Edge Detection in Image corrupted by Gaussian Noise Using Ant Colony Optimization

Vaibhav Ranjan, Avneesh Pandey, Prakash Chandra Joshi

Abstract— **Feature detection and Feature extraction are the major areas of computer vision and image processing. Edges in images provide structural information, feature extraction and object segmentation. However if the image is noisy, its hard to detect edges completely .In this paper; we introduce a new approach to detect edges in noisy images. We apply ant colony optimization algorithm for edge detection in an image having Gaussian noise. Removal of Gaussian noise from image causes lightening of edges and hence edge detection should be done before denoising an image**

Index Terms— **Ant Colony Optimization, Gaussian noise, Edge, Image edge detection.**

I. INTRODUCTION

Edges can be determined by identifying and highlighting the high intensity pixels contained within the image. Edge is the main characteristic of the image and provides useful information. However, in a noisy image it is difficult to find diminished edges. In this paper we add Gaussian noise to some sample images and detect edges. Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution[1][10]. Our aim is to detect the pixels where discontinuities or sharp change in gray level occurs in image .We apply Ant Colony Optimization algorithm for this problem.

Ant colony optimization (ACO) is a nature-inspired Optimization algorithm [2], [3].We use pheromone matrix in our algorithm .Pheromones are semiochemicals secreted from the body of individual ants to impact the behavior of another ant following it.

Our proposed algorithm drives ants to move within the image area and the movement is controlled by the local variation of the image's intensity values, to establish a pheromone matrix, which represents the edge.

II. ANT COLONY OPTIMIZATION

ACO uses guided search (i.e. path followed by ants moving ahead) in finding the optimal paths in a fully connected image. Ants move in image space from one to another, by constructing the pheromone matrix. If, K ants are applied to find the optimal solution in a space χ which consists of M1 × M2 nodes Ant colony optimization can be stated as follows [5]

i)Step 1 **Initialize the positions of totally K ants, as well as the pheromone matrix $\tau^{(0)}$**

ii) Step 2 **For the construction-step index n = 1 : N,**

– For the ant index k = 1 : K, .
consecutively move the k-th ant for L steps, according to a probabilistic transition matrix $p^{(n)}$ (with a size of M1M2 ×M1M2).

– Update the pheromone matrix $\tau^{(n)}$.

iii)Step 3 **Make the solution decision according to . the final Pheromone matrix $\tau^{(N)}$**

We establish two matrices, the probabilistic transition matrix $p^{(n)}$ and the update of the pheromone matrix $\tau^{(n)}$,It is determined by the probabilistic action rule, the source and the destination node. n is number of construction-step , k is the number of ant , i is the source node and j is the destination node. The probabilistic function is defined as follows [5]

$$P_{i,j}^{(n)} = \frac{(\tau_{i,j}^{(n-1)})^{\alpha} \quad (\eta_{i,j})^{\beta}}{\sum_{j\in\Omega_i}(\tau_{i,j}^{(n-1)})^{\alpha} \quad (\eta_{i,j})^{\beta}} \quad , \text{if } j \in \Omega_i, \qquad (1)$$

$\tau_{i,j}^{(n-1)}$ gives pheromone information of the path connecting nodes i and j; Ω_i is the neighborhood nodes for the ant a_k ; the constants α and β represent the influence of pheromone information and heuristic information, respectively; $\eta_{i,j}$ is the heuristic information for going from node i to node j, which is fixed to be same for each construction-step[4].Two consecutive updates of pheromone matrix take place.First after the movement of ant within each construction step, the pheromone matrix is updated as [5]

$$\tau_{i,j}^{(n)} = \begin{cases} (1-\rho).\tau_{i,j}^{(n)} + \rho.\Delta_{i,j}^{(k)} if\ (i,j), \\ \tau_{i,j}^{(n-1)} , \end{cases} \qquad ....(2)$$

ρ is the evaporation rate of the pheromones secreted by ants. Optimum results are gained as per criteria's defined by user. It could be either the best tour found in the current construction-step, or the best solution found since the start of the algorithm, or a combination of both of the above two [4]. The second update is performed after the move of all

