Quantitative Analysis of Feature Detection Using Adaptive Canny Edge Detector and Enhanced Ant Colony Optimization

Zhengmao Ye, Habib Mohamadian, and Yongmao Ye

***Abstract*—Feature detection is a fundamental technique in broad fields of image processing, pattern recognition and computer vision. A digital image in general contains objects, edges, noises and background. Critical changes in properties of objects can be captured via detecting sharp variations in image brightness. The edges can be detected via numerous approaches on a basis of image intensity changes. Edge broken and false detection are typical problems using classical methods, which will result in information loss and feature deformity. The notion of optimization is thus introduced into edge detection. The Canny edge detector and Ant Colony Optimization (ACO) detector are among the most successful and effective approaches for edge detection. The Canny edge detector is designed to capture edges by searching local optima of the gradient of the intensity. It is susceptible to noises presenting on the raw images, so details of images could be slightly changed when Gaussian smoothing is applied. To improve accuracy, the adaptive edge tracing scheme is proposed. On the other hand, artificial intelligence has also been introduced. Being one of metaheuristic optimization approaches, the evolutionary computing oriented ACO becomes a promising approach for feature capturing without necessity of smoothing filters. Selection of maximum intensity difference as the path visibility function for ACO will contribute better to generate true edges and avoid false edges. Both the adaptive Canny edge detection and enhanced ACO are proposed in this article. Comparative studies are also conducted to evaluate the edge detection qualities. The outcomes are analyzed and evaluated from both qualitative and quantitative points of view, where merits and drawbacks of the two schemes have been indicated.**

***Index Terms*—Feature detection, ant colony optimization, canny edge detector, quantitative analysis.**

I. Introduction

Edge detection is the primary digital image processing technique to identity sharp intensity changes and feature discontinuities, due to diverse illumination, surface orientation, object size, background and material conditions. The ideal edge detector leads to a set of connected curves that represent boundaries of objects, boundaries of markings, and discontinuities in surface orientation. Thus, applying an edge detection algorithm to an image may significantly reduce the amount of data to be processed and filter out information less relevant, while also preserve the important structural properties of an image. Search-based and zero-crossing based approaches are two major edge detection methods.

The search-based methods detect edges by computing a measure of edge strength, like the first order gradient magnitude, and then searching for its local directional optima of the gradient magnitude. The zero-crossing based methods search for zero crossings in a 2nd-order Laplacianof Gaussian filter computed to find edges. If the edge detection is successful, a subsequent task of interpreting the information content in the raw image could be substantially simplified. However, ideal edges can seldom be captured. Instead, missing segments and false edges always occur upon nature image feature extraction. Certain traditional edge detection approaches (e.g., Sobel operator, Prewitt operator) adopt specific templates or combine smoothing functions, resulting in broken edges and information loss. Thus some compensation techniques (e.g., Hough transformation, hybrid method) have been used for connecting edges. But it is difficult to make connection accurately. The Canny edge detector and ACO algorithm are therefore introduced. Some basic applications have been made in recent years [1]-[9].

The Canny method finds edges by searching local optima of the intensity gradient using a Gaussian filter. It uses two thresholds to detect strong and weak edges. Upper threshold is used to find the start of an edge. The weak edges will then be included if connected to those strong edges. The path of the edge is traced through the image pixel by pixel, marking an edge above the lower threshold. This method is less likely to be noise sensitive, more likely to detect true weak edges. Edge thinning is a technique used to remove the unwanted spurious points on the edges of an image. It results in one pixel thick edge elements. 8-connectivity is preferred with all immediate pixels surrounding a particular pixel [10]-[11].

The ACO algorithm is a probabilistic technique which can be employed to finding good paths through graphs. In the real world, ants seek a path randomly between the colony and sources of food. The pheromone trails to food sources traversed by the ants will have a larger chance to be followed by other ants, after the ants return to the colony. In turn, the pheromone intensity will be reinforced if other ants also find food. Pheromone evaporates to avoid the convergence to a locally optimal solution. The actual pheromone density depends on both the reinforcing process and evaporation process. The solution exploration will be

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constrained. All ants tend to follow an optimal path upon positive feedback eventually. Over time, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel along a path and back again, the more time the pheromones have to evaporate. A short path can be passed over faster, and thus remains high pheromone intensity as it is laid on the path as fast as it can evaporate. If there is no evaporation at all, paths chosen by the first ant will tend to be excessively attractive to the following ants. In that case, exploration of a solution space should be constrained. Positive feedback eventually leads all the ants following a single shortest path to the source. It is a self-organized stigmergy system where ants will exchange information indirectly by depositing pheromones [11]-[15].

