Jurnal Ilmu Komputer dan Informasi (Journal of Computer Science and Information). 7/2 (2014), 76-82
DOI: http://dx.doi.org/10.21609/jiki.v7i2.260

ADAPTIVE ANT COLONY OPTIMIZATION BASED GRADIENT FOR EDGE DETECTION

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Abstract

Ant Colony Optimization (ACO) is a nature-inspired optimization algorithm which is motivated by ants foraging behavior. Due to its favorable advantages, ACO has been widely used to solve several NP-hard problems, including edge detection. Since ACO initially distributes ants at random, it may cause imbalance ant distribution which later affects path discovery process. In this paper an adaptive ACO is proposed to optimize edge detection by adaptively distributing ant according to gradient analysis. Ants are adaptively distributed according to gradient ratio of each image regions. Region which has bigger gradient ratio, will have bigger number of ant distribution. Experiments are conducted using images from various datasets. Precision and recall are used to quantitatively evaluate performance of the proposed algorithm. Precision and recall of adaptive ACO reaches 76.98% and 96.8%. Whereas highest precision and recall for standard ACO are 69.74% and 74.85%. Experimental results show that the adaptive ACO outperforms standard ACO which randomly distributes ants.

Keywords: *gradient, adaptive, random ant distribution, ant colony optimization*

Abstrak

Ant Colony Optimization (ACO) merupakan algoritma optimasi yang terinspirasi oleh tingkah laku semut dalam mencari makan. Karena keunggulan yang dimilikinya, ACO banyak digunakan untuk menyelesaikan permasalahan non-polinomial yang sulit, salah satunya adalah deteksi tepi pada citra. Pada tahapan awal, ACO menyebarkan semut secara acak, hal ini dapat menyebabkan ketidak seimbangan distribusi semut yang dapat mempengaruhi proses pencarian jalur. Paper ini mengusulkan algoritma adaptif ACO untuk mengoptimalkan deteksi tepi pada citra dengan cara menyebarkan semut awal secara adaptif berdasarkan analisis gradient. Semut disebarkan berdasarkan perbandingan gradient dari tiap bagian citra. Bagian citra dengan perbandingan gradient yang lebih besar akan mendapatkan pembagian semut yang lebih banyak dibandingkan bagian lainnya. Percobaan dilakukan pada beberapa citra yang berasal dari berbagai data set. Precision dan recall digunakan sebagai alat untuk mengukur citra keluaran algoritma yang diusulkan secara kuantitatif. Berdasarkan hasil uji coba, adaptif ACO mampu mencapai precision dan recall hingga 76.98 % dan 96.8 %. Sedangkan, nilai precision and recall tertinggi menggunakan ACO murni mencapai 69.74% dan 74.85%. Hasil ini menunjukkan bahwa adaptif ACO mampu menghasilkan citra keluaran yang lebih baik dibandingkan ACO murni yang sebaran semut awalnya dilakukan secara acak.

Kata Kunci: *gradient, adaptif, sebaran semut acak, ant colony optimization*

1. Introduction

Edge detection is process of extracting edge information from image. It is considered as fundamental step used in most image processing applications [1]. It is also a fundamental problem in image analysis. Edges in an image can be regarded as boundary between two different regions. An edge is easy to detect due topixel intensity difference between regions whichis relatively easy to calculate.

Many approaches have been proposed to extract this image feature. Some commonly used methods are sobel, prewitt, and canny edge detector [2]. Sobel edge detector uses local gradient operators, which is able to detect edges that have a high spatial frequency and more specific orientation. Sobel edge detector produces poor results in blurred and noisy image. Prewitt operator proposed to extract the contour feature by installing the least-square error (LSE) squared surface for 3 * 3 picture window. Whereas, canny edge detector works in the multistage detector.