Manuscript received Sep, 2014.
Vaibhav Ranjan*, M.Tech ,Computer Science & Engineering, Uttarakhand Technical University/ Dev Bhoomi Institute of Technology, +91 9897890546 Dehradun, India,*
Avneesh Pandey*, M.Tech ,Computer Science & Engineering,Uttarakhand Technical University/ Dev Bhoomi Institute of Technology,+91 9410979816 Dehradun, India,*
Prakash Chandra Joshi*, M.Tech ,Computer Science & Engineering, Uttarakhand Technical University/ Dev Bhoomi Institute of Technology,+91 8979491424 Dehradun, India,*

K ants within each construction-step; and the pheromone matrix is updated as [5]

$$\tau^{(n)} = (1-\psi).\tau^{(n-1)} + \psi.\tau^{(0)} \;, \qquad \ldots(3)$$

ψ is the *pheromone decay coefficient* .

III. PROPOSED ACO-BASED IMAGE EDGE DETECTION APPROACH IN NOISY IMAGE

Several ACO-based approaches to the edge detection problem have been proposed [7-9]. In our proposed method, ants move on a image from one node to another, constructing a pheromone matrix .Entries of this matrix represents the edge information at each pixel location of the image. The movements of the ants are controlled by the local variation of the image's intensity values. Following are the steps for our proposed technique.

A. Preprocessing

Gaussian noise is added into image I , having size M1×M2 Gaussian function is defined as follows

b = J + sqrt (p4)* randn (size(J)) + p3 ……. (4)

where I represents the input image , J is the converted gray image p3 is mean to be distributed and p4 is the variance. In proposed approach we keep variance p4 = 0.058 .

B. Initialization Process

K ants are randomly assigned on an image **I** with a of dimensions M1 ×M2 using random function. Initial value of each component of the pheromone matrix $\boldsymbol{\tau^{(0)}}$ is set to be a constant τ_{init} and kept small and non zero.

C. Iterative Construction Process

Construction process involves movement of the ant from one node to another. Ant moves from the node (l,m) to its neighboring node (i, j) according to a transition probability function. The transition function according t which the ant moves within the image from one pixel to another is as follows.[4]

$$P^{(n)}_{(l,m).(i,j)} = \frac{(\tau^{(n-1)}_{i,j})^{\alpha} \quad (\eta_{i,j})^{\beta}}{\sum_{(i,j)\in\Omega_{(l,m)}} (\tau^{(n-1)}_{i,j})^{\alpha} \quad (\eta_{i,j})^{\beta}} \;, \quad (5)$$

Where $\tau^{(n-1)}_{i,j}$ is the pheromone value of the node (i, j), Ω(l,m) is the neighborhood nodes of the node (l,m), $\eta_{i,j}$ represents the heuristic information at the node (i, j). The constants α and β represent the influence of the pheromone matrix and the heuristic matrix, respectively. Heuristic information $(\eta_{i,j})$ in the iterative construction process is determined with the help of following equation

$$\eta_{i,j} = \frac{1}{Z} V_c(I_{i,j}) \qquad \ldots\ldots \quad (6)$$

Where , Z is the normalization factor and can be mathematically written as .

$$Z = \textstyle\sum_{i=1:M_1} \sum_{j=1:M_2} V_c(I_{i,j}) \qquad ..(7)$$

Ii,j is the intensity value of the pixel at the position (i, j) of the image **I**, The function $V_c(I_{i,j})$ is a function that operates on the local group of pixels around the base pixel.

