A Hybrid Approach to Edge Detection using Ant Colony Optimization and Fuzzy Logic

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Abstract

Edge detection aims to mark sharp intensity changes in an image and is a basis for a large number of image analysis and machine vision applications. Ant colony optimization is an evolutionary optimization algorithm which is inspired by food searching behaviour of ant species. An edge detection algorithm that combines an ant colony optimization and fuzzy logic is presented in this paper. The heuristics information for movement of ants is decided by using fuzzy logic. Experimental results are provided to demonstrate the superior performance of proposed method.

Keywords: *Ant colony optimization (ACO), Edge detection, Fuzzy logic*

1. Introduction

Edge is an important feature in an image and carries important information about the objects present in the image. Extraction of edges is known as edge detection. Edge detection aims to localize the boundaries of objects in an image and significantly reduces the amount of data to be processed. Ant colony optimization (ACO) is a nature inspired optimization algorithm that is motivated by natural foraging behaviour of ants [1]. It is a heuristic method that imitates the behaviour of real ants to solve discrete optimization problems [2]. The real ants communicate by means of a chemical substance called pheromone which they deposit on the ground in order to mark some preferred path that should be followed by other ants of the colony. The first ACO algorithm called the ant system was proposed by Dorigo et al. [3]. Since then a number of ACO algorithms have been developed [4] such as the Max-Min ant system [5] and the ant colony system [6].

Several approaches based on ACO have been proposed for edge detection [7]-[11]. In most papers, heuristic information for movement of ants is decided by values of pixels gray level gradient. In [12] improved ACS with pseudorandom proportional rule which strengthens the exploitation of the search experience accumulated by the ants is used. However selection of appropriate parameters used in their algorithm depends upon the nature of image. In [13] combination of ACO and statistical estimation of pixels intensity in its circular neighborhood is used for edge detection. In [14] ACO with fuzzy derivative is used for edge detection. The number of ants acting on the image is decided by the variation of fuzzy probability factor calculated from fuzzy derivatives.

However results obtained using this method are not very satisfactory. Many researchers have used fuzzy logic for edge detection, edge segmentation and image quality assessment. Several approaches based on fuzzy 'If – Then' rules have been reported for edge detection [16] [17] [18] 19]. In most of these methods, adjacent points of pixels are assumed in some classes and then fuzzy system inference are implemented using appropriate membership function defined for each class [20].

Proposed approach is different from the existing ACO based edged detection in following three ways. First, this approach uses ant colony system [6] while Nezambadi-Pour et al's[9] method uses ant system. Second, in our study, heuristics information for ant's movement is decided by fuzzy logic with simple rules. Third, the relative influence of the pheromone and heuristic information is not fixed as used in other methods [7]-[11] but dynamically updated. The paper is organized as follows. In section 2 fundamental concept of ACO for edge detection is presented. Section 3 describes the proposed method. Experimental results are presented in section 4. Finally section 5 concludes the paper.

2. Ant Colony Optimization for Edge Detection

ACO is a meta-heuristic population based approach for finding optimal solutions [1]. The basis of ACO is the food searching behaviour of real ants. While walking from their nest to the food source and vice versa, ants deposit on the way a kind of substance called pheromone whose concentration becomes weaker with elapse of time due to evaporation. Pheromone is used to exchange information about which path should be followed. The more the number of ants traces a given path, the stronger the pheromone concentration and thus more attractive this path becomes. The pheromone trail can help the ants find quickly the shortest way to the food sources.

In ACO algorithm for edge detection, ants move through a search space, the graph which consists of nodes and edges. The pixels in the digital image can be considered as the nodes of a graph. The movement of ants from a pixel to another pixel is probabilistically dictated by the transition probabilities. The transition probability reflects the likelihood that an ant will move from a given pixel to another. The transition probability depends upon the heuristic information and pheromone information. All pixels of the image are initialized with small value of pheromone. The heuristics information in most of the ACO based methods for edge detection is determined by local statistics at the pixel position. When an ant visits a pixel, it will deposit certain amount of pheromone. The more ants visit a pixel, the more pheromone deposition will be there on that pixel. In the end, edges can be detected by analyzing the pheromone distribution in the image. The whole procedure of the ACO is summarised as follows [4].

ACO Algorithm

- Initialize the positions of all ants as well as pheromone matrix (same size as image).
- For the construction step, move the ant K for L steps according to the probability transition matrix.
- Update the pheromone matrix.
- Make the binary decision to decide if there is an edge or not based on final pheromone matrix.