Some Canny edge detectors and ACO schemes are proposed for different engineering applications [10]-[15]. For example, Canny edge detection uses bilinear interpolation and tri-linear interpolation to convert between square and hexagonal structures. The estimated pixel edge strength on the square structure is used for the Canny edge detection, which improves the accuracy and efficiency [11]. Fuzzy-Rule-Based systems via continuous ant-colony optimization has been designed. It uses an online-rule-generation method to determine the number of rules and identify suitable initial parameters for the rules and then optimizes all the free parameters using continuous ACO. ACO improves the path-selection method and this approach optimizes parameters in the continuous domain with greater learning accuracy [12]. ACO is used to find solutions to combinatorial optimization problems. An ACO edge detection technique establishes a pheromone matrix that represents the edge information at each pixel based on routes formed by ants dispatched on the image, missing edges are clearly observed, however [13]. ACO is also applicable for optimizing regulator circuits with discrete components. An extended ACO can search for the optimal continuous values of components like inductors to optimize power electronic circuits via the orthogonal design method [14]. Furthermore, ACO has been used for forecast construction management which produces good optimal and suboptimal solutions [15]. In this research, the roles of two enhanced algorithms will be investigated for edge detection.

II. Article Outline

The adaptive Canny edge detector will introduced at first, followed by the enhanced scheme of ACO. Using a set of digital images, the detected images from two enhanced schemes will be examined from qualitative and quantitative points of view, which are used to further determine the image processing quality. The source digital images selected are pictures of the Eiffel Tower in France, the Corner Pavilion in China, the Kofukuji Pagoda in Japan and the Sun Pyramid in Mexico, in which all objects are dominant components.

Fig. 1. Source Image of Eiffel Tower

Fig. 2. Source Image of Corner Pavilion

Fig. 3. Source Image of Kofukuji Pagoda

Fig. 4. Source Image of Sun Pyramid

III. Enhanced Scheme for Canny Edge Detector

The Canny edge detector detects edges at zero-crossings of the second order directional derivative of the image. The Canny operator is implemented step by step and it uses an optimal Gaussian smoothing filter beforehand.

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\pi\sigma^2}\right) \tag{1}$$

The digital image is smoothed by Gaussian convolution.

$$H(x, y) = G(x, y) * I(x, y) \tag{2}$$

where G is Gaussian smoothing filter; I is the intensity of the original image, H is the intensity of the smoothed image, * denotes convolution operation. The 2D first order derivative operator is applied to the smoothed image to calculate both the gradient magnitude and direction.

The edge location is then computed at the local optima of first order derivative of H(x, y) in the direction n, which is the zero-crossing point of the second order derivative of H(x,y). The edge direction is rounded to one of eight angles to representing vertical, horizontal and diagonal directions. Non-maximal suppression is then applied to the gradient image. Accordingly, the edge points that gradient magnitude (strength) reaches a local maximum are located.

$$\frac{d^2(G*I)}{dn^2} = \frac{d(\frac{dG}{dn}*I)}{dn} = 0 \tag{3}$$

where, n is the direction of the gradient magnitude of the image. Each pixel's edge gradient is computed and then compared with the gradients of its 8 neighbors along the gradient direction.

Adaptive edge tracking is conducted to connect the broken edges. TheChain Code criterion is appliedto each visiting node. A digital curve is represented by an integer sequence based on the position of the current edge node to neighbors at the 2D spatial domain. The 8-connectivity Chain Code is selected with all the immediate pixels surrounding the testing node. It is used to depict the pixel thin line trajectory. To calculatethe thin chain code, starting from one endpoint, test in a counter-clockwise direction on the next searching point, and encode the point until stagnation occurs or the maximum number of cycles has been reached. It is shown in Fig. 5.