$V_c(I_{i,j}) = f(|I_{i-2,j-1} - I_{i+2,j+1}| + |I_{i-2,j+1} - I_{i+2,j-1}| + |I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j-1} - I_{i+1,j+1}| + |I_{i-1,j} -$ *Ii+1,j+Ii−1,j+1−Ii−1,j−1+Ii−1,j+2−Ii−1,j−2+Ii,j−1−Ii,j+1*) … (8)

To determine the function in (8), following four functions (9-10) are defined as follows.[4]

$$f(x) = \lambda x, for\ x \geq 0. \quad \ldots\ldots\ldots\ldots\ldots (9)$$

$$f(x) = \lambda x^2 \,, for\ x \geq 0. \quad \ldots.. \ldots\ldots..(10)$$

$$f(x) = \begin{cases} \sin(\frac{\pi x}{2\lambda}) & 0 \leq x \leq \lambda \ldots \ldots(11) \\ 0 & \end{cases}$$

$$f(x) = \begin{cases} \frac{\pi x \sin(\frac{\pi x}{\lambda})}{\lambda} & 0 \leq x \leq \lambda \ldots.\ (12) \\ 0 & \end{cases}$$

else, reshape is done by the parameter λ.

We use either the 4-connectivity neighborhood or the 8-connectivity neighborhood to find the permissible range of ant within the image. An ant can move to any adjacent pixel. But, this is restricted by the condition that an ant moves only to a node that it has not recently visited. This is to prevent the ants from visiting the same set of nodes repeatedly. In order to keep track of the recently visited nodes, each ant has a memory.

$I_{i-1,j+1}$	$I_{i,j+1}$	$I_{i+1,j+1}$
$I_{i-1,j}$	$I_{i,j}$	$I_{i+1,j}$
$I_{i-1,j-1}$	$I_{i,j-1}$	$I_{i+1,j-1}$

Fig.1. Neighborhood gray marking of pixel $I_{i,j}$ having 4-connectivity neighborhood.

ISSN: 2278 – 1323

$I_{i-1,j+1}$	$I_{i,j+1}$	$I_{i+1,j+1}$
$I_{i-1,j}$	$I_{i,j}$	$I_{i+1,j}$
$I_{i-1,j-1}$	$I_{i,j-1}$	$I_{i+1,j-1}$

Fig.2. Neighborhood gray marking of pixel $I_{i,j}$ having 8-connectivity neighborhood.

D. Iterative Update Process

Global pheromone update is performed on pixels that have been visited by at least one ant. We perform two updates operations for updating the pheromone matrix. The first update is performed after the movement of each ant within each construction-step. Each component of the pheromone matrix is updated according to following. [4]

$$\tau_{i,j}^{(n)} = \begin{cases} (1-\rho).\tau_{i,j}^{(n-1)} + \rho\,.\Delta_{i,j}^{(k)} if(i,j) \\ if\ vistedby\ the\ current\ k-th \\ ant\ otherwise\,, \\ \tau_{i,j}^{(n-1)}\,, \end{cases} \quad …... (13)$$

$\Delta_{i,j}^{(k)}$ is determined by the heuristic matrix; that is, $\Delta_{i,j}^{(k)} = \eta_{i,j}$. the movement of all ants within each construction-step according to ,second updation is done according to equation [4] ,

$$\tau\,(n) = (1-\psi)\,.\tau^{(n-1)} + \psi\,.\tau^{(0)} \quad …..(14)$$

where ψ is defined in (3).

D. Decision Process

This process is performed at each node to classify it as edge or not, by applying a threshold T on the final pheromone matrix $\boldsymbol{\tau}^{(N)}$. The node is a edge or not at all .Threshold calculations are done on the basis of Threshold functions developed in [6].The initial threshold $T^{(0)}$ is selected as the mean value of the pheromone matrix. Now ,the entries of the pheromone matrix is classified into two categories according to the criterion that its value is lower than $T^{(0)}$ or larger than $T^{(0)}$ Then the new threshold is computed as the average of two mean values of each of above two categories[4]. This loop is iterated till threshold becomes constant.

Step 1: Initialize $T^{(0)}$ as

$$T^{(0)} = \frac{\sum_{i=1:M_1}\sum_{j=1:M_2}\tau_{i,j}^{(N)}}{M_{1}\,M_{1}} \quad (15)$$

and set the iteration index as l = 0.

