Edge Detection Using Adaptive Thresholding and Ant Colony Optimization

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***Abstract*- In this paper, we present an approach for edge detection using adaptive thresholding and Ant Colony Optimization (ACO) algorithm to obtain a well-connected image edge map. Initially, the edge map of the image is obtained using adaptive thresholding. The end points obtained using adaptive threshoding are calculated and the ants are placed at these points. The movement of the ants is guided by the local variation in the pixel intensity values. The probability factor of only undetected neighboring pixels is taken into consideration while moving an ant to the next probable edge pixel. The two stopping rules are implemented to prevent the movement of ants through the pixel already detected using the adoptive thresholding. The results are qualitative analyze using Shanon's Entropy function.**

Keywords-Ant colony optimization, Adaptive thresholding, pheromone, Entropy, End points,

I. INTRODUCTION

An edge can be defined as sudden change of intensity in an image. In binary images, edge corresponds to sudden change in intensity level to 1 from 0 and vice versa. The most of the edge detectors are devised based on this criterion only. In the past years, many algorithms and approaches have been put forward to extract the edges of an image. For example, the Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction. The Prewitt [1] operator calculates the maximum response of a set of convolution kernels to find the local edge orientation for each pixel. The Canny detector [2] uses a multi-stage algorithm to detect a wide range of edges in images and defines edges as zero-crossing of second derivatives in the direction of greatest first derivative. Marr *et al* [3] proposed an algorithm that finds edges at the zero-crossings of the image Laplacian. Non-linear filtering techniques for edge detection also saw much advancement through the SUSAN [4]. However, these methods often result in some drawback like the broken edges which leads to loss of information. Many methods have been proposed in the past to link the broken edges too in order to improve the edge detection. In some approaches, Hough transformation [1, 5] is performed and specific shape is extracted to link the broken edges. However, the edges do not always have fixed shapes. Some other methods use hybrid techniques [6-7] to connect broken edges.

Ant colony optimization (ACO) is heuristic method that imitates the behavior of real ants to solve the discrete optimization problem [8]. Ant colony optimization takes inspiration from the foraging behavior of some ant species [9]. A foraging ant deposits a chemical (pheromone) which increases the probability of following the same path by other ants.

The first ACO algorithm, called the *ant system*, was proposed by Dorigo *et al.* [10]. Since then, a number of ACO algorithms have been developed, such as ant colony system [11], Max-Min ant system [12], ant colony algorithm for solving continuous optimization problem [13], an improved ACO for solving the complex combinatorial optimization problem [14-15], a novel fuzzy ant system for edge detection [16], edge improvement by ant colony optimization [17], ant colony optimization and statistical estimation approach to image edge detection [18], adaptive artificial ant colonies for edge detection in digital images [19], are reported in the literature. Recently, O.P. Verma *et al.*[20] have developed an algorithm for edge detection using BF in which direction of movement of bacteria is found using a directional probability matrix derived from ACO.

In the proposed study ant colony optimization is used to link the discontinuities in the edges while the edges are detected by adaptive thresholding [21]. The edge point information supplied by the adaptive thresholding is more than that supplied by the Sobel operator. Therefore the proposed study of applying ACO to the edges extracted from adaptive thresholding gives better results. The ACO methods are an iterative, probabilistic meta-heuristic for finding solutions to combinatorial optimization problems. They are based on the foraging mechanism employed by real ants attempting to find a short path from their nest to a food source.

The rest of the study is organized as follows: Section 2 gives a brief introduction of the ant colony optimization. The proposed technique is presented in Section 3. Section 4 presents experimental results and conclusions are drawn in Section 5.

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II. ANT COLONY OPTIMIZATION

Ant colony optimization (ACO) is a nature-inspired optimization algorithm that is motivated by the natural foraging behavior of ant species. Ants deposit the pheromone on the ground to mark paths between a food source and their colony. Pheromone is followed by other members of the colony. Over a time, pheromone trails evaporate. The amount of pheromone evaporation depends on the time taken by the ants to travel down the path and back again. The shorter paths get marched over faster. Pheromone densities remain high on shorter paths because pheromone is laid down faster. This positive feedback mechanism eventually leads the ants to follow the shorter paths. It is this natural phenomenon that inspired the development of the ACO metaheuristic.

