scale edges detection

Because an image segmentation is different from the simple optimization on the shortest route of  $n$  cities, the latter is only the construction of a closed route. But the former is about a population optimization among route groups composed of many closed and open routes. So it is necessary to combine the radiation signature of IR images when the cleavage and mergence are used to segment an image into regions in accordance with the homogeneity firstly and then execute edges detection based upon the Canny multi-scale in each region, searching for the shortest route problem of  $n$  cities TSP composed of wavelet transformation module maximum values. The specific steps are as follows,

1. According to the equivalent black body temperature distribution of an IR radiation image, specify the initial regions conformed to homogeneity requirements. Supposing the maximum number of an image segmentation is  $n1$ , the individual chromosome coding is an integer sequence  $I_k = \{r_i | i=1, 2, \dots, n1\}$ . Where  $r_i$  is a sub-region order number and  $k$  is an individual number.

Crossover operation: it is completed by use of the improved PMX crossover method. Here the gene codes in sequence coding may be repeated after finishing a crossover operation. Just based upon gene codes generate repeatedly, an image region is able to execute the further cleavage and mergence. If the region  $r_i$  is merged with an adjacent region  $r_j$ ,  $I_k[i]=l$ ,  $I_k[j]=i$ , the region  $r_l$  merged with the region  $r_j$  is also combined with the region  $r_i$ ,  $I_k[l]=i$ . So the gene code of the region combined with the region  $r_i$  is  $i$ .

Mutation operation: it is the design of a dynamic mutation operator in conjunction with a local contrast. The operator is used to measure the information vagueness degree of the region borders. The distance between the rejoin  $r_i$  and its adjacent region  $r_j$  is

$$d_{ij} = \frac{1}{n_{ij}} \sum_{k=1}^{n_{ij}} |x_{ijk} - x_{jik}|^2 \quad (6)$$

where  $x_{ijk}$  ( $j=1,2,\dots, n_i$ ;  $k=1,2,\dots, n_{ij}$ ) is the  $k$ -th pixel on the border between the region  $r_i$  and its adjacent region  $r_j$ ;  $n_{ij}$  is the total pixels number of the border between the region  $r_i$  and its adjacent region  $r_j$ . The relative distance between the region  $r_i$  and its adjacent region  $r_j$  is

$$u_{ij} = d_{ij} / \left( \sum_{j=1}^{n_i} d_{ij} \right) \quad (7)$$

Because  $u_{ij}$  is conformed to  $u_{ij} \in [0, 1]$ , it may be used as a probability of the choice between the cleavage and mergence. According to the definition of a relative distance between regions, define the local contrast in any region,

$$C_i = \begin{cases} \min\left(\frac{\min_j(u_{ij})}{\max_j(u_{ij}) - \min_j(u_{ij})}\right), & \min_j \neq \max_j \\ 1, & \min_j = \max_j \end{cases} \quad (8)$$

Individual fitness estimation: the region segmentation estimation, with no a segmentation reference, includes the region homogeneity measurement and edge vagueness measurement.

- Region homogeneity measurement  
The region homogeneity measurement is defined as follows

$$AI_i \approx \frac{1}{n_k n_l} \sum_{k=1}^{n_k} \sum_{l=1}^{n_l} (g_{kl} - \mu_i)^2 \tag{9}$$

where  $g_{kl}$  is the grey scale of the pixels in the region  $r_i$ ,  $\mu_i$  is the average grey scale in the region  $r_i$ . And the reason why the above equation is not an equality is that the region  $r_i$  is not always a rectangle.

- Edge vagueness measurement  
The integrated measurement definition for all region edges vagueness is as follows,

$$E = \sum_{(i,j)} \frac{u_{ij}(|\nabla G|)}{u_{ij}(|\nabla G'|)} \tag{10}$$

where  $|\nabla G|$  is the grey scale gradient of the pixels after cleavage and mergence.  $|\nabla G'|$  is the grey scale at the pixels in an initial region division. Because there exists always  $|\nabla G(i,j)| \leq |\nabla G'(i,j)|$ , so here is  $0 \leq E \leq 1$ .