3. The Proposed Method

In the proposed approach, relative degree of edgeness for each pixel in the image is computed by segmenting the image by a floating 3x3 matrix. Edgeness is defined as degree to which a pixel at (i, j) is believed to be an edge when only local intensity variation around the pixel (i, j) is taken into account. Edgeness of a pixel is decided by first computing mean of intensities. Statistics mean is computed along rows and columns by applying statistics theory.

$$\text{Mean} = \frac{\sum f(\text{x, y})}{N} \tag{1}$$

In equation (1), x, y and f(x, y) denote the coordinate and gray level value of the pixels respectively and N denoted number of pixels along a row or a column. Pixel configuration is shown in Figure 1.

i-1, j-1	i, j-1	i+1, j-1
i-1, j	i, j	i+1, j
i-1,j+1	i, j+1	i+1, j+1

Figure 1. Pixel Configuration

3.1. Algorithm of the Proposed Method

In the proposed method, we compute Mrow, Mcol and Idiag which are defined as follows.

Step 1: Mrow = Mean of first row pixels intensity + Mean of third row pixels intensity -2* Mean of second row pixels intensity.

Mcol = Mean of first column pixels intensity + Mean of third Column pixels intensity -2* Mean of second column pixels intensity.

$$Idiag= |I_{i-1, j-1} - I_{i, j} + I_{i+1, j+1} - I_{i, j} + I_{i, j-1} - I_{i,j} + I_{i, j+1} - I_{i, j} + I_{i+1, j-1} - I_{i, j} + I_{i-1, j+1} - I_{i, j} + I_{i-1, j} - I_{i, j} + I_{i+1, j-1} - I_{i, j}|$$

Step 2: Compute edgeness of each pixel using rule based fuzzy inference system and multiply it with standard deviation of pixel intensities in 3x3 floating window.

Step 3: Construct pheromone matrix using modified ACO.

Step 4: Make the binary decision to decide if there is an edge or not based on final pheromone matrix.

Pixel configuration for computing Idiag is shown in Figure 2.

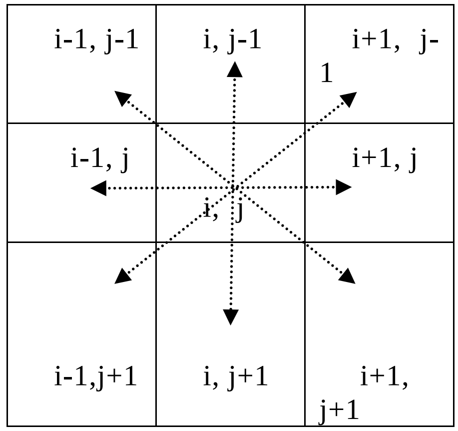

Figure 2. Configuration for Computing Idiag

The edgeness of each pixel is computed using mamdani type fuzzy rule based system. A gray level intensity image is first converted into double format (intensity range 0-1). Three classes for each of fuzzy inputs Mrow (Mrow_L, Mrow_M, Mrow_H), Mcol (Mcol_L, Mcol_M, Mcol_H) and Idiag (Idiag_L, Idiag_M, Idiag_H) are defined. A gaussian membership function is used for both inputs and outputs. In the output of fuzzy system, degree of edginess is denoted by Edgeness_L, Edgeness_M and Edgeness_H.

The parameters for each membership function were decided experimentally. Figure 3 shows the defined classes and membership function for Mrow, Mcol, Idiag and output respectively. Fuzzy rules used are defined as follows.

Rule 1: If (Mrow is Mrow_H) and (Idiag is Idiag_H) and (Mcol is Mcol_H) then (output is Edgeness_H).

Rule 2: If (Mrow is Mrow_L) and (Idiag is Idiag_H) and (Mcol is Mcol_M) then (output is Edgeness_H).

Rule 3: If (Mrow is Mrow_M) and (Idiag is Idiag_L) and (Mcol is Mcol_L) then (output is Edgeness_L).

Rule 4: If (Mrow is Mrow_H) and (Idiag is Idiag_L) and (Mcol is Mcol_L) then (output is Edgeness_L).

Rule 5: If (Mrow is Mrow_L) and (Idiag is Idiag_L) and (Mcol is Mcol_L) then (output is Edgeness_L).