Step 2: Separate the pheromone matrix $\boldsymbol{\tau}^{(N)}$ into two class using $T^{(l)}$ where the fist class consists entries of $\boldsymbol{\tau}$ that have smaller values than $T^{(l)}$, while the second class consists the rest entries of $\boldsymbol{\tau}$ .Next, calculate the mean of each of the above two categories via

$$m_L^{(l)} = \frac{\sum_{i=1:M_1}\sum_{j=1:M_2} g_{T^{(l)}}^{L}\ \tau_{i,j}^{(N)}}{\sum_{i=1:M_1}\sum_{j=1:M_2} h_{T^{(l)}}^{L}\ \tau_{i,j}^{(N)}} \quad …….(16)$$

$$m_U^{(l)} = \frac{\sum_{i=1:M_1}\sum_{j=1:M_2} g_{T^{(l)}}^{U}\tau_{i,j}^{(N)}}{\sum_{i=1:M_1}\sum_{j=1:M_2} h_{T^{(l)}}^{U}\ \tau_{i,j}^{(N)}} \quad …….(17)$$

Where

$$g_{T^{(l)}}^{L}(x) = \begin{cases} x\,, if\ x \le T^{(l)} \\ 0\ otherwise \end{cases} \quad …………(18)$$

$$h_{T^{(l)}}^{L}(x) = \begin{cases} 1\,, if\ x \le T^{(l)} \\ 0\,, otherwise \end{cases} \quad …………..(19)$$

$$g_{T^{(l)}}^{U}(x) = \begin{cases} x\,, if\ x \ge T^{(l)} \\ 0\ otherwise \end{cases} \quad …………..(20)$$

$$h_{T^{(l)}}^{U}(x) = \begin{cases} 1\,, if\ x \ge T^{(l)} \\ 0\ otherwise \end{cases} \quad ……………(21)$$

Step 3: Set the iteration index l=l + 1, and update the threshold as

$$T^{(l)} = \frac{m_L^{(l)} + m_U^{(l)}}{2} \quad (22)$$

Step 4: If $|\, T^{(l)} - T^{(n-l)}\,| > \epsilon$, then go to *Step 2*; otherwise, the iteration process is terminated and a binary decision is made on each pixel position (i, j) to determine whether it is edge (i.e., $E_{i,j} = 1$) or not (i.e., $E_{i,j} = 0$), based on the criterion

$$E_{i,j} = \begin{cases} 1, if\ \tau_{i,j}^{(N)} \ge\ T^{(l)} \\ 0\ otherwise \end{cases} \quad …..(23)$$

IV. Experimental Results

In this paper, Ant colony optimization algorithm is successfully applied to noisy images. This algorithm has been tested for various standard test images of different sizes and extensions. We used four standard images (a) cameraman image with dimension 128×128 pixels and extension .bmp; (b) Lena image with dimension 256×256 pixels and extension .bmp ;(c) House image with dimension 256×256 pixels and extension .png ; (d) parrot image with dimension 256×256 pixels and extension .png;. The proposed approach yields superior subjective performance to that of the existing edge detection algorithms in noisy images .Following are the results for the same. Some user defined parameters, used in this paper are as follows. However these values can be varied for different results for different images:

S.no	Variable	Used Value(can be varied)	Description
1	K	$\lfloor\sqrt{M_1 \times M_2}\rfloor$	Total Ants
2	τ_{init}	0.0001	Initial value, pheromone matrix
3	α	1	Weighting factor of pheromone matrix
4	β	0.1	Weighting factor of heuristic information
5	Ω	Range , 8	8-connectivity neighborhood
6	λ	1	Adjusting factor , equations(9-12)
7	ρ	0.1	Evaporation rate (13)
8	L	40	Number of movement steps
9	ψ	0.05	Pheromone decay coefficient (14)
10	ϵ	0.1	Tolerance value for decision box
11	N	4	Number of construction steps.
12	p4	0.058	Intensity of Gaussian noise(4)