Recent works uses ACO to perform image edge detection. ACO is a nature-inspired optimization algorithm which is motivated by ant foraging behavior. Ant uses special chemical compound called pheromone to mark path between food source and their colony. Pheromone trails are used by subsequent ant as reference to find food since pheromone increases the likelihood of path to be choosen.

Due to its favorable advantages, ACO has been widely used to solve several NP-hard problems, which are Traveling Salesman Problem (TSP), Edge Detection, Network Packet Routing, Vehicular Routing, Quadratic Assignment Problem, and so on. In this paper we are using ACO for edge detection purpose. Since ACO and edge detection are well-researched field, there exist many algorithms for detecting edges using ACO.

Agrawal et al. [3] implemented ant colony optimization for edge detection which was compared with Sobel and Canny edge detector. The result of proposed approach outperformed edge detection using Sobel and Canny.

Edge detection using ant colony system was proposed by Tian et al.[4]. They proposed formula to calculate the number of ants. This method gave superior result compared to ACO which implemented ant system.

Verma and Sharma [1] presented edge detection approach using ACO which was combined with universal law of gravity. Theory of universal gravity was implemented to calculate the heuristic function which lead ant towards the most promising solution.

Fuzzy-ACO approach was proposed by Verma et al.[2]. The number of ants was calculated and placed at end point of image edges filtered by Sobel edge detector. Fuzzy derivative technique implemented fuzzy probability factor to decide the next most probable pixel to be edge.

ACO can avoid premature convergence by way of distributed computing but it converges slowly [1]. Since initially ants are randomly distributed, it may cause imbalance ant distribution which later affects path discovery process. Therefore, in this paper adaptive ACO is proposed to optimize ant distribution using gradient. The number of distributed ant is adaptively adjusted based on the number of gradient within image regions.

2. Methods

Ant Colony Optimization

ACO is meta heuristic approach, where the first ACO algorithm, called antsystem, was proposed in by Dorigo et al. Afterwards, there are several ACO approaches that improve basic ACO algorithm, which are Ant Colony System (ACS), Min-Max Ant System (MMAS), Elitist Ant System (EAS), Rank-Based Ant System (ASRank) and so on.

The main mechanism of ACO is the best path discovery using ant's pheromone updates. Each ant initially moves in random way to find the food. After getting food, ant returns back to its colony while laying down pheromone trails. Pheromone trails are used to mark the path between a food

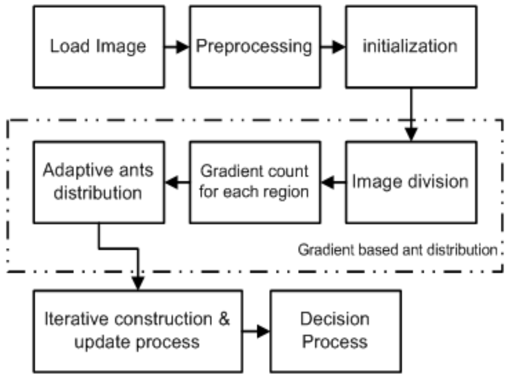

Figure 1. Flow Mechanism of Adaptive ACO

source and its colony. Afterwards, pheromone trails are used as references for subsequent ants to find foods. Subsequent ants may follow the existing path or create new path.

Pheromone may be evaporated over time. Thus, if there is no ant crosses the existing paths, those paths will soon dissappear. It also depends on time amount needed by ants to travel between nodes. In the other hand, if the existing paths are followed by ant, it may strengthen the pheromone trails on those paths.

Pheromone density remains high in shorter paths because pheromone set faster than evaporation. Since pheromone increases the likelihood of subsequent ants to choose the path, this mechanism leads ants to get better solution. In addition, ACO also uses heuristic information to help determining ant movement. It may be vary depends on the application. For instance pixel intensity is used as heuristic information in edge detection, whereas TSP uses distance between each node.