In the ACO method, artificial ants use virtual pheromone to update their path through the image edges. ACO iteratively find the optimal solution of the target pixels through the movements of a number of ants over the image, by depositing and evaporating the pheromone trail. The probability for the ant's movement from one pixel to another is decided by probability transition matrix.

Establishment of probabilistic transition matrix and pheromone update is the two key issues in the ant colony optimization technique. During the n^{th} construction step, the k^{th} ant moves according to the probabilistic transition matrix defined as [22]:

$$Pij(n) = \frac{(\tau_{ij}{}^{(n)})^{\alpha}(\eta_{ij})^{\beta}}{\sum_{j\in\Omega_i}(\tau_{ij}{}^{(n)})^{\alpha}(\eta_{ij})^{\beta}} \qquad (1)$$

where $\tau_{i,j}^{(n)}$ is the pheromone information value of the arc linking the node i to the node j, $\eta_{i,j}$ represents the heuristic information for pixel (x,y) for going from node i to node j which is calculated using Eq. (2) ,and the constants α and β influence the pheromone information and heuristic information, respectively. All the possible neighboring pixels surrounding the central pixel at (x,y) are shown in Fig.1, where I (x,y) represents the intensity value at x,y.

I(x-1,y+1)	I(x,y+1)	I(x+1,y+1)
I(x-1,y)	I(x,y)	I(x+1,y)
I(x-1,y-1)	I(x, y-1)	I(x+1,y-1)

Fig. 1 Pixel (x, y) with its neighborhood pixel

The $\eta_{i,j}$ is calculated as [15]

$$\eta_{ij} = \frac{\max_{ij}\begin{pmatrix} |I(x-1,y-1) - I(x+1,y+1)|, \\ |I(x-1,y+1) - I(x+1,y-1)|, \\ |I(x,y-1) - I(x,y+1)|, \\ |I(x-1,y) - I(x+1,y)| \end{pmatrix}}{\eta_{\max}} \qquad (2)$$

Where η_{ij} is the heuristic information of pixel (x,y) and η_{max} is maximum heuristic value.

Pheromone intensity attracts the ant to follow the paths traversed by other ants. Hence, pheromone is updated twice, once after the movement of each ant and secondly after movement of all the ants. Each time an ant visits a pixel, it immediately performs a local update on the associated pheromone. The $\tau_{i,j}^{(n)}$, is updated by[22]:

$$\tau_{ij}{}^{(n)} = (1 - \Psi).\tau_{ij}{}^{(n-1)} + \Psi.\tau_{ij}{}^{(0)} \qquad (3)$$

where ψ ϵ (0,1] is the pheromone decay coefficient which diversifies the search by decreasing the desirability of edges that have already been traversed.

After the movement of all the ants during the construction step pheromone is updated globally using [16]:

$$\tau^{(n)} = \begin{cases} (1-\rho).\tau^{(n-1)} + \rho.\Delta\tau^{(k)} if\,(i,j) besttour, \\ \tau^{(n-1)}, otherwise \end{cases} \qquad (4)$$

where ρ ϵ (0,1] is the evaporation constant. ρ decreases the pheromone value related to the bad solution and thus prevents premature convergence to sub-optimal solutions. $\Delta\tau^{(k)}$is the amount of pheromone deposited by the ant which is given as follows[23]:

$$\Delta\tau^{(k)} = \frac{C}{L^k} \qquad (5)$$

whereL^k is the path length travelled by the k^{th}ant and C is a constant.

III. PROPOSED APPROACH

In the proposed approach, initially edges are extracted using adaptive thresholding. The connectivity of the edges so obtained is then increased using modified ACO.