2. For each region above divided take a Canny multi-scale edge detection. Suppose the unit vectors  $\mathbf{n}_j(u) = (\cos Af(u, 2^j), \sin Af(u, 2^j))$  and  $\nabla(f * \bar{\theta}_{2^j})(u)$  are linear each other. At a  $2^j$  scale, the  $Mf(u, 2^j)$  in the direction of  $u = v + \lambda \mathbf{n}_j(v)$  gets a local maximum at a point  $u=v$ , when  $|\lambda|$  becomes small enough. Such a point is the edge point in this region, and is also called the wavelet transformation module maximum point.
3. Take the wavelet module maximum point from 2) as the universal point for  $n$  cities and constitute a TSP problem. The GA+SA+TABU is applied to the solution of an optimal route curve and to the formation of an optimal edge curve.
4. Change the scale  $2^j$  and return to 2). Continue the edge detection and re-find the  $n$  wavelet module maximum points as the universal points for cities, and then go to the next optimization step.
5. Here is the measurement for a region uniformity computation. The uniformity measurement of an image segmentation denotes that the weighting sum for the uniformity measurement of all regions:

$$G = \frac{1}{n} \sum_{i=1}^n w_i(p_i) G_i \tag{11}$$

where  $n$  is the sum of segmented regions.  $w_i(p_i)$  is the weighting coefficient of a region area.  $p_i$  is a region area. The computation of a weighting coefficient is in accordance with the following eq.

$$w_i(p_i) = \begin{cases} 2p_i^2 / \beta^2, & \alpha \leq p_i < 2 / \beta \\ 1 - 2(p_i - \beta)^2 / \beta^2, & 2 / \beta \leq p_i < \beta \\ 1, & p_i \geq \beta \end{cases} \tag{12}$$

where  $\alpha$  and  $\beta$  denote the minimum and maximum area respectively.

For image segmentation based on a genetic algorithm the multiplication of the equations (10) and (11) is applied to a composite individual fitness estimation.

$$F = E \cdot G \quad (13)$$

When the value got from eq. (13) is satisfied with the setting objective value the optimization searching ceases, otherwise returns to the 2) step for continuous optimization computations.

#### 4. Experiment results and analysis

In the course of a FLIR target image detection, take a target point source as the initial information of a potential target and determine an initial growing point of signature regions according to the sequence images inputed.

The five threshold values of equal intervals[5] are employed in this paper, that is  $t_{max} > t_0 > t_1 > t_2 > t_{min}$ . where  $t_{max}$  is towards the maximum equivalent black body radiance temperature of a target image,  $t_{min}$  towards the minimum grey temperature scale of a target image. The first level of isothermal region is determined by  $t_{max}-t_0$  interval, and the second isothermal region  $t_{max}-t_1$  is determined by  $t_{max}-t_1$  interval. For the division of isothermal regions by use of a genetic algorithm, any grey scale interval in the above regions may be used as a seeding region for a target pixel seed till one of the following two conditions is satisfied.

1. the region grows large enough to reach the edge;
2. the equivalent black body radiance temperature or radiance intensity of a searching region degrades too much.

