OPTIMAL EDGE DETECTION FILTER USING GENETIC ALGORITHM

تحسين المرشحات للكشف عن الحافات باستخدام الخوارزمية الجينية

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Abstract

The process of finding the limits of the image (edge detection) means finding the boundary between the neighboring regions which differ from each other in gray levels value. The extraction of features such as edges and curves from an image is useful for many purposes. Features, such as edges and curves are useful in i) texture analysis ii) 3-D surface restructuring iii) segmentation iv) image matching. Edges are important features in an image since they represent significant local intensity changes. They provide important clues to illumination.

Due to the absence of specific suitable method to detect all types of edges, the present work try to find an optimal filter to define image edges and compare it with traditional filters, the GA algorithm used to do so.
Keywords Image processing, GA, edge detection

الخلاصة

ان عملية ايجاد الحافات الخاص للصور تعني ايجاد الحدود بين المناطق التي تختلف فيما بينها في شدة الالوان.
ان عملية استخراج الحافات او المنحيات من الصور يكون مفيد في العديد من الاغراض. الخصائص مثل الحافات او المنحنيات يكون مفيد في 1) تحليلات الكتابة 2) اعادة هيكلة المساحات ذات الابعاد الثلاثي 3) التقطيع 4) مطابقة الصور. الحافات تكون من الخصائص المهمة للصور حيث تمثل التغير الواضح في الشدة.هي تعطي فكرة مهمة عن المناطق المضيئة للصور.
بسبب غياب الطرق المناسبة لاستخراج جميع انواع الحافات، فان العمل الحالي يحاول لايجاد مرشح مثالي لكي يتم التعرف على حافات الصورة ومقارنتها مع المرشحات العادية.الطريقة الخوارزمية الجينية استخدمت لذلك.

1. Introduction.

A large number of edge detection techniques have been proposed. Edges can be detected in many ways such as Laplacian Roberts, Sobel and gradient. In both intensity and color, linear operators can detect edges through the use of masks that represent the ‘ideal’ edge steps in various directions [4]. The common approach is to apply the first (or second) derivative to the smoothed image and then find the local maxima (or zero-crossings).An important issue in edge detection is the scale of detection filter. Small-scaled filters are sensitive to edge signals but also prone to noise, whereas large-scaled filters are robust to noise but could filter out fine details. Multiple scales could be employed to describe and synthesize the varieties of edge structures [1]. Chang HS, Kang K [7] presented a fast and systematic scheme to classify the edge orientation of each block in Discrete Cosine Transform (DCT) compressed images It is a non-iterative post-processing algorithm with two steps two steps: low-pass filtering and then predicting. Predicting the original image from the low-pass filtered image is performed with less arithmetic operations. Chung KL, and Wu ST [8] presented a novel edge-based LUT method for inverse half toning, which improves the quality of the reconstructed gray image Dubbed recovery of image blocks using the method of alternating projections (RIBMAP), is developed by Park6. B. K. Gunturk [9] approach is also capable of incorporating known source statistics and other reconstruction constraints to impose blocking artifact reduction and edge enhancement as part of the solution. C and Salama[10] using global motion estimation and compensation techniques for boundary recovery, consists of three steps: boundary extraction from shape; boundary patching using global motion compensation; and boundary filling to reconstruct the shape of the damaged video object planes. Park considers the problem of recovering a high-resolution image from a sequence of low-resolution DCT-based compressed observations. ChengjieTu, and Trac.D [11], presents a simple, fast, and efficient adaptive block transform image coding algorithm based on a combination of pre filtering, post filtering, and highorder space–frequency context modeling of block transform coefficients.

Edge detection of images does not admit a unique solution because subjectiveness and contest may take part in the decision phase. It follows that general solutions are not possible and each proposed technique can only be used to solve a class of problems. In this work genetic algorithm is implemented for optimal edge detection filter.