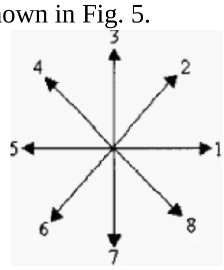


Fig. 5 Direction of 8-connectivity chain code

The direction of the Chain Code is defined as $N_i \in \{1, 2, 3, 4, 5, 6, 7, 8\}$, where,

1 – East, corresponding to an angle of 0°;
2 – Northeast, corresponding to an angle of 45°;
3 – North, corresponding to an angle of 90°;
4 – Northwest, corresponding to an angle of 135°;
5 – West, corresponding to an angle of 180°;
6 – Southwest, corresponding to an angle of 225°;
7 – South, corresponding to an angle of 270°;
8 – Southeast, corresponding to an angle of 315°.

This proposed adaptive Canny edge detector is tested to be suitable for solid edge tracing, clear marking, appropriate localization and low response. Assume that the important edges should be located along continuous curves, then the faint section of a given line is tracked and those noisy nodes that produce large gradients are discarded. Thresholding with hysteresis (with high and low thresholds) will be another step. The high threshold is applied at first to locatetrue edges as starting endpoints. A high threshold may miss important informationlike subtle anddiscontinuous edges. If no starting point is captured, the adaptive algorithm lowers the high threshold so that starting points can be detected. Directional information being derived is then introduced so that edges can be traced across images. The low threshold will detect more edges, however,noisy and irrelevant features will be also detected, so both false edges and poor localization might be possible. The smoothing Gaussian filter used in the Canny algorithm will partially compensate for this effect. In some cases, the parameters of the Gaussian smoothing filter can also be adjusted for better edge detection.

IV. Enhanced Scheme for Ant Colony Optimization

The ACOalgorithm is a population-based metaheuristic optimization approach to estimate solutions. Its application toedge detection is simplified into an optimization problem of searching paths on a weighted graph, where the artificial ants build solutions to a combinatorial optimization problem by moving on the connected construction graph. Each artificial ant starts from a randomly selected node and tracks solutions along the edges of the graph. At each construction step, an ant chooses an edge randomly to follow among edgesthat lead to those unvisited nodes. The ants move from node to node along the edges of construction graph exploiting information provided by the pheromone values. The solution is reached when an ant has visited all nodes of the graph.The solution construction is a stochastic process. Each ant will memorize its path and deposit certain amount of pheromone on nodeson the trip. Other ants will utilize pheromone information as a reference towards more promising regions of the search space.

The pheromone intensityin fact representsthe cumulated experience of the ant colony based on the memory. The parameters in the pheromone model are modified across the time. The objective is to increase pheromone intensities associated with good solutions and to evaporate those associated with bad solutions. Once all ants have completed their trips, the pheromone on edges is updated. Ateach iteration, the pheromone intensityis also evaporated on edges across the trail, so as to encourage subsequent ants to choose other edges to produce different solutions. This will result in diversity to avoid local stagnation. In an ACO algorithm, the shortest path is combined based on several paths. The ants will mark the best solutions and use previous markings for optimization.This procedure will be repeatedly applied until a termination criterion is reached. The ACO is formulated in two coordinated stages: A. Edge Selection; B. Pheromone Update.

In the edge selection stage, an ant movesfrom nodei to node j with aprobability. The path visibility is designed to be the ratio of the maximum variation of intensity and the maximum intensity. In this case, edge pixels are expected to have relatively larger values of visibility. The selection rule is defined as (4).

$$p_{i,j} = \frac{(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}} \tag{4}$$

where,

α is a parameter to adjust the impact of $\tau_{i,j}$;

β is a parameter to adjust the impact of $\eta_{i,j}$;
$\tau_{i,j}$ is the pheromone amount on edge betweeni and j;
$\eta_{i,j}$ is the path visibilityof betweeni and j.