The seed regions are defined as  $\{t_{max}-t_0, t_{max}-t_1, t_{max}-t_2, t_{max}-t_{min}\}$  where  $\{t_{max}, t_0, t_1, t_2, t_{min}\}$  is used, in a genetic algorithm, as five inner nodes of each segmentation region for construction of four layers of equivalent black body temperature differences. Fig.2(a) shows the original long wave FLIR image of a running truck, and Fig.2(b) and Fig.2(c) respectively illustrate the target IR image segmentation results by means of Laplace-Gauss edge detection or wavelet nerve-network algorithm<sup>[6]</sup>. Although the Laplace-Gauss edge detection algorithm is able to locate target contours, a great deal of target details are lost. For the PCA analysis about a target region the wavelet nerve-network algorithm embedded in a wavelet time-frequency analysis could keep the high frequency details of region contours. Fig.2(d) shows the image segmentation based on the genetic and wavelet multi-scale edge detection. Compared with the former segmentation algorithms this detection algorithm could not only extract edges of a target clearly but also the edges succession behaves better because of the "non-maximum restraint" for pixels gradient in course of optimization. From Fourier transformation frequency spectra Fig.3(a), Fig.3(b) and Fig.3(c) relative to Fig.2(b), Fig.2(c) and Fig.2(d) the effect of the Laplace-Gauss edge detection<sup>[7]</sup> could be evaluated. Their energy is basically along the main axis and lower inside quadrants with a great loss of details information. The high energy of an image processed by a wavelet nerve-network algorithm is distributed along the two axes from the original point, but the energy distribution inside each quadrant exists low state. So the number of little targets with bad pixels is available to be restrained. The energy spectrum gotten from the genetic and a wavelet multi-scale edge detection is focused around the spectrum center and basically exists low value distribution with no mixture of medium value energy. This signature of the frequency spectrum distribution has an instant relationship with the segmentation structure

of an image because the latter algorithm pays more attention to the edges segmentation inside image textures. As is showed in Fig.4 the Pratt quality factor is used as the evaluation of edges detection. Under a low signal-noise ratio the Pratt quality factor of a genetic and wavelet multi-scale edge detection algorithm is much more superior than other two detection algorithms, and more suitable to an image with complex texture and fine construction.