In this paper, instead of using Ant System, we prefer to use ACS algorithm. Since ACS has pseudorandom proportional rule to optimize ant's movement. Pseudorandom proportional rule uses user defined threshold (q_0),whose value is between 0 to 1, to complement traditional random proportional rule. On each ant's movement, it is needed to randomly generate q whose value is distributed between 0 and 1. If q is greater than q_0, then random proportional rule is used to decide ant's movement. However, if $q \leq q_0$, ant should move according to transition that maximizes $\tau_{ij}^{\alpha}\eta_{ij}^{\beta}$. Random proportional rule is given in equation(1).

$$P_{ij} = \frac{(\tau_{ij})^{\alpha}\,(\eta_{ij})^{\beta}}{\Sigma_{j\epsilon\Omega i}\,(\tau_{ij})^{\alpha}\,(\eta_{ij})^{\beta}}\ if\ j\ \epsilon\ \Omega_i \qquad (1)$$

The probability of ant movement to pixel on row i andcolumn j (P_{ij}) equals to multiplication of pheromone (τ)and heuristic information (η) which is divided by total multiplication of its 8-connectivity neighborhood. Both pheromone and heuristic information are equipped with pheromone wei-

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Do initialization procedures
Do image division into 4 regions
Do gradient count for each region
Do ant distribution based on gradient
ratio
for each iteration n = 1:N do
   for each construction_step l = 1:L do
      for each ant k = 1:K do
        Select and go to next pixel
        Update pixel's pheromone
      end
   end
   Update visited pixels' pheromones
end
```

Figure 2. Pseudocode of Adaptive ACO

ghting factor (α) and heuristic information weighting factor (β).

In addition, ACS has two pheromone update mechanisms, which are local pheromone update and global pheromone update. Local pheromone update is firstly introduced in ACS and cosidered as the most interesting contribution of ACS [4]. Formulas for local pheromone and global pheromone updates are defined in equation(2) and equation(3).

$$\tau_{ij} = (1 - \varphi).\tau_{ij} + \varphi.\tau_0 \quad (2)$$

$$\tau_{ij} = (1 - \rho).\tau_{ij} + \rho\,.\Delta\tau_{ij} \quad (3)$$

Local pheromone update aims to diversify the search performed by subsequent ants during an iteration [5]. It is implemented by using pheromone decay (φ) and pheromone init (τ_0) to decrease the pheromone concentration on the traversed edges. Therefore subsequent ants can produce different solutions. Whereas pheromone evaporation rate (ρ) and total deposit pheromone ($\Delta\tau_{ij}$) are used to implement global pheromone update.

Adaptive ACO

In this paper, we proposed new approach to optimize ant distribution in ACO for edge detection. Standard ACO used to randomly generate ants and place it over the image. This may cause imbalance ant distribution which later affects path discovery process.