Rule 6: If (Mrow is Mrow_M) and (Idiag is Idiag_M) and (Mcol is Mcol_M) then (output is Edgeness_M).

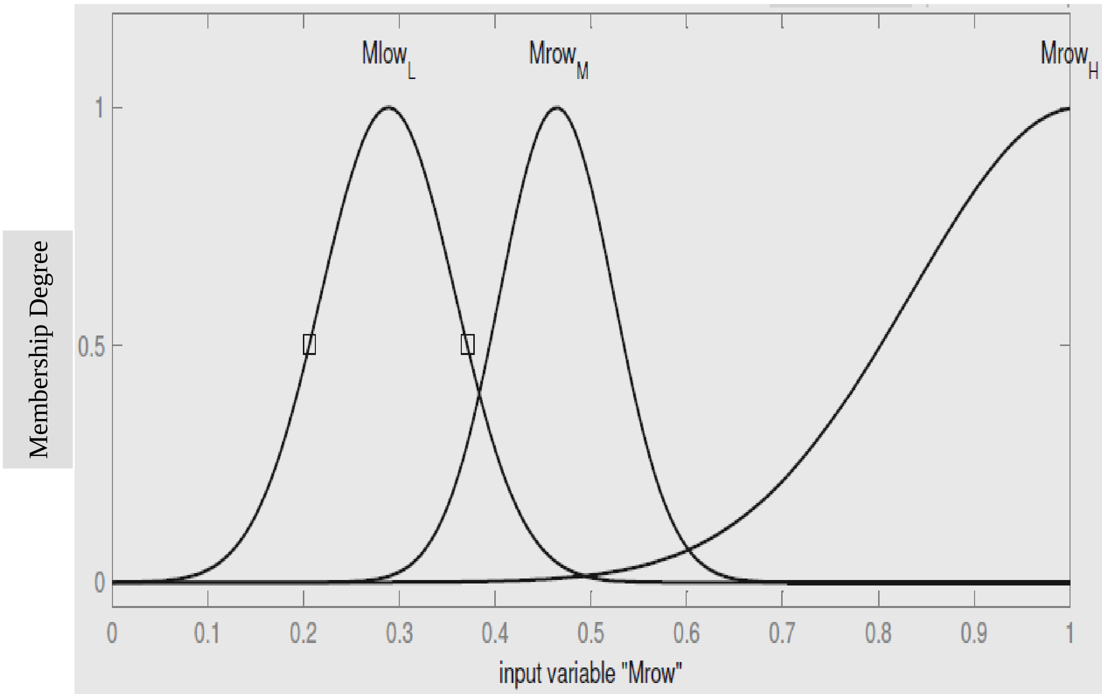

Figure 3(a).