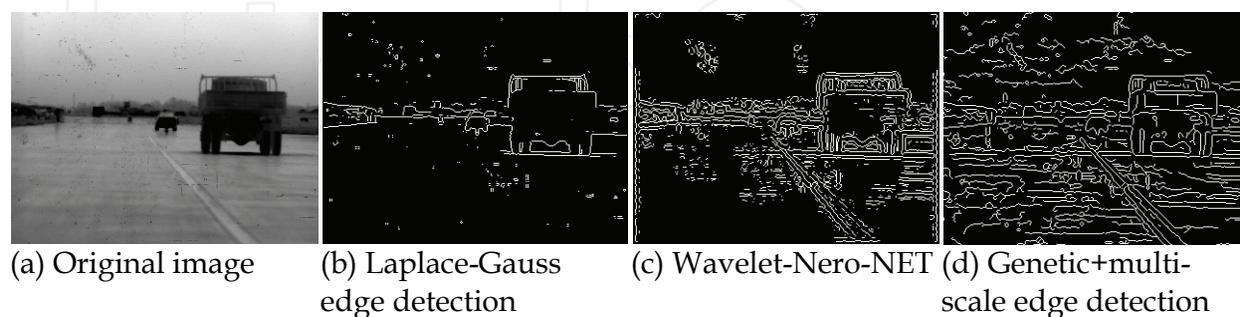


Fig. 2. Experimental results

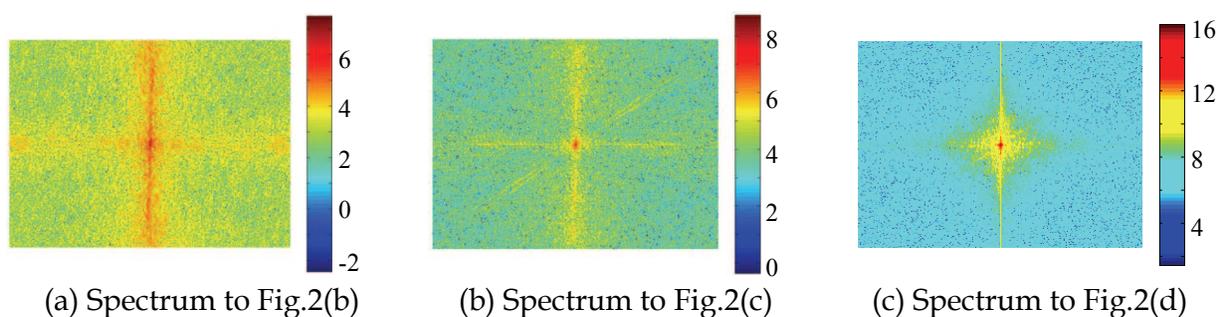


Fig. 3. Fourier transform spectrum

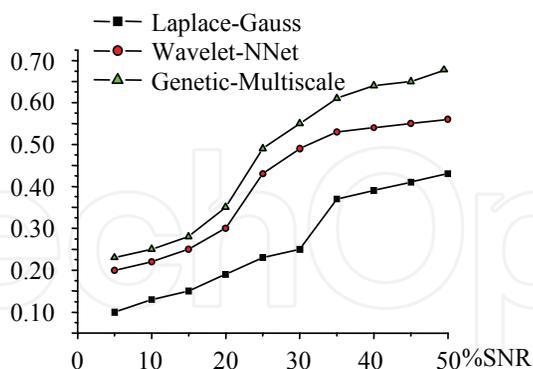


Fig. 4. Pratt qualities for different algorithms

### 5. Conclusions

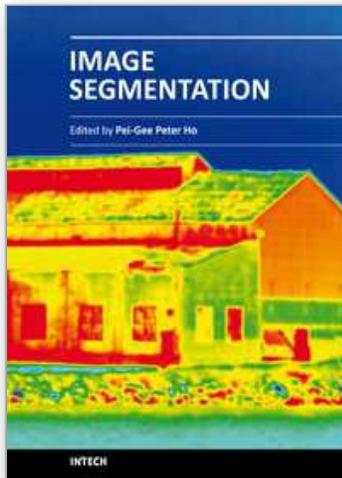
The image segmentation based upon a genetic and wavelet multi-scale edge detection is very much suitable for the contour extraction of a dynamic IR target in clutters. It could restrain clutter background signals of a target image while reserving its high frequency signature. From the view of energy spectra the energy spectra of an IR target image after a

genetic and wavelet multi-scale edge detection procession could be expressed according to the IR radiance energy levels of the target so as to avoid the loss of fine details (high frequency contents) inside the target image while its image edge is extracted.

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## **Image Segmentation**

Edited by Dr. Pei-Gee Ho

ISBN 978-953-307-228-9

Hard cover, 538 pages

**Publisher** InTech

**Published online** 19, April, 2011

**Published in print edition** April, 2011

It was estimated that 80% of the information received by human is visual. Image processing is evolving fast and continually. During the past 10 years, there has been a significant research increase in image segmentation. To study a specific object in an image, its boundary can be highlighted by an image segmentation procedure. The objective of the image segmentation is to simplify the representation of pictures into meaningful information by partitioning into image regions. Image segmentation is a technique to locate certain objects or boundaries within an image. There are many algorithms and techniques have been developed to solve image segmentation problems, the research topics in this book such as level set, active contour, AR time series image modeling, Support Vector Machines, Pixon based image segmentations, region similarity metric based technique, statistical ANN and JSEG algorithm were written in details. This book brings together many different aspects of the current research on several fields associated to digital image segmentation. Four parts allowed gathering the 27 chapters around the following topics: Survey of Image Segmentation Algorithms, Image Segmentation methods, Image Segmentation Applications and Hardware Implementation. The readers will find the contents in this book enjoyable and get many helpful ideas and overviews on their own study.

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Li Zhaohui and Chen Ming (2011). IR Image Segmentation by Combining Genetic Algorithm and Multi-scale Edge Detection, Image Segmentation, Dr. Pei-Gee Ho (Ed.), ISBN: 978-953-307-228-9, InTech, Available from: <http://www.intechopen.com/books/image-segmentation/ir-image-segmentation-by-combining-genetic-algorithm-and-multi-scale-edge-detection>

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