Our proposed method intends to divide image into 4 equal regions anda adaptively distributes ants according to the number of potential edge within each region. Since edges are assumed to be high gradient pixel [6], proposed method uses gradient to forecast the ratio of potential edge within each region.Region which has bigger gradient value will get bigger number for ant distribution. Therefore it can optimize path discovery process in ACO. Flow mechanism and pseudo code of

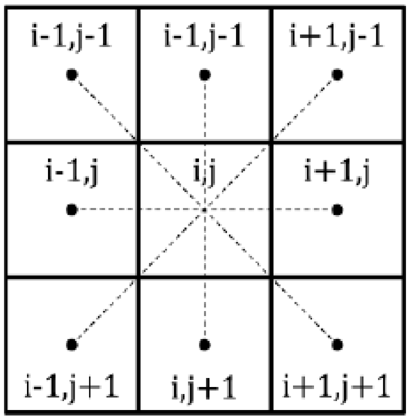

Figure 2. Pseudocode of Adaptive ACO

proposed method are presented in Figure 1 and Figure 2.

After being loaded, each image is converted to grayscale image and resized into user predefined size. Initialization comprises defining value for ACO parameters, which are number of ants (K), construction step (L), iteration (N), pheromone evaporation rate, and pheromone decay as well as the weighting factor for pheromone and heuristic information. K is taken from square root of image's high and image's width multiplication [4]. Formula to determine the number of ants is presented in equation(4).

$$K = \sqrt{width * height} \quad (4)$$

Heuristic information count and pheromone initialization are also conducted within this step. Pheromone init for each pixel is uniformly distributed between 0 and 1. Whereas, heuristic Information is derived from local variation of pixel intensity. Figure 3 presents configuration for computing local intensity variation of specific pixel.

Gradient based ant distribution covers mechanism to distribute ants based on gradient value within each region. Image will be divided into 4 equal regions whose gradients are counted separately. The proposed approach uses prewitt operator masks to count gradient value of each region as presented in Figure 4.

Iterative construction and update process represents path discovery process to find the best path as solution. For each iteration, ants movements are stored in special database called tabulist to ensure that ants do not visit the same pixel twice. Moreover, as presented in Figure 5, ant movement is restricted to 8-connectivity neighborhood. Whereas decision process implements Otsu thresholding to determine the best solution based on pheromone amount which is deposited in each pixel.

-1	0	1
-1	0	1
-1	0	1

-1	-1	-1
0	0	0
1	1	1

Figure 4. Convolution masks for counting gradient

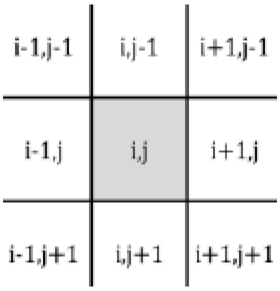

Figure 58-connectivity neighborhood : Permissible range of ant movement

3. Results and Analysis