The maximum intensity variation function is proposed as (5) to maximize the potential chance of true edge detection.

$$\eta_{i,j} = \frac{\underset{[m,n]=(i-1,j-1)}{\overset{(i+1,j+1)}{\mathrm{Max}}} |I(m,n)-I(i,j)|}{I_{MAX}} \tag{5}$$

Where I denotes the pixel intensity.The higher the pheromone intensity variation(representing the path visibility) is, the higher the probability an ant will choose that particular edge

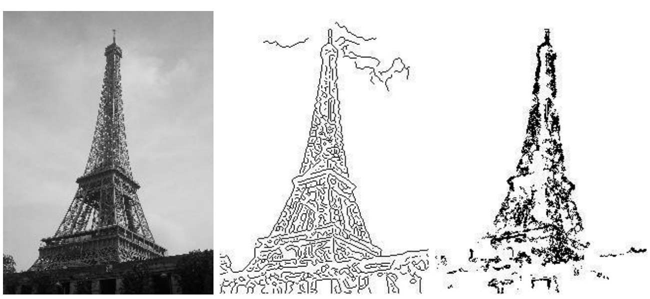
In the pheromone update stage, evaporation of pheromone will help to avoid consistent accumulation of the pheromone intensities. For any node not chosen by ants, its pheromone intensity value decreases exponentially. To avoid stagnation of the searching process, constraint minima of pheromone intensity is set. Each of pheromone intensities is reduced by evaporation and then increased by depositing extra amount of pheromone based on solutions available. The updating rule is defined as (6).

$$\tau_{i,j} = (1 - \rho)\tau_{i,j} + \Delta\tau_{i,j} \tag{6}$$

where,
ρ is the rate of pheromone evaporation ($0 < \rho < 1$);
$\tau_{i,j}$ is the pheromone amount on edge betweeni and j;
$\Delta\tau_{i,j}$ is the amount of pheromone deposited;
$\Delta\tau_{i,j} = \eta_{i,j}$if the ant travels on edge betweeni and *j*.

To solve the edge detection problem, each pixel is assumed to be connected with its 8-neighborhood pixels within an image. The ants are placed on strong endpoints and extend the search region to find compensation segments to repair the fragmented edges. Thresholding will be used to detect each pixel location and make a binary decision if it lies in edge or not. A high threshold setting can miss important information. On the contrary, low threshold setting will falsely identify irrelevant information such as noises. To avoid redundancy and false edge generation, parameter selection for thresholding should ensure that total number of iterations be within a limit range.

V. Subjective Assessment of Enhanced Schemes



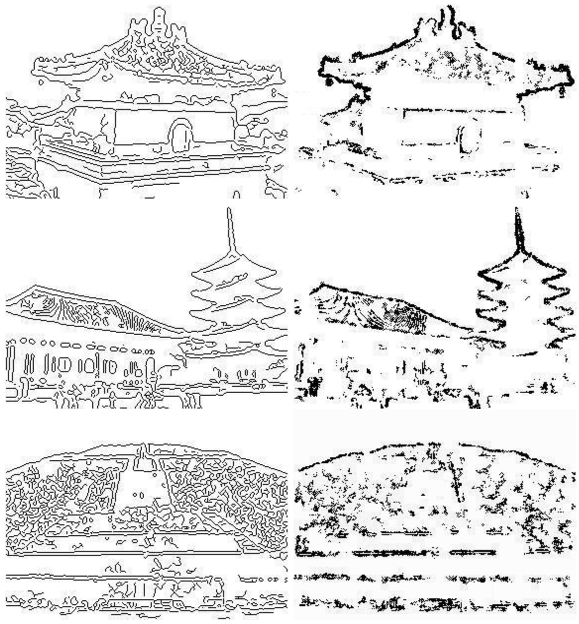


Fig. 6. Edge Detection via Enhanced Canny Detection and ACO

In Fig. 6, simulation results from the adaptive Canny edge detector and enhanced ACO algorithm are depicted. The outcomes are based on four source images. Results of Canny detection are placed to the left and those of ACO algorithms are placed to the right. It can be seen that both enhanced schemes produce satisfactory outcomes. A preferable set of detection edges is application dependent, thus it is unlikely to make subjective comparison and conclusion in general. Based on observation, Canny detection produces better connectivity and graphical appealing for each case. The irrelevant trivial information (e.g, cloud, grass, people, noise, etc), however, is also extracted and emphasized besides the primary objects. On the other hand, the enhanced ACO scheme does not make connectivity as good as Canny detection does, while it represents the true edges with little information deformity. It delivers relatively fuzzy edges with more pixels. To make further comparisons, objective assessment should be conducted as well.