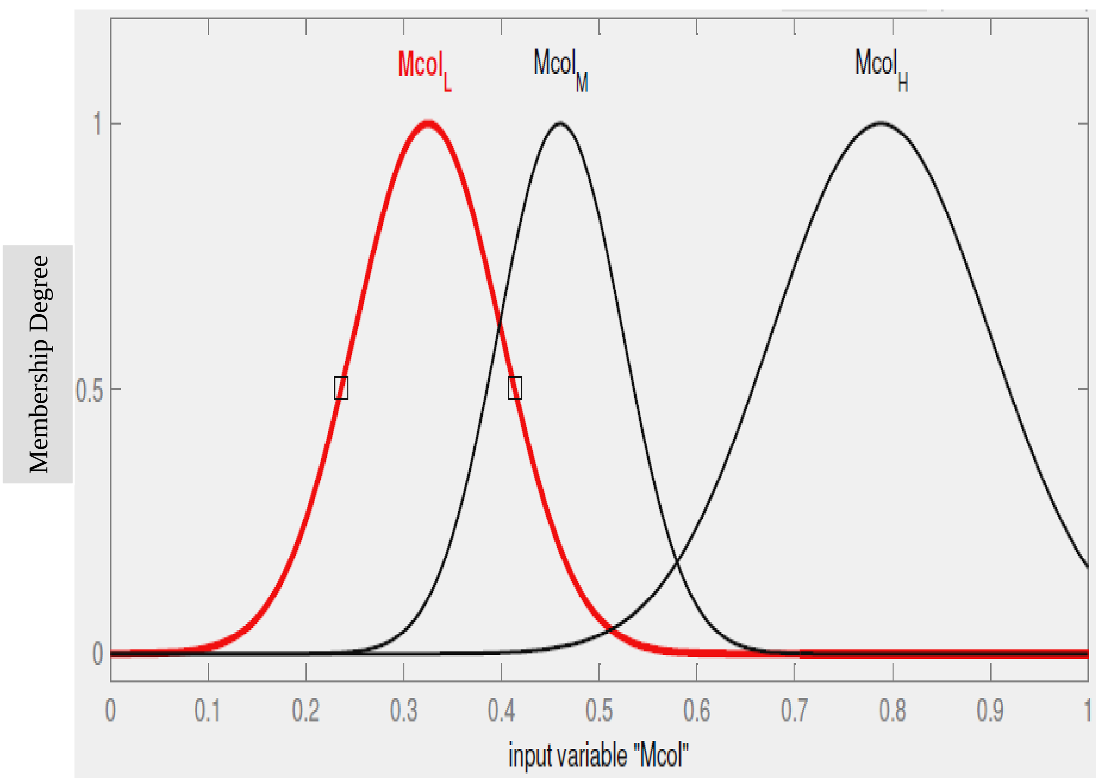

Figure 3(b).

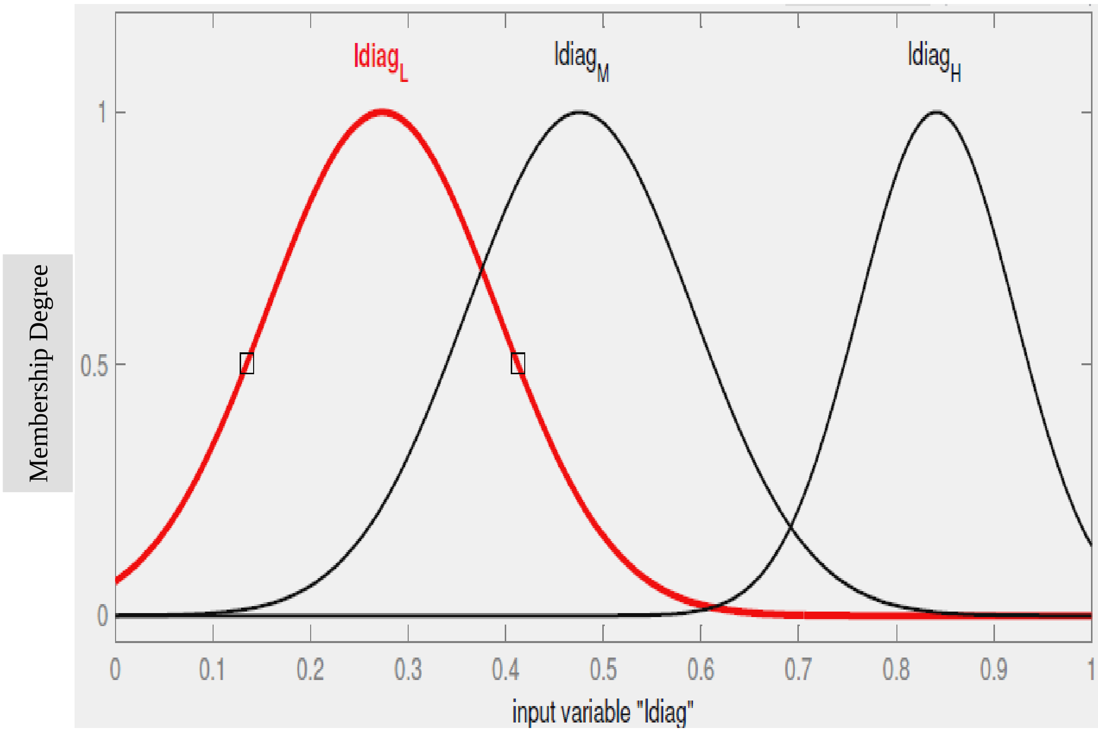

Figure 3(c).