Series of experiments are conducted to evaluate the performance of the proposed method using five test images which are (1) apple logo, (2) giraffe, (3) box, (4) church, and (5) dinosaur. Test images are taken from various image datasets. Apple logo and giraffe are taken from Brown University's image dataset [7]. Box and dinosaur belong to MIT Intrinsic images dataset [8]. Whereas church is Matlab image dataset [9]. Each image has different asymmetry degree which is presented in Table 1. As comparison, Figure 6 presents the preprocessed images with 128 x 128 resolution.

Previously, we had conducted several experiments to evaluate ACO parameter values which are not reported here. From those experiments, we have concluded that ACO parameter values are taken as presented in Table 2

Based on Table 3, standard ACO distributes ants randomly. However, adaptive ACO distributes ants adaptively based on gradient analysis. For apple logo image, ant distribution in both standard and adaptive ACO do not show significant difference due to its low degree of asymmetry. On the contrary, church and dinosaur have high degree of ant distribution. Since both images have high asymmetry degree.

Adaptive ACO combines the theory of standard ACO with Prewitt operator which is used for gradient calculation. Thus, we compare the result image among these three algorithms which are adaptive ACO, standard ACO, and Prewitt edge detector. In addition, we use the groundtruth image as standardization. Groundtruth of test images is provided in Figure 7. Whereas Figure 8, Figure 9, and Figure 10 present experimental results of standard ACO, adaptive ACO, and Prewitt edge detector.

TABLE 1
ASYMMETRY DEGREE OF IMAGES

Image	Gradient Ratio	The Asymmetry Degree
Apple logo	1:1:1:1	Low
Giraffe	2:1:2:1	Medium
Box	2:1:3:3	Medium
Church	4:1:5:2	High
Dinosaur	1:6:11:8	High

TABLE 2
PARAMETER VALUES FOR ACO

Parameter	Parameter Value
K	128
L	200
N	20
α	1
β	1
ρ	0.1
$\boldsymbol{\varphi}$	0.05

TABLE 3
PARAMETER VALUES FOR ACO

Image	Ant Distribution							
	Region (Standard ACO)				Region (Adaptive ACO)			
	1	2	3	4	1	2	3	4
Apple logo	37	33	24	34	28	29	34	37
Giraffe	37	30	30	31	32	20	51	25
Box	37	35	28	28	27	15	38	48
Church	32	34	32	30	42	10	51	25
Dinosaur	35	22	37	34	5	32	53	38

Figure 7 is more similar with Figure 8 than Figure 9 and Figure 10. It means that adaptive ACO returns more similar image to groundtruth than standard ACO and Prewitt edge detector. Since ants are distributed according to each region's gradient, region which has bigger gradient value get bigger number for ant distribution. On the contrary, region with lower gradient value will get fewer ants. Therefore ants can effectively move and edges are easier to be detected. However, eventhough potential edges have been found, ants will continuously search through image. Unfortunately, this may lead to edge thickening.