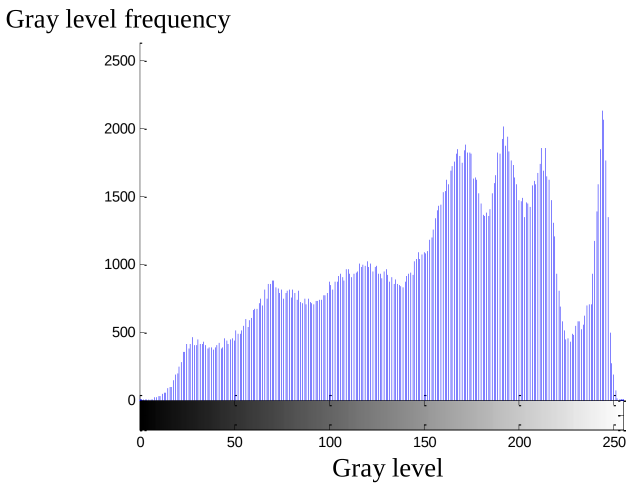
2. Traditional edge detectors

An edge defined in an image as a boundary or contour at which a significant change occurs in some physical aspect of the image. Edge detection is a method as significant as threshold. Four different edge detector operators were examined and it is shown that the Sobel edge detector provides very thick and sometimes very inaccurate edges, especially when applied to noisy images. The LOG operator provides slightly better results. Traditional edge detectors were based on a rather small 3x3 neighborhood, which only examined each pixel's nearest neighbor. This may work well but due to the size of the neighborhood that is being examined, there are limitations to the accuracy of the final edge. These local neighborhoods will only detect local discontinuities, and it is possible

that this may cause 'false' edges to be extracted. A more powerful approach is to use a set of first or second difference operators based on neighborhoods having a range of sizes (e.g. increasing by factors of 2) and combine their outputs, so that discontinuities can be detected at many different scales.

Figures (2 a,b,c,d,and e) represent the result of obtaining the edge detection filters (Prewitt, Sobel, Roberts, and Laplace)respectively on the image in Figures (1).By comparing their histograms(Figures (3 a,b,c,and d) the edge detection filters accuracy have been detected according to the total number of ones in histogram figure.

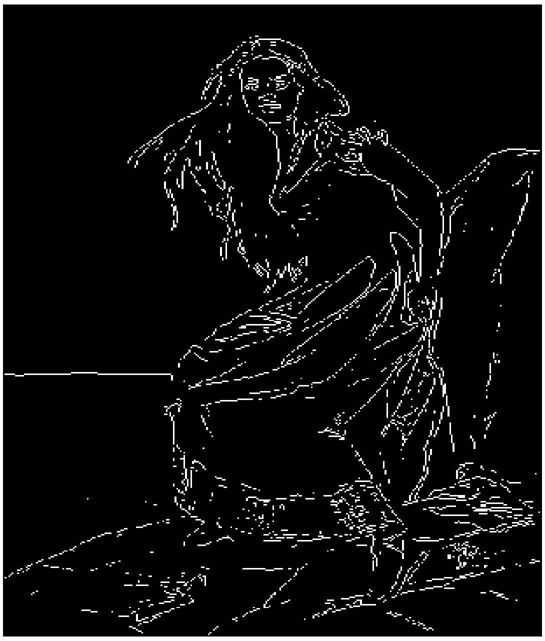
(a)



(b)

Figure (1): (a) The original image. (b) The original histogram

(a)



(b)

(c)

(d)

Figure (2) (a) Edge map using Prewitt operator (b) Edge map using Sobel operator (c) Edge map using Roberts operator (d) Edge map using Laplace operator