Table 1. Parameters used in this approach

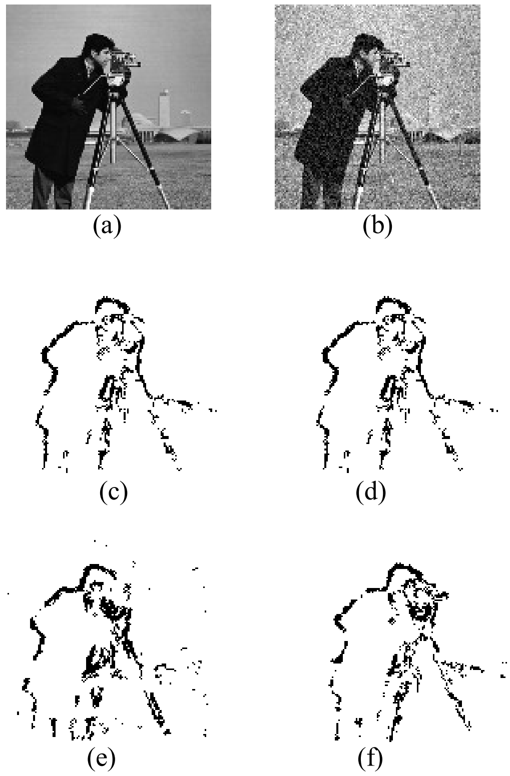


Fig.3. (a) Sample image cameraman with dimension 128×128 And extension .bmp ;(b) Added Gaussian noise of intensity 0.058; (c) Edge detected from noisy image with the help of function defined in(9) ;(d) Edge detected from noisy image with the help of function defined in(10) (e) Edge detected from noisy image with the help of function defined in(11); (f) Edge detected from noisy image with the help of function defined in(12)

ISSN: 2278 – 1323

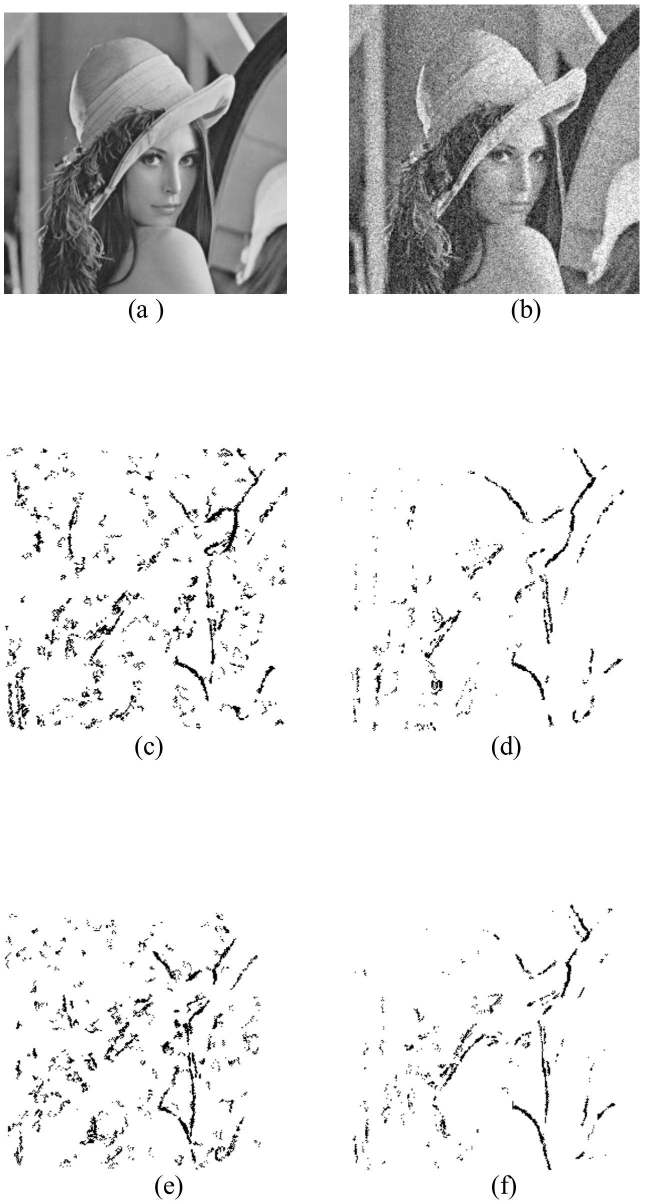


Fig .4. Fig (a) Sample image Lena with dimension 256×256 and extension .bmp ; (b) Added Gaussian noise of intensity 0.058 to Lena image ; (c) Edge detected from noisy image with the help of function defined in(9) ; (d) Edge detected from noisy image with the help of function defined in(10) ;(e) Edge detected from noisy image with the help of function defined in(11);(f) Edge detected from noisy image with the help of function defined in(12).