In order to compare the quality of proposed method, we quantitatively evaluate the performance using precision and recall. Precision or positive predictive value is the fraction of retrieved instances that are relevant. Precision equals to the number of true edge divided by the number of retrieved edge. Whereas recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Recall equals to the number of retrieved true edge divided by the number of edges that should have been returned. Precision and recall are expressed in equation(5) and equation(6).

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \quad (5)$$

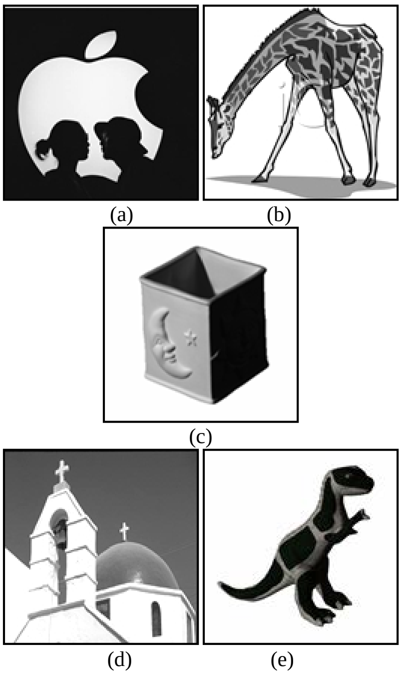

Figure 6. The original image dataset in 128 x 128 (a) Apple Logo (b) Giraffe (c) Box (d) Church (e) Dinosaur

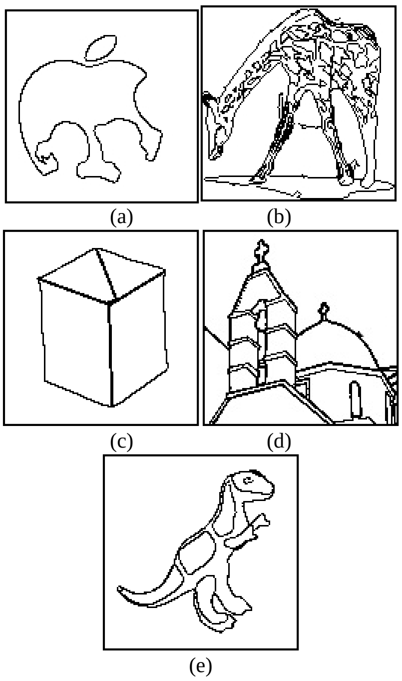

Figure 7. Groundtruth of (a) Apple Logo (b) Giraffe (c) Box (d) Church (e) Dinosaur

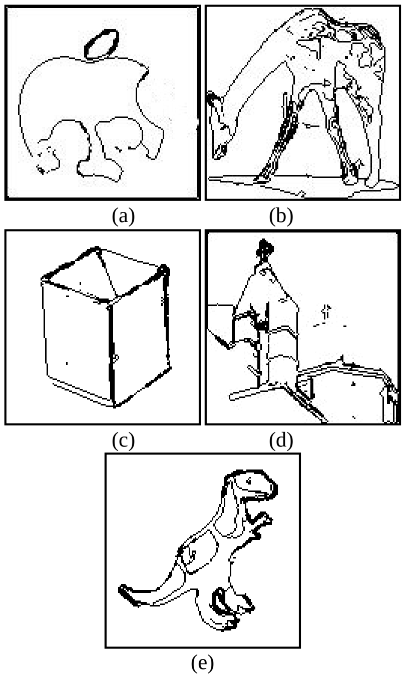

Figure 8. Experimental results of adaptive ACO in (a) Apple Logo (b) Giraffe (c) Box (d) Church (e) Dinosaur

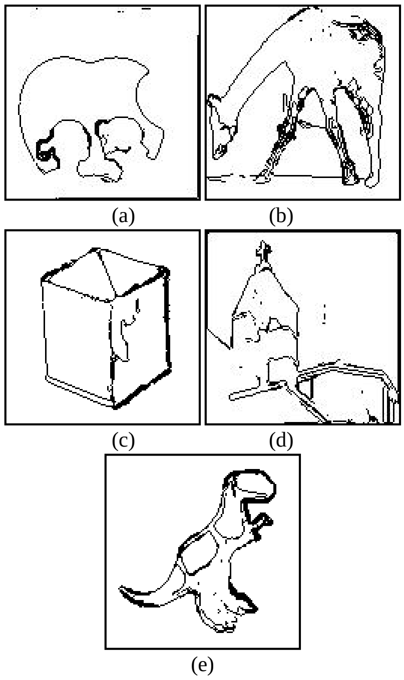

Figure 9. Experimental results of standard ACO in (a) Apple Logo (b) Giraffe (c) Box (d) Church (e) Dinosaur

$$Recall = \frac{true\ positive}{true\ positive + false\ negative} \qquad (6)$$

Based on equation(5) and equation(6), we calculate precision and recall using combination of true positive, false negative, and false positive. True positive is the number of retrieved true edge. False positive represents the number of retrieved background which is incorrectly classified. Whereas false negative is the number of pixel which is incorrectly classified as edge. Further details about

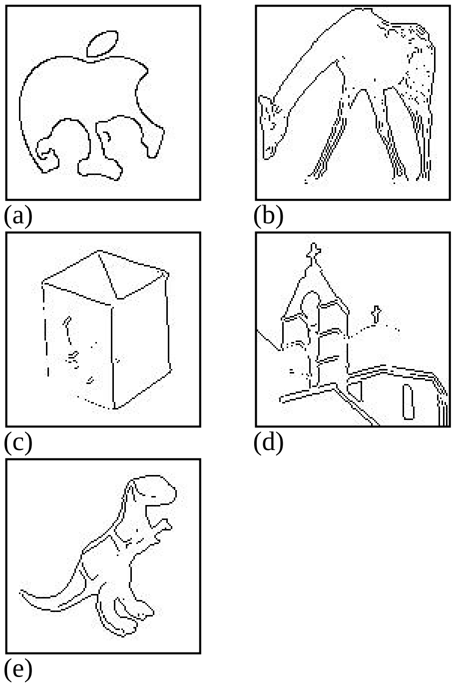

Figure 10. Experimental results of prewitt edge detector in (a) Apple Logo (b) Giraffe (c) Box (d) Church (e) Dinosaur

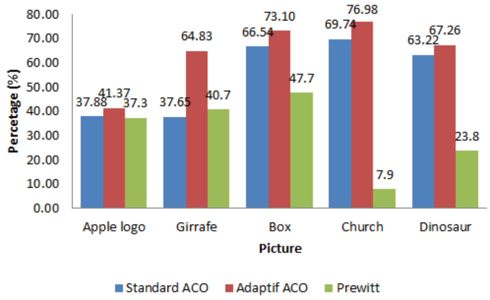

Figure 11. Performance evaluations of adaptive ACO, standard ACO, and Prewitt edge detector using precision

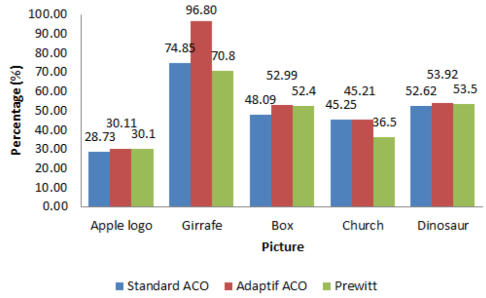

Figure 12. Performance evaluations of adaptive ACO, standard ACO, and Prewitt edge detector using recall

the comparison of precision and recall are presented in Figure 11 and Figure 12.

Edge thickening increases the number of false positive and decreases recall. However, based on Figure 11, the proposed method has the highest precision among those algorithms. It can be inferred that proposed approach can handle the excessive edge detection better than standard ACO and Prewitt edge detector. The proposed method can be applied in all test images which have various degree of asymmetry.