3.1 Edge Detection using Adaptive Thresholding

Like global thresholding, the adaptive thresholding is used to separate desirable foreground image objects from the background based on the difference in pixel intensities of each region. Global thresholding uses a fixed threshold for all pixels in the image and therefore cannot deal with images containing a varying intensity gradient. Local adaptive thresholding, on the other hand, selects an individual threshold for each pixel based on the range of intensity values in its local neighbourhood.

Adaptive thresholding typically takes a gray scale or color image as input and, in the simplest implementation, outputs a binary image representing the edge information. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value. The flowchart for edge detection using adaptive thresholding is shown in Fig.2.

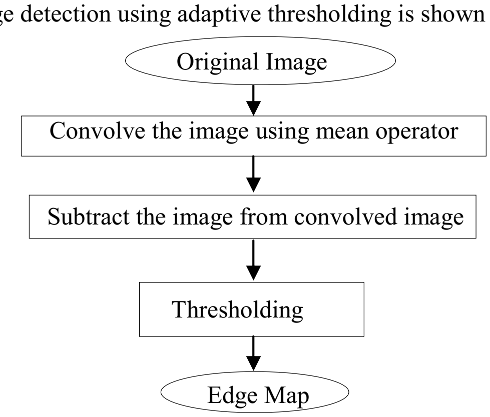


Fig.2 Flowchart for edge detection using adaptive thresholding

The edges obtained using above method contains some thick edges also therefore a thinning algorithm is implemented for the pre-processing for an efficient end point analysis [24]. The processed image is then analysed to obtain the end point information of the broken edges. The edges extracted from the above steps provide larger end point information as compared with that provided by Sobel operator.

3.2 Edge Improvement

Several discontinuities appear in the image after the application of adoptive thresholding. All the possible neighboring pixels surrounding the central pixel at (x,y) are shown in Fig 2. A central pixel position (x, y) is considered as the endpoint if only one (out of eight) of the neighboring pixels is white and the central pixel itself is also white. This is shown in Fig. 3, where the position (x, y) is the end point. A number of ants is equal to the number of endpoints and the ants are placed at the positions of the endpoints

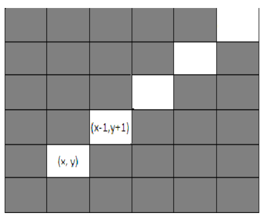


Fig.3 End point pixel (x,y)[16].

Following transition rule of has been used to find the next pixel position:

Transition rule: The transition rule takes into account the probability of undetected edge pixels only. For the ant movement, the probability factor for eight neighbouring pixels is calculated using probability transition matrix according to Eq. (1). The pixel with maximum probability factor of the undetected neighbouring pixels is included in the set of edge pixels.
To reduce the redundant movement of ants the stopping rules proposed in [16] has been implemented. These rules are shown in the Fig. 4.
Rule 1) The movement of the ant is stopped when it touches the track already traversed by another ant.
Rule 2) When all the neighboring pixels (8 pixels in 3*3 grid) are already traversed by the ant, then the movement of ant stops.

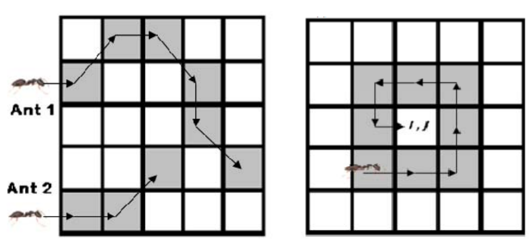


Fig.4 Ant's movement representing rule(1) and (2)[16]

3.3 The Ant Colony Algorithm for Edge Improvement
The ACO algorithm is used to increase the connectivity of the edges in the image obtained after applying local adaptive thresholding. The steps are as follows:

1) Initialize the ant's position by placing them only at end points.
2) Initialise the pheromone matrix and calculate the heuristic information using Eq.(2)
3) Construction Process:
For the ant index 1 : k
Move the k^{th} ant for L steps according to the probabilistic transition matrix using Eq. (1)
4) Calculate maximum probability of transition as per the t*ransition rule* and move the ant accordingly.
5) Perform local pheromone update process using Eq. (3)
6) Check whether all ants have moved one step, if yes, perform the global pheromone update using Eq. (4).
7) Check whether the ant can move to the next position by applying the stopping rules, if not, stop the ant.
8) Decision Process:
The pheromone matrix so produced is used to extract the complete edge trace by applying thresholding.
9) The edge pixels obtained are combined with the edge pixels obtained by adaptive thresholding to get the complete edge information.

The flow chart of the proposed algorithm is shown in Fig. 5.

IV. RESULTS AND DISCUSSION

4.1 Comparison with other techniques
This section presents the experimental results of the proposed technique against traditional edge detectors such as Canny, Edison, Prewitt, Sobel and Susan. In these experiments, traditional edge detectors are executed by MATLAB toolbox. The codes for our method were also written in MATLAB. The results were obtained using the following values of parameters: $\alpha = 0.5\ and \beta$=1. The edge pixels are colored white on a black background.

Fig.5. Shows the original images used for experiments. The Fig. 6(a)-(e) to 8 (a)-(e) shows the output after application of different edge detectors, Fig. 6(f) to 8(f) shows the output after adaptive thresholding, Fig 6(g) to 8(g) shows the output of ACO and Fig. 6(h) to 8(h) shows the output of the proposed method. The default values (which gives the best edge map) of the thresholding is selected while using the MATLAB function directly for the edge detectors. It can be seen that the more connected edge map is obtained by the proposed method. For example in Lena image the edge pixels pointed as A, B, C and D have not been detected by any other edge detectors. The proposed algorithm results in more edge pixels with reduced noise. Above discussion shows that the proposed method performs well as compared to other conventional edge detectors. It provides more edge information with noise reduced to a greater extent.

4.2 Shanon's Entropy
The performance of most of the edge detectors proposed in the literature is visually analyzed. Sometimes the visual analysis is insufficient to prove that the proposed method gives more connected edges. To overcome this problem we use the entropy function for quantitative analysis.
The information content of the output image is measured by using Shannon's entropy function. It gives the indefiniteness in an image and is calculated as:

$$H(I) = -\sum_{i=0}^{n} p_i \log p_i \qquad (6)$$

where, I stand for image whose entropy is to be measured. $p_i$is the frequency of pixels with intensity I. Table 1 shows the entropy values for various edge detectors. Higher the value of entropy higher will be the information content. However, a very large value of entropy shows larger noise content or double edges.

The Canny edge detectors produce double edges and SUSAN method produces a larger noise content, therefore the entropy value obtained using this two methods is higher as compared to the proposed method. The other edge detector namely Sobel, Prewitt and Edition gives the less edge information; therefore the entropy values obtained using these methods are less than the proposed method.