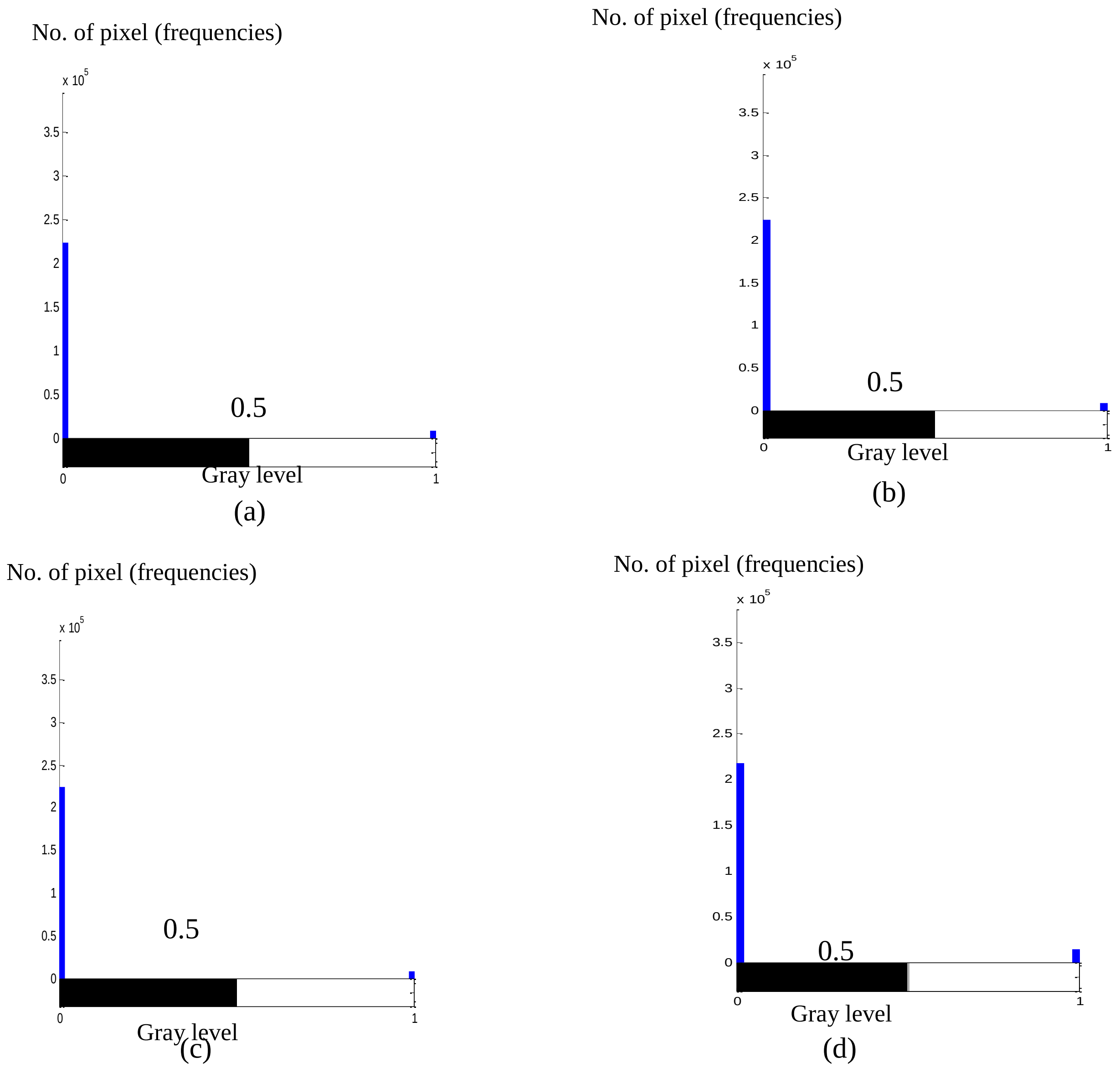


Figure (3) (a) Prewitt operator histogram (b) Sobel operator histogram (c) Roberts operator histogram (d) Laplace operator histogram