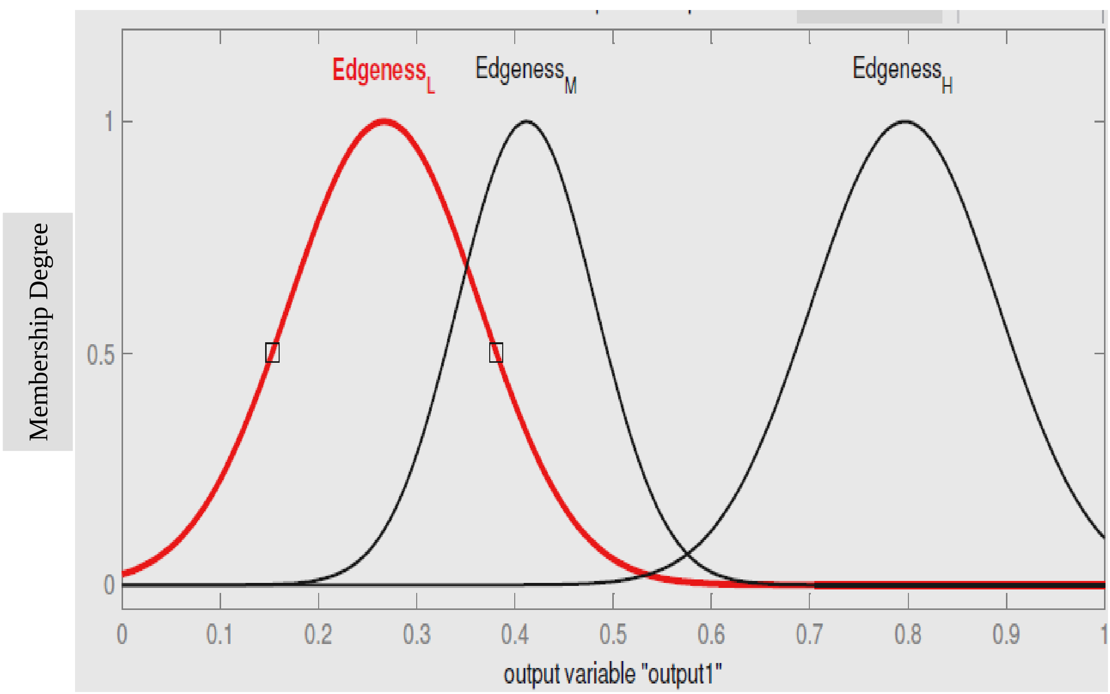

Figure 3(d).

Figure 3(a)-(d). Fuzzy Membership Functions of Mrow, Mcol, Idiag and Edgeness

The functions adopted to implement the “and” and “or” operations are the minimum and maximum functions respectively. Mamdani defuzzifier method is applied to produce the final edgeness of each pixel in the image. Each pixel in the edgeness image was normalized with total intensity of the edgeness matrix. ACO is then applied on the resultant matrix to generate pheromone matrix as follows.

The total number of ants is set to K (K = √ (M x N), M is number of rows and N is number of columns in the image). These ants are randomly assigned on the image with maximum one ant on each pixel. At each step, one ant is randomly selected and this ant will consecutively move on the image for T movement steps. The probability $P_{i,j}$ of ant k from pixel i to j at each step is given by equation (2).

$$P_{i,j} = \frac{(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum_{j\in L}(\tau_{i,j})^{\alpha}(\eta_{i,j)})^{\beta}} \tag{2}$$

Where $j \in L$ indicates all the pixels in the 8 neighbourhood of pixel i.

The pheromone value at pixel i, j is denoted by $\tau_{i,j}$. $\eta_{i,j}$ represents the heuristic information. Edgeness computed by fuzzy logic as described above represents the heuristic information in this case. The values of α and β are not constant but updated based on $\eta_{i,j}$. If the difference between maximum and minimum value of $\eta_{i,j}$ in 8–neighborhood of pixels is greater than 0.00003, the value of α is decreased by 0.00001 while value of β is increased by same amount else the reverse process is followed. These values have been decided experimentally. The purpose of updating α and β is to control the relative influence of heuristics information and pheromone value deposited at pixel. According to equation (2), an ant k at pixel i will move to pixel j which has the highest value of $P_{i,j}$.

The proposed approach performs two updates (local and global) for updating the pheromone matrix. The goal of the pheromone update is to increase the pheromone values associated with good solutions and decrease those associated with bad ones. Local pheromone update diversifies the search by decreasing the desirability of edges that have already been traversed. In other words the purpose of the local pheromone update rule is to make the visited edges less and less attractive as they are visited by ants, indirectly favouring the exploration of not yet visited edges. As a consequence, ants tend not to converge to a common path. The local update is performed after an ant moves from the current pixel i to next pixel j by using equation (3) and (4).

$$\tau_{i,j} = (1-\rho).\tau + \rho.\Delta\tau_{i,j} \tag{3}$$

$$\Delta\tau_{i,j} = \eta_{i,j} \tag{4}$$

Where $0 < \rho < 1$ indicates the pheromone evaporation rate, $\tau_{i,j}$ is current value of pheromone on that node, $\Delta\tau_{i,j}$ is the amount by which pheromone is increased.