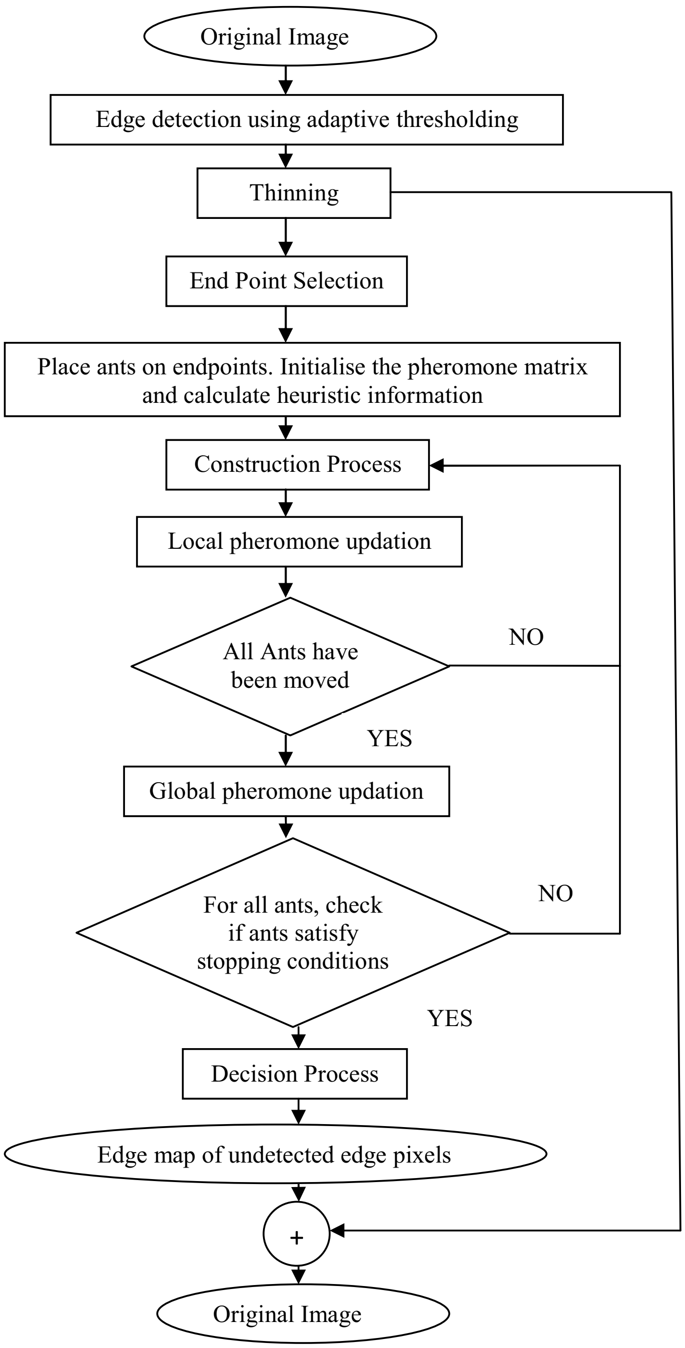


Fig.5 Flowchart for proposed algorithm

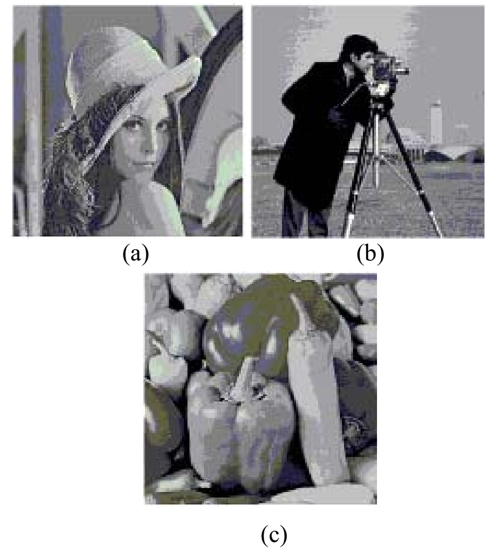


Figure 5 Original Images (a) Lena (b) Cameraman (c) Peppers.