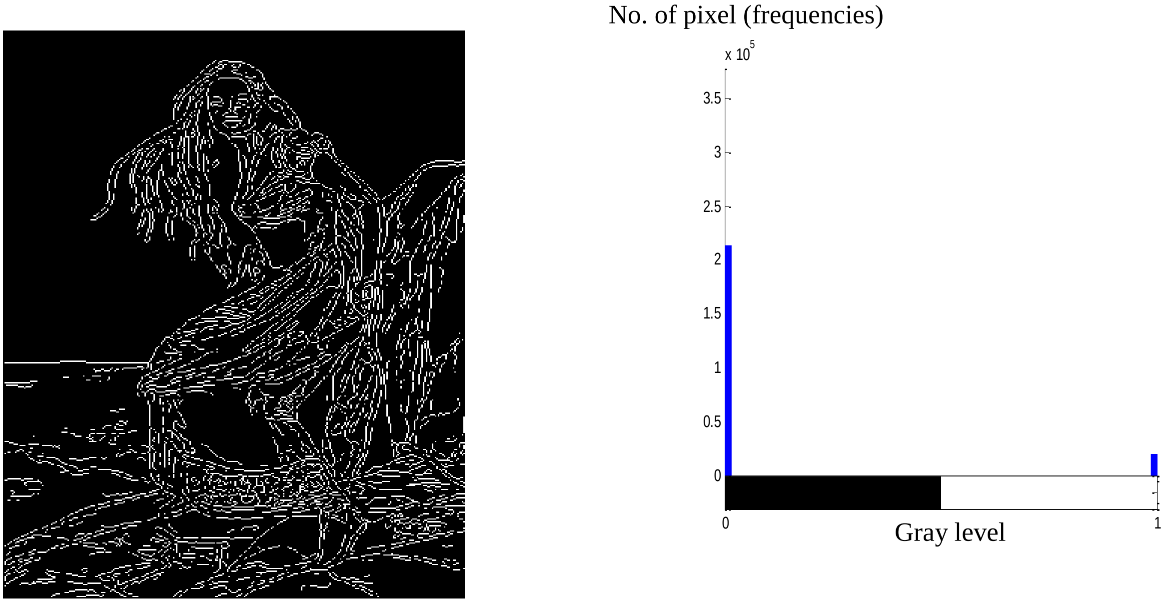
The Canny edge detector [4] is based on computing the squared gradient magnitude. Local maxima of the gradient magnitude that are above some threshold are then identified as edges. The motivation for Canny's edge operator was to derive an “optimal” operator in the sense that minimizes the probability of multiply detecting an edge, minimizes the probability of failing to detect an edge and minimizes the distance of the reported edge from the true edge.

The objective function was designed to achieve the following optimization constraints:

(i) Maximize the signal to noise ratio to give perfect detection. This favours the marking of true positives.

(ii) Achieve perfect localization to accurately mark edges.

(iii) Minimize the number of responses to a single edge. This favours the identification of true negatives, that is, non-edges are not marked Figure (4) shows the result of using Canny method.



(a) (b)

Figure (4) (a) The canny result, (b) the histogram

Table (1) the Standard Deviation

The filter name	Standard Deviation
Canny	0.2773
Log	0.2389
Sobel	0.1904
Prewitt	0.1897
Roberts	0.1816

By comparing the standard deviations in table (1), the Canny filter has the maximum standard that means more details (i.e edges) in the image has been found.

3. Filter optimization

The top part of Figure (5 (a)) shows the side view of an ideal edge [5]. An edge is where the gray level of the image moves from an area of low values to high values or vice versa. The edge itself is at the center of this transition. An edge detector should return an image with gray levels like those shown in the lower part of Figure (5 (b)). The detected edge gives a bright spot at the edge and dark areas everywhere else. Calculus fans will note the detected edge is the derivative of the edge. This means it is the slope or rate of change of the gray levels in the edge. The slope of the edge is always positive or zero and it reaches its maximum at the edge. For this reason, edge detection is often called image differentiation.