VI. Objective Assessment Of Enhanced Schemes

A. Discrete Entropy

The histogram is used to display the brightness of the gray level content, showing the occurrence frequency of the pixel counts for each of the 256 intensity levels. The occurrence of the gray level component is described as the co-occurrence matrices of relative frequencies. The probability function of the gray level image is estimated from the percentages of the count at certain intensity level.The discrete entropy is the measure of image information content, which has been interpreted as the average uncertainty of information source. It is formulated as the sum of the products of the probability of outcome multiplied by log of the inverse of the outcome probability, taking into considerations of all possible outcomes {1, 2, …, n} in the event $\{x_1, x_2, \ldots, x_n\}$, where n is the gray level; p(i) is the probability distribution, considering all the histogram counts. It is expressed as (7).

$$H(x)=\sum_{i=1}^{k} p(i)\log_2 \frac{1}{p(i)} = -\sum_{i=1}^{k} p(i)\log_2 p(i) \tag{7}$$

TABLE I: DISCRETE ENTROPY

Entropy	Source Image	Canny Edge Detector	Ant Colony Optimization
Eiffel Tower (France)	6.9708	2.1180	1.5169
Corner Pavilion (China)	7.3973	2.7727	2.1451
Kofukuji Pagoda (Japan)	7.0063	2.4334	2.2361
Sun Pyramid (Mexico)	7.4235	3.1372	2.9207

The discrete entropy is a measure how many bits needed for coding the image data, which is a statistical measure of randomness. The maximal entropy occurs when all potential outcomes are equal. When the outcome is certainty, the minimal entropy occurs which is equal to zero. When the probability distribution is uniform, the maximum discrete entropy occurs with the discrete entropy value of $\log_2(n) = 8$ bits (n=256).The discrete entropy represents average amount of information conveyed from each individual image. In Table I, the entropies of source images and detected edge images based on two schemes have been shown. Through edge detection, entropies are much smaller than those of source images. The entropy from adaptive Canny edgedetection is in factbigger than that from the enhanced ACO algorithm. It indicates that resulting images of adaptive Canny edgedetection cover more information and resulting images from the enhanced ACO algorithm will cover less information. This is partially due to different level of connectivity and contributions of irrelevant information.

B. *Relative Entropy*

Assume that two discrete probability distributions of the images have probability functions of p and q. The relative entropy of one with respect to another is then defined as the sum of all possible states, which is formulated as (8).

$$d=\sum_{i=1}^{k} p(i)\log_2 \frac{p(i)}{q(i)} \tag{8}$$

In Table II, for all four cases, the relative entropiesfrom the adaptive Canny edgedetector is less than that from the enhanced ACO algorithm. It indicates that the enhanced ACO algorithm will lead torelatively greater similarities between the detected images and source images. Although the enhanced ACO algorithm does not give rise to relatively better connectivity, it covers more true edge information in fact. In this case, each scheme has merits and drawbacks.

TABLE II: RELATIVE ENTROPY

Relative Entropy Between Raw Image and Edges	Canny Edge Detector	Ant Colony Optimization
Eiffel Tower(France)	1.9874	2.6523
Corner Pavilion(China)	0.7736	1.1668
Kofukuji Pagoda(Japan)	3.9886	4.1072
Sun Pyramid(Mexico)	2.0963	2.2833

C. *Mutual Information*

The mutual information is also applied as aquantitative metric. The mutual information acts as the symmetric function, which is formulated in (9).It is interpreted as the information that *Y* can tell about *X* is equal to the reduction in uncertainty of *X* due to the existence of *Y*. It also illustrates the relationship of the joint and product distributions.

$$I(X;Y)=H(X) - H(X|Y)=\sum_{X,Y} p_{XY}(X, Y)\log_2 \frac{p_{XY}(X, Y)}{p_X(X)p_Y(Y)} \tag{9}$$
$$= -\sum_{X} p_X(X)\log_2 p_X(X) + \sum_{X,Y} p_{XY}(X, Y)\log_2 \frac{p_{XY}(X, Y)}{p_Y(Y)}$$

where I(X; Y) represents the mutual information; H(X) and H(X|Y) are entropy and conditional entropy values. The results are shown in Table III.