The global update is performed after the movements of all ants within each cycle are completed. The pheromone matrix is updated using equation (5) as follows.

$$\tau_{i,j} = (1-\psi).\tau_{i,j} + \psi.\tau_0 \quad (5)$$

ψ is the pheromone decay coefficient and τ_0 is the initial value of pheromone. At the end, binary decision is made at each pixel to determine whether it is an edge or not by applying a threshold on the final pheromone matrix.

4. Experimental Results

The experiments and results are presented in this section. Three gray scale images (cameraman, Lena and Rice) are used as test images. In the algorithm, initial value of pheromone matrix was set to 0.0001. The control parameter α was changed from 5.0 to 4.0 in step of 0.00001 and β was increased from 0.3 in step of 0.00001. The pheromone evaporation rate (ρ) and pheromone decay coefficient (ψ) were set to 0.1 and 0.06 respectively. The total number of steps (T) in each cycle was taken as 35. Experimental results are provided to compare with Jing Tian et. al [18] and O.P. Verma et. al. edge detection method [24]. As seen from figure 4 and 5, the proposed method outperforms Jing Tian [18] and O.P. Verma et al [24] method in terms of visual quality of extracted image information.

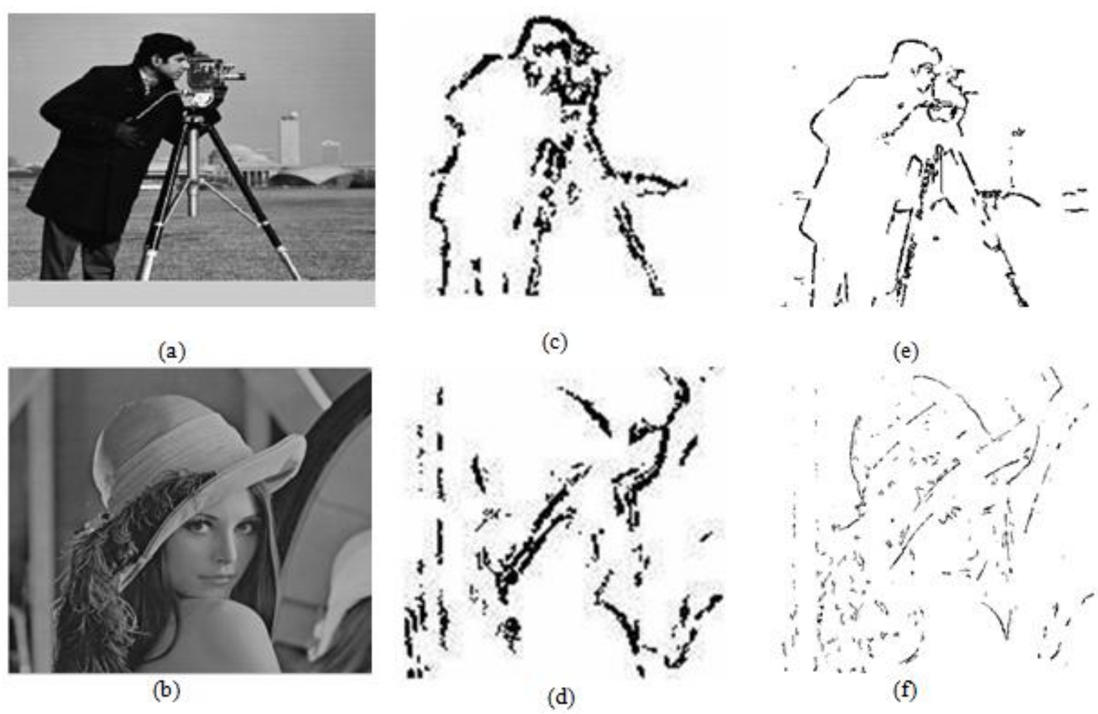

Figure 4. Original images and test results : (a) original image cameraman,(b) Lena, results of Jing Tian method (c),(d), results of proposed method;(e), (f)