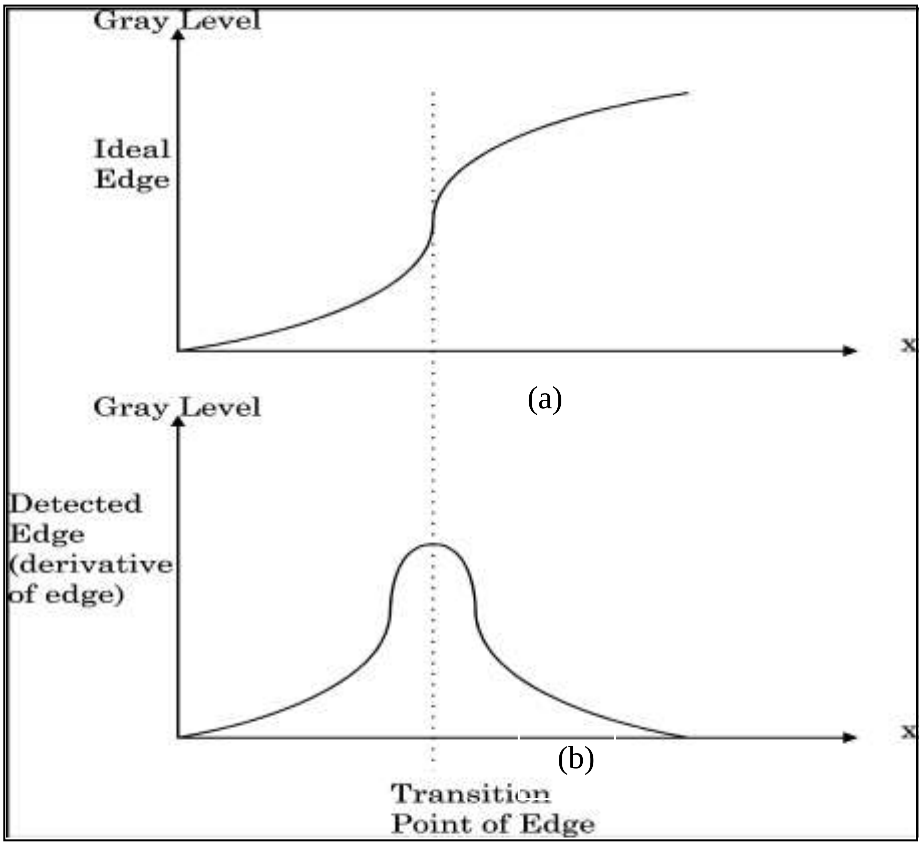


Figure (5): Graphs of Gray Scale Values at Edges

The problem in edge detection is how to calculate the derivative (the slope) of an image in all directions. Convolution of the image with filters (masks) is the most often used technique of doing this [5.6]. The idea is to take a 3 x 3 array of numbers and multiply it point by point with a 3 x 3 section of the image and sum the products and place the result in the center point of the image. The question in this operation is how to choose the 3 x 3 mask. The number of masks used for edge detection is almost limitless. Researchers have used different techniques to derive masks and then experimented with them to discover more masks. In our research GA is used to find different masks with optimum case. Each masks can be consist of two masks, one used to detect edge in x-direction(Δf_x) and other used in y-direction(Δf_y) Edges are characterized by their strength[5].

$$\boldsymbol{Strengthoffrequency} = \boldsymbol{E}(\boldsymbol{i},\boldsymbol{j}) = \sqrt{[\Delta \boldsymbol{f}_x(\boldsymbol{i},\boldsymbol{j})]^2 + [\Delta \boldsymbol{f}_y(\boldsymbol{i},\boldsymbol{j})]^2} \qquad (1)$$

The strength of frequency represent the intensity of grey level as shown in Figure (5)

The mask which calculates Δf_x must be produced from the mask that calculates Δf_y, by rotation by 90°[5].

4. Genetic algorithm

Genetic algorithms are based on natural selection discovered by Charles Darwin [2]. They employed natural selection of fittest individuals as optimization problem solver. Optimization is performed through natural exchange of genetic material between parents. Off springs are formed from parent genes. Fitness of off springs is evaluated. The fittest individuals are allowed to breed only. In computer world, genetic material is replaced by strings of bits and natural selection replaced by fitness function. Matting of parents is represented by crossover and mutation operations.