TABLE III: MUTUAL INFORMATION

Mutual Information Between Raw Image and Edges	Canny Edge Detector	Ant Colony Optimization
Eiffel Tower(France)	4.8528	5.4540
Corner Pavilion(China)	4.6246	5.2522
Kofukuji Pagoda(Japan)	4.5728	4.7701
Sun Pyramid(Mexico)	4.2864	4.5029

In Table III, for all four cases, the mutual informationfrom adaptive Canny edgedetection is less than that from the enhanced ACO algorithm. It has shown again that the enhanced ACO algorithm will result inrelatively greater similarities between the detected images and source images. Although the enhanced ACO algorithm will not generate the relatively better connectivity, higher amount of information on the true edge will be discovered. In other words, little information deformity or image disillusion will occur using the enhanced scheme of ACO. Integrating merits of adaptive Canny edge detection (connectivity, appealing) and enhanced ACO scheme (true information, less false edge) could be a potential solution to improve the quality of edge detection.

D. *Correlation*

Correlation is a standard measure of the image contrast to analyze the linear dependency of gray levels of neighboring pixels. It indicates the amount of local variations across a gray level image. The higher the contrast is, the sharper the structural variation is. This measure is formulated as:

$$COR=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{(i-\mu_i)(j-\mu_j)}{\sigma_i\sigma_j}g(i,j) \tag{10}$$

$$\sigma_i=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(i-\mu_i)^2 g(i,j);\ \mu_i=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[i*g(i,j)] \tag{11}$$

$$\sigma_j=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(j-\mu_j)^2 g(i,j);\ \mu_j=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[j*g(i,j)] \tag{12}$$

wherei and j are coordinates of the co-occurrence matrix; g(i, j) is the element in the co-occurrence matrix at the coordinates i and j; M and N represent total numbers of pixels in row and column of the digital image. μ_i and σ_i are the horizontal mean and variance whileμ_j and σ_j are the vertical mean and variance. The variance is a measure of the gray tone variance of an image.

In Table IV, for all four cases, correlationfrom adaptive Canny edgedetection is less than that from the enhanced ACO algorithm and also much less than that from source images. It has shown again that the enhanced ACO algorithm produces better similaritiesbetween the detected images and source images.

TABLE IV: CORRELATION

Correlation	Source Image	Canny Edge Detector	Ant Colony Optimization
Eiffel Tower (France)	0.9124	0.2439	0.5968
Corner Pavilion (China)	0.9575	0.2658	0.5837
Kofukuji Pagoda (Japan)	0.9597	0.2810	0.5737
Sun Pyramid (Mexico)	0.8028	0.2160	0.4839

D. Dissimilarity

The metric of dissimilarity depends on the local distance representation. For two gray level images, the dissimilarity is described as the distance between any two co-occurrence matrix representations. It is simply expressed as (13).

$$\text{DisSim}=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} g(i,j)\,|i-j| \tag{13}$$

where g(i, j) is the element in the co-occurrence matrix at the coordinates i and j; M and N are the total numbers of pixels in the row and column of the digital image.

In Table V, for all four cases, the dissimilarity from adaptive Canny edgedetection is much higher than that from the enhanced ACO algorithm, where less similarities are observed. It shows again that the enhanced scheme of ACO will produce results covering larger amount of true information.