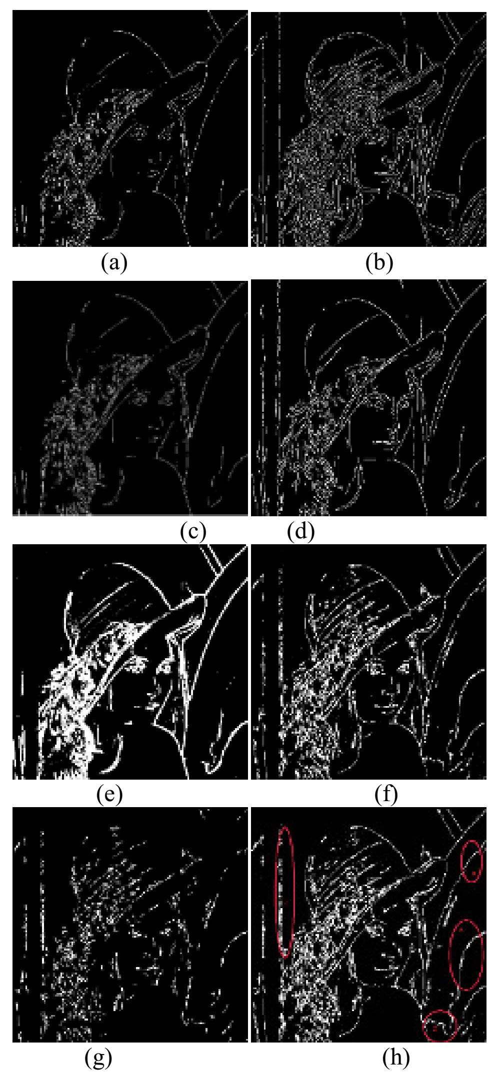
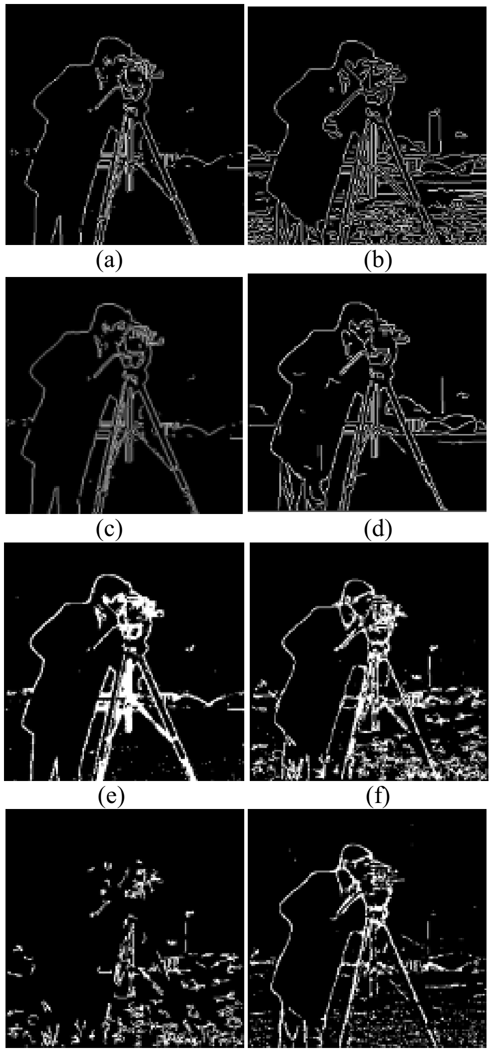
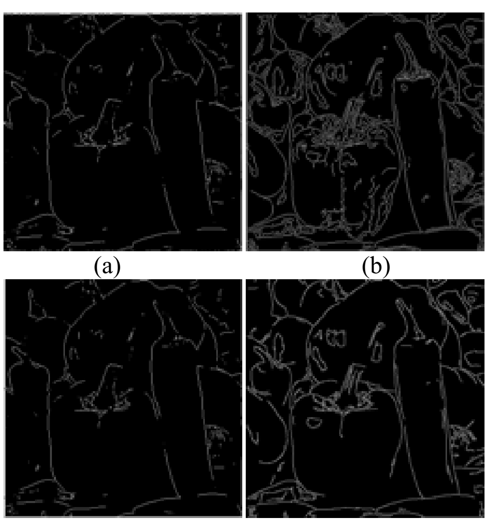


Figure 6. Edge map using (a) Sobel (b) Canny (c) Prewitt (d) Edison (e) SUSAN (f) Adaptive (g) ACO (h) Proposed.