A simple GA (Figure 6) consists of five steps [3]:

1. Start with a randomly generated population of N chromosomes, where N is the size of population, l – length of chromosome x.
2. Calculate the fitness value of function φ(x) of each chromosome x in the population.
3. Repeat until N off springs is created:

3.1. Probabilistically select a pair of chromosomes from current population using value of fitness function.

3.2. Produce an offspring y_i using crossover and mutation operators, where i = 1, 2, …, N.

4. Replace current population with newly created one.
5. Go to step 2.

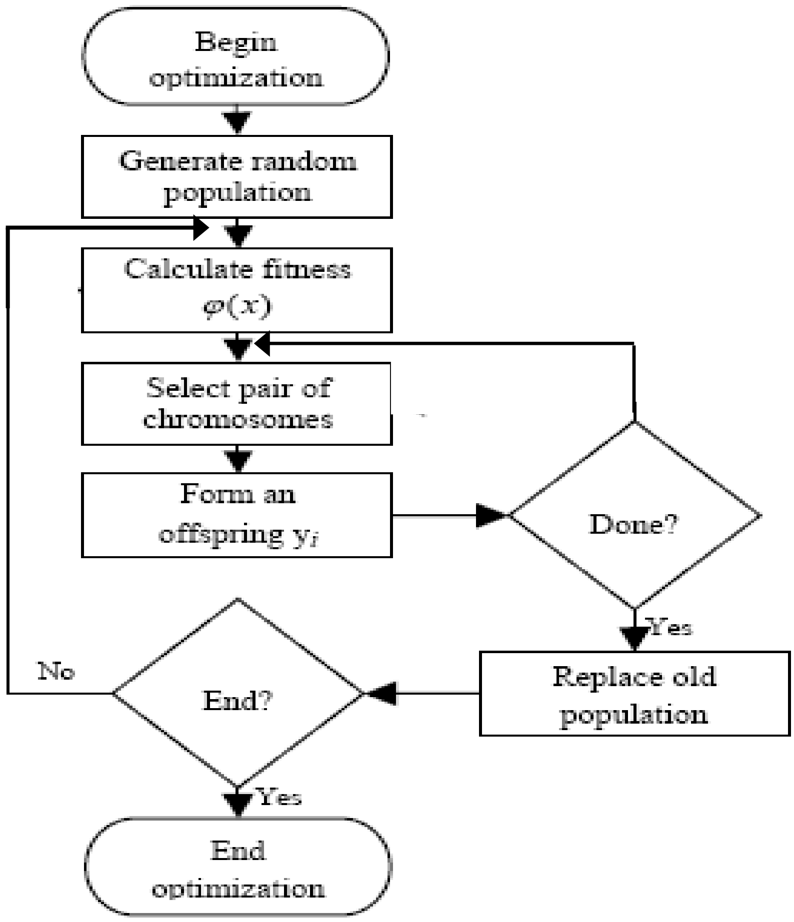


Figure (6): genetic algorithm flowchart

5. THE GA IMPLEMENTATION

In section 4, the genetic algorithm had been explained in general however the main steps can be applied for any application. In following, there are steps which explain how the GA can be used for edge detection.

1- Chose the number of variable. In edge detection the number of variable is the number of filter coefficients. For the 3 x 3 mask, the number of coefficients is 9.

X_{11}	X_{12}	X_{13}
X_{21}	X_{22}	X_{23}
X_{31}	X_{32}	X_{33}

Mask for Δf_y

X_{13}	X_{23}	X_{33}
X_{12}	X_{22}	X_{32}
X_{11}	X_{21}	X_{31}

Mask for Δf_x

2- Initialize the population size. In our application the population size of 20 is selected. With higher population size, the region of search will increase but might increase the rate of convergence and execution time. Initialization applied to Δf_y while Δf_x can be produced by rotation of Δf_y by 90°.

3- Application of mask filters on the image for two direction and compute the strength for each pixel according to eq. (1).

4- Selection of the cost function to be minimized. It is the most important item for GA. The chose of cost function depend on what condition is needed. it is obvious for image with edge detection that it has low standard deviation as shown in table (1).