TABLE V: DISSIMILARITY

Dissimilarity	Source Image	Canny Edge Detector	Ant Colony Optimization
Eiffel Tower (France)	0.2875	0.7822	0.4705
Corner Pavilion (China)	0.2658	0.9041	0.4111
Kofukuji Pagoda (Japan)	0.2688	0.7918	0.5021
Sun Pyramid (Mexico)	0.6547	1.3678	0.7767

VII. CONCLUSION

Two novel approaches are presented for edge detection, using adaptive Canny edge detection and enhanced scheme of ACO. The objective has been reached to compensate for the broken edges and reduce the false edges. Based on the two leading schemes for feature extraction, comparative studies are made from both subjective and objective points of view, where the merits and drawbacks of each approach have been examined accordingly. Quantitative metrics based on the information theory are also introduced to evaluate the quality of digital image feature detection. It is concluded that the proposed adaptive Canny edge detection has better connectivity with less broken edges, while the enhanced scheme of ACO will produce outcomes with greater amount of intrinsic content, less irrelevant information and less false edge recognition.

REFERENCES

[1] R. Gonzalez and R. Woods, “Digital Image Processing,” 2nd Edition, Prentice-Hall, 2002

[2] Engelbrecht, "Computational Intelligence: An Introduction", 2nd Edition, John Wiley & Sons, 2000

[3] Simon Haykin, “Neural Networks – A Comprehensive Foundation”, 2nd Edition, Prentice Hall, 1999

[4] D. MacKay, "Information Theory, Inference and Learning Algorithms", University of Cambridge Press, 2005

[5] M. Dorigo, C. Blum, “Ant colony optimization theory: A Survey”, *Theoretical Computer Science*, 344(2–3):243–278, 2005

[6] M. Dorigo and L. M. Gambardella, “Ant Colony System: A cooperative learning approach to the traveling salesman problem”, IEEE Transactions on Evolutionary Computation, 1(1):53–66, 1997

[7] Z. Ye, H. Mohamadian and Y. Ye, "Digital Image Wavelet Compression Enhancement via Particle Swarm Optimization", Proceedings of the 2009 IEEE International Conference on Control and Automation, Dec. 9-11, 2009, Christchurch, New Zealand

[8] Z. Ye and G. Auner, “Raman Spectrum Baseline Identification and Its Optimization Using Genetic Algorithm”, in *Proceedings of the 2004 IEEE International Symposium on Intelligent Control*, pp. 489-494, Sept. 2-4, 2004, Taipei, Taiwan

[9] Z. Ye, J. Luo and P. Bhattacharya, "Optimal Approach for Enhancement of Large and Small Scale Near-Infrared and Infrared Imaging", Proceedings of the 2005 IEEE International Conference on Industrial Electronics and Control Applications (ICIECA05), 6 pp., Nov. 29 - Dec. 2, 2005, Quito, Ecuador

[10] Z. Ye, H. Cao, S. Iyengar and H. Mohamadian, "Medical and Biometric System Identification for Pattern Recognition and Data Fusion with Quantitative Measuring", Systems Engineering Approach to Medical Automation, Chapter Six, Artech House Publishers, 2008, pp. 91-112, ISBN 978-1-59693-164-0, Oct 2008

[11] X. He, W. Jia and Q. Wu, “An Approach of Canny Edge Detection with Virtual Hexagonal Image Structure”, 2008 10th International Conference on Control, Automation, Robotics and Vision, Hanoi, Vietnam, December 17–20, 2008

[12] C. Juang and P. Chang, "Designing Fuzzy-Rule-Based Systems Using Continuous Ant-Colony Optimization", IEEE Transactions on Fuzzy Systems, pp. 138-149, VOL. 18, NO. 1, FEB 2010

[13] A. Baterina and C. Oppus, "Image Edge Detection Using Ant Colony Optimization", International Journal of Circuit, Systems and Signal Processing, pp.26-33, Issue 2, Vol 4, 2010

[14] J. Zhang, H. Chung, A. Lo, and T. Huang, “Extended Ant Colony Optimization Algorithm for Power Electronic Circuit Design”, IEEE Transactions on Power Electronics, VOL. 24, NO. 1, Jan 2009

[15] H. Abdallah, H. Emara, H. Dorrah, A. Bahgat, “Using Ant Colony Optimization Algorithm for Solving Project Management Problems”, Expert Systems with Applications 36 (2009) 10004–10015

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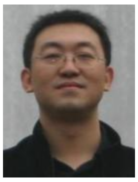

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