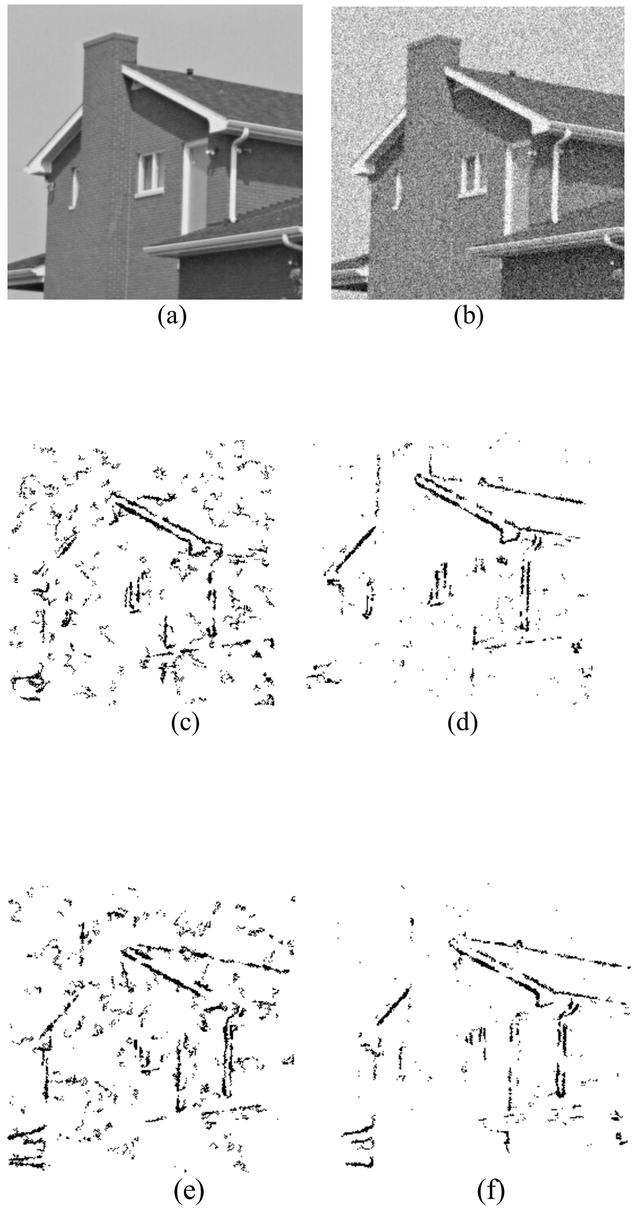
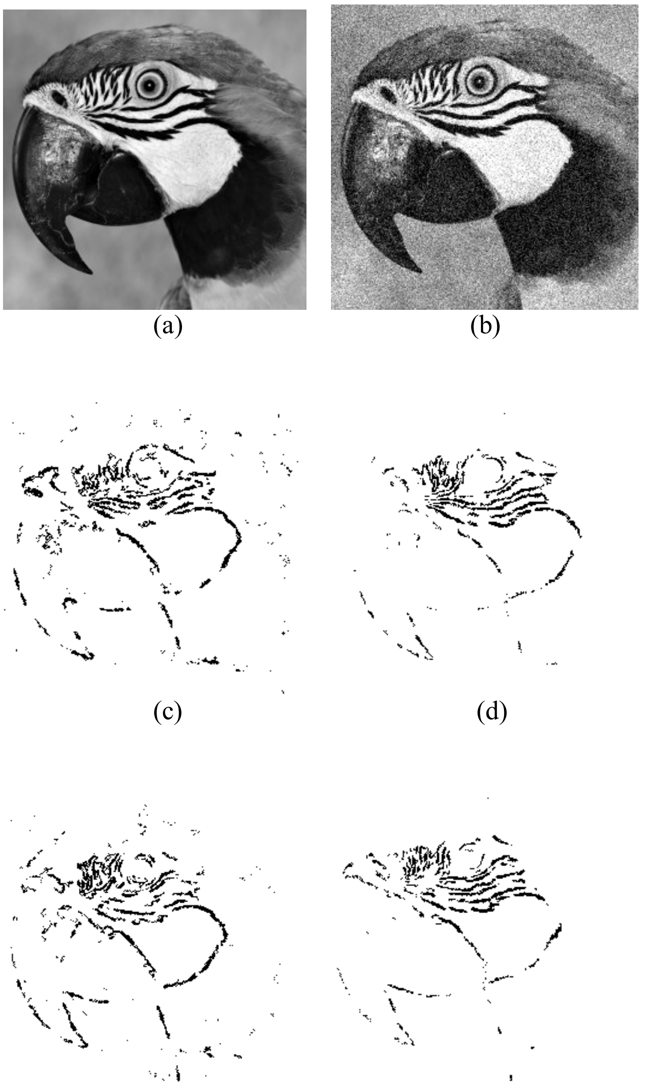