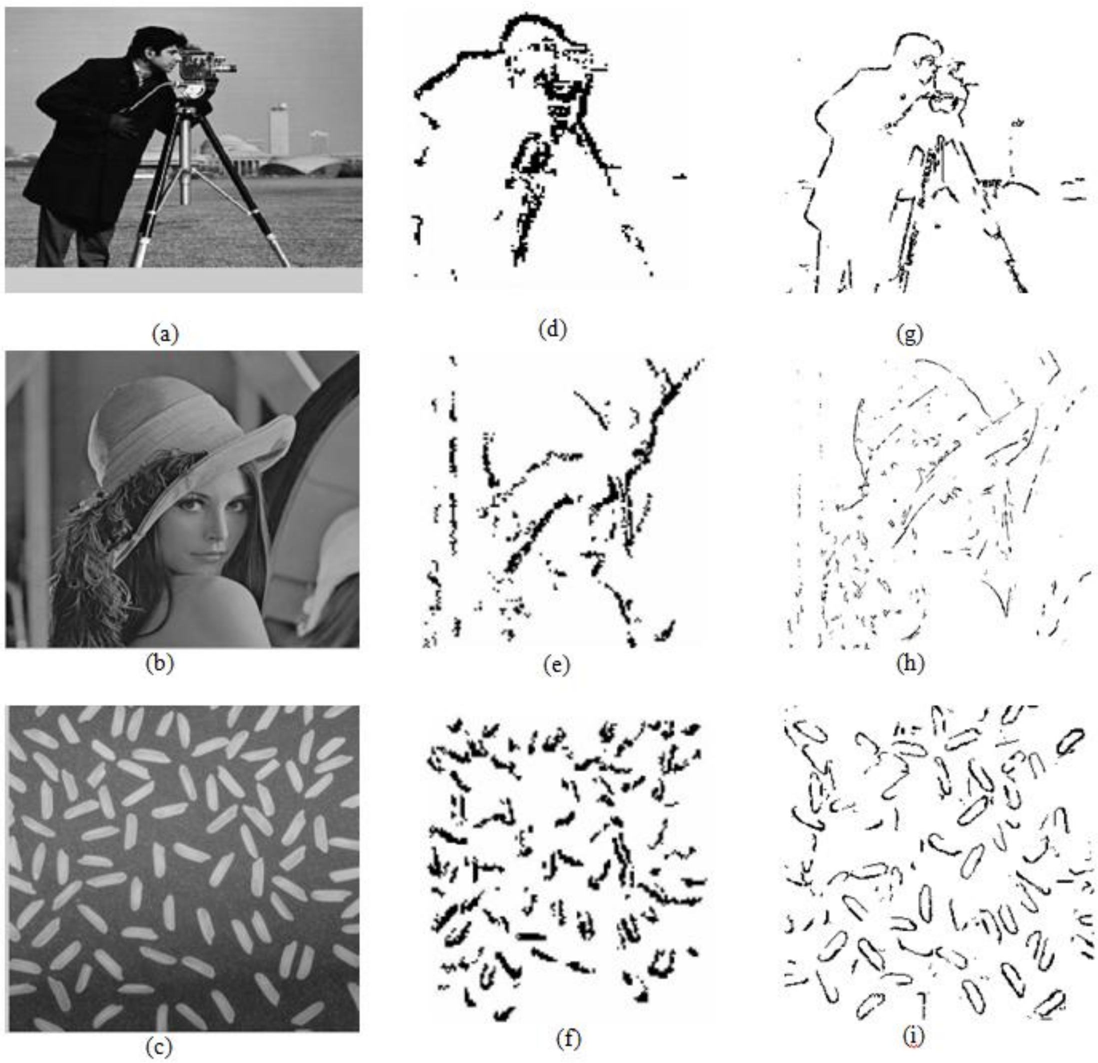

Figure 5. Original images and test results:(a) original image (a)cameraman,(b)Lena (c) Rice, Results of O.P. Verma's method (d),(e),(f), Results of proposed method;(g), (h), (i)

5. Conclusions

A hybrid approach for edge detection has been successfully developed by combining fuzzy logic and ACO. Superior performance of the proposed method is indicated in comparison with other ACO based methods for edge detection. In future work, methods to automatically set membership parameters used in fuzzy system will be explored.

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