So the cost function is

$$\cos tfunction = s = \sqrt{\frac{1}{(M*N)-1}\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j)-\bar{X})^2} \qquad (2)$$

Where s is standard deviation and $\bar{\boldsymbol{X}} = \dfrac{1}{\boldsymbol{M}*\boldsymbol{N}}\sum_{\boldsymbol{i}=1}^{\boldsymbol{M}}\sum_{\boldsymbol{j}=1}^{\boldsymbol{N}}\boldsymbol{X}(\boldsymbol{i},\boldsymbol{j})$

It obvious from above cost function, we can get minimum standard deviation but we cannot get certain magnitude of it. So we need to modify the cost function to obtain specific magnitude of standard deviation. Assume that we need standard deviation equal C, then the new cost function will be:

$$\cos \boldsymbol{tfunction} = |\boldsymbol{s}-\boldsymbol{C}| \qquad (3)$$

Where C is the required magnitude of standard deviation

5- when GA apply on this cost function as minimize for first iteration then the lowest cost with associated chromosomes are selected to continue, while the rest are deleted. After that a mating and mutation are applied to get a new population which goes through the same cycle starting from cost function evaluation.

The number of iterations is different from one to other. Sometimes, it converges to a solution much before 100 iterations are completed.

The following example gives the sequence of operation with practical results to get more understand about GA for edge detection. This example describes the operation to get approximate standard deviation equal to 0.3 (with ± 0.05), which is one of six situations considered as practical results as shown in section 6.

the sequence of operation is as follows. (the operation was done by MATLAB program).

1- The random mask filter was generated for Δf_y to get the following mask

-0.00639	0.00002	-0.07148
7.59735	0.50196	0.00771
9.84727	-1.18132	0.26466

Mask for Δf_y

and Δf_x can be get by rotate Δf_y by 90^o as following.

-0.07148	0.00771	0.26466
0.00002	0.50196	-1.18132
-0.00639	7.59735	9.84727

Mask for Δf_x

2- The mask filter was applied on the origin image.
3- For the new image, standard deviation was computed according to Eq.(2) (with the origin mask filter the obtained standard deviation is 7.1094)
4- If standard deviation is not required value (the value is certain by user), then apply GA for mask filter to get new mask, then go to step 2.
5- In the end of the operation, the required standard deviation and the required mask can be found
For the situation with this example, the final mask of operation is shown below.

-0.00469	0.00192	-0.00369
0.00053	-0.0219	0.00048
-0.00222	0.00211	-0.00312

Mask for Δf_y

And

-0.00369	0.00048	-0.00312
0.00192	-0.0219	0.00211
-0.00469	0.00053	-0.00222

Mask for Δf_x

For this mask, the standard deviation is 0.3458.
The following operation was chosen for GA program.

Table (2) the GA options

Operation	Option
Coding	Binary coding
NO. of chromosomes	8 chromosomes
Population size	20 bit
Selection	Stochastic uniform
Crossover	Scattered
Mutation	Gaussian

6. Results and conclusions

Experiments were conducted over one image. At the decoder, random generation of chromosomes decides the value of scaling parameter and the coefficients of the mask. Here standard deviation is considered as the fitness function. Population of different sizes for different chromosomes is incorporated and the genes are tested for specific number of generation. Experimental results infer that convergence is effective when the number of chromosomes in the population and the number of generations are greater than or equal to eight.

Traditional edge detectors methods such as Roberts Cross, the Sobel Operator and Prewitt operator failed to perform adequately in such applications due to the noisy nature of remotely sensed data. They are not able to detect the edges of the object while removing all the noise in the image.

By comparing the image for different standard deviation in figure (7),we note that the minimum standard deviation is not the required aim for edge detection but it is obvious that good edge detection is between about ($s = 0.3$ to $s = 0.7$). So the user can specify the standard deviation when GA applies.

The advantage of the edge detection method using GAs is intelligent. It is effective to the edge detection for the colony image with randomness because of not using the pixel data but using the local texture feature, and the arrangement of the edge regions is accomplished based on the simple idea that the shortest individual within the candidate edge regions is the optimum edge regions.

The implementation of the previously described approach was programmed on Matlab, with the Genetic Programming toolbox [7]. The results for different standard deviation were obtained for the one image as shown in figure (7).

Standard deviation = 0. 2426

Standard deviation = 0.268

Standard deviation = 0. 3458

Standard deviation = 0. 5473

Standard deviation = 0. 6806

Standard deviation = 0. 8200

Fig. (7): Edge detection for different standard deviation

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