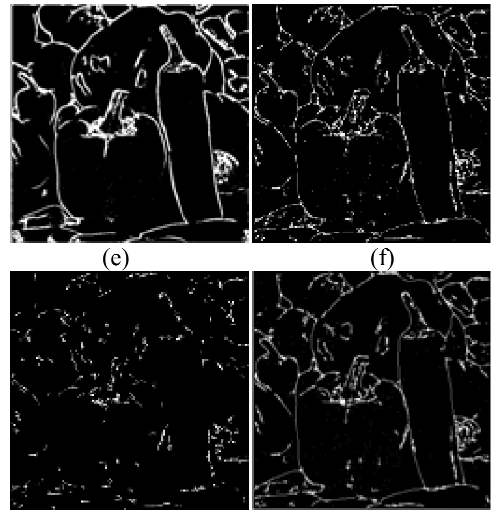


(a) (b)
(c) (d)
(e) (f)
(g) (h)

Figure 7. Edge map using (a) Sobel (b) Canny (c) Prewitt (d) Edison (e) SUSAN (f) Adaptive (g) ACO (h) Proposed.



(a) (b)
(c) (d)



(e) (f)
(g) (h)

Figure 8. Edge map using (a)Sobel (b)Canny (c)Prewitt (d)Edison (e) SUSAN (f)Adaptive (g)ACO (h)Proposed

4.3 Effect of parameter variation

In most of the application of ACO the selection of the two parameters namely α *and* β, affects the results. We examine the effect of these parameters on entropy value calculated for a test image (Lena). This effect is illustrated in Fig 9 and Fig 10. It is shown that entropy value is almost constant with the variation over a large range of these parameters.

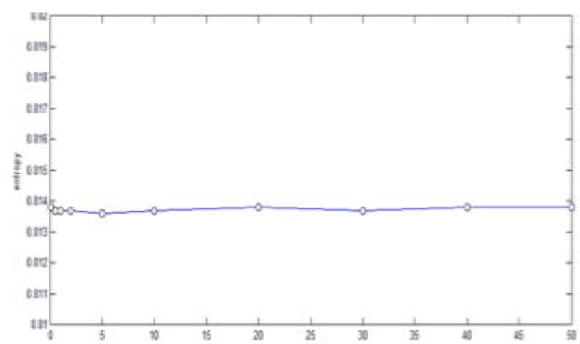


Figure 9. Variation of entropy with alpha

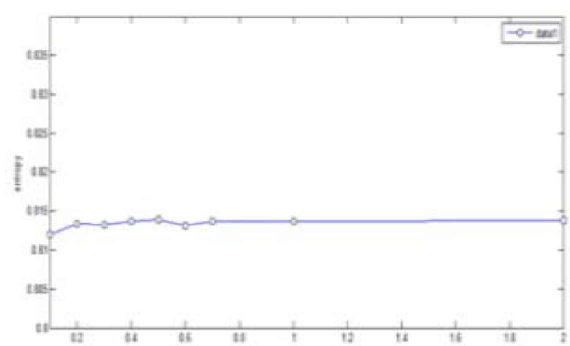


Figure 10. Variation of entropy with β

Table I Entropy values for different edge detectors

Image\Method	Sobel	Prewitt	Edison	Susan	Canny	Proposed
Lena	0.5314	0.5247	0.6774	1.05	0.8866	0.8137
Cameraman	0.5633	0.5629	0.6852	1.4081	0.9931	0.8013
House	0.4483	0.4447	0.8085	1.12	0.7354	0.6677
Pepper	0.3596	0.3493	0.6184	0.8894	0.7846	0.6837

V. CONCLUSIONS

Adaptive thresholding and ACO based image edge detection has been undertaken in this study. The adaptive thresholding is used for edge detection and ACO is used for edge improvement. The ants in the proposed study move on the edge pixels undetected by the adaptive thresholding method. This reduces the redundant edge pixels and results in more connected edges. For the qualitative analysis of the proposed method over the traditional edge detectors, the results are analyzed using Shannon's Entropy function. The edge detection through adaptive thresholding provides larger end points information as compared to traditional edge detector, therefore in the proposed study edges extracted from adaptive thresholding is preferred over the traditional edge detectors.

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