Figure 12 presents performance evaluation using recall. The proposed method has the highest recall. It means that the proposed approach can detect the true edge better. Adaptive ACO can be applied in all images with various degree of asymmetry. However, recall of proposed approach in image which has high degree of asymmetry does not show significant difference with other methods.

The proposed algorithm can produce images with better precision and recall of the adaptive ACO are better than standard ACO and Prewitt edge detector since the proposed approach can distribute ants adaptively based on image gradient.

4. Conclusion

It can be inferred from experimental results that the adaptive ACO outperforms standard ACO and Prewitt edge detector. Adaptively distributing ants using gradient can help optimizing results. Further research is needed not only to find automatic stopping criteria when all edges have been detected, but also to specify values of ACO parameters as well as the number of regions.

References

[1] Verma, Om P., & R. Sharma. "An Optimal edge Detection Using Universal Law of Gravity and Ant Colony Algorithm" *in World Congress on. IEEE*, pp. 507-511, 2011.

[2] Verma, Om P., Hanmandlu. M, Sultania. A Kumar, & Dhruv., "A Novel Fuzzy Ant System For Edge Detection," *In IEEE/ACIS International Conference on Computer and Information Scien*ce, pp. 228-233, 2010

[3] Agrawal, Prateek., Kaur, Simranjeet., & Dhiman, Amita., "Analysis and Synthesis of an Ant Colony Optimization Technique for Image Edge Detection" *in IEEE International Conference on Computing Sciences*, pp. 127 :131, 2012

[4] Tian, Jiang., Yu, Weiyu., & Xie Shengli, "An Ant Colony Optimization Algorithm For Image Edge Detection" *in IEEE Congress on Evolutionary Computation*, pp. 751: 756, 2008

[5] M. Dorigo, M. Birattari, & T. Stutzle, "Ant Colony: Artificial Ants as a Computational

Intelligence Technique" *in IEEE Computational Intelligence Magazine*, pp. 28 – 39, 2006.

[6] Gupta, C., & S. Gupta. "Edge Detection of an Image Based on Ant Colony Optimization Technique," *International Journal of Science and Research*, vol. 2.6, pp. 114-120, 2013.

[7] Brown University, Available Software and Databases, http://vision.lems.brown.edu/content/available-software-and-databases, 2010, retrieved March 13, 2014.

[8] Grosse, Roger., K. Johnson, Micah., H. Adelson, Edward., & T. Freeman, William. MIT Intrinsic Images, http://www.cs.toronto.edu/~rgrosse/intrinsic/gallery.html, 2009, retrieved March 13, 2014.

[9] Khaire, Pushpajit. Comparison of Edge Detectors, http://www.mathworks.com/matlabcentral/fileexchange/40005-comparison-of-edge-detectors/content/Comparison_of_Edge_detectors.zip, 2013, retrieved March 13, 2014.