Fig.5. (a) Sample image House with dimension 256×256 and extension .png; (b) Added Gaussian noise of intensity 0.058 to house image; (c) Edge detected from noisy image with the help of function defined in (9) ;(d) Edge detected from noisy image with the help of function defined in (10) ;(e) Edge detected from noisy image with the help of function defined in (11); (f) Edge detected from noisy image with the help of function defined in (12).



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

Fig.6. (a) Sample image parrot with dimension 256×256 And extension .png; (b) Added Gaussian noise of intensity 0.058 to parrot image; (c) Edge detected from noisy image with the help of function defined in (9); (d) Edge detected from noisy image with the help of function defined in (10) ;(e) Edge detected from noisy image with the help of function defined in (11) ;(f) Edge detected from noisy image with the help of function defined in (12).

REFERENCES

[1] Tudor Barbu (2013). "Variational Image Denoising Approach with Diffusion Porous Media Flow". Abstract and Applied Analysis 2013: 8. doi:10.1155/2013/856876.

[2] M. Dorigo and S. Thomas, Ant Colony Optimization. Cambridge:MIT Press, 2004.

[3] H.-B. Duan, Ant Colony Algorithms: Theory and Applications. Beijing:Science Press, 2005

[4] Jing Tian, Weiyu Yu, and Shengli Xie ,An Ant Colony Optimization Algorithm For Image Edge Detection, 2008 IEEE Congress on Evolutionary Computation (CEC 2008)

[5] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization,"IEEE Computational Intelligence Magazine, vol. 1, pp. 28–39, Nov. 2006.

[6] N. Otsu, "A threshold selection method from gray level histograms," IEEE Trans. Syst., Man, Cybern., vol. 9, pp. 62–66, Jan. 1979.

[7] A. Rezaee, Extracting Edge of Images with Ant Colony, *Journal of Electrical Engineering*, Vol.59, No.1, 2008, pp. 57-59.

[8] H. Nezamabadi-pour, S. Saryazdi, and E. Rashedi, Edge Detection Using Ant Algorithms, *Soft Computing*, Vol.10, 2006, pp. 623-628.

[9] X. Zhuang, Edge Feature Extraction in Digital Images with the Ant Colony System, *IEEE International Conference in Computational Intelligence for Measurement Systems and Applications*, 2004.

[10] Barry Truax, ed. (1999). "Handbook for Acoustic Ecology" (Second ed.). Cambridge Street Publishing. Retrieved 2012-08-05.

Vaibhav Ranjan[1] [M.Tech Computer science and engineering, DBIT Dehradun][B.Tech Computer science and engineering, PTU] .Research area : Digital image processing , Wireless Sensor Network.

Avneesh Pandey[2] [M.Tech Computer science and engineering, DBIT Dehradun][B.Tech Computer science and engineering, PTU]
Research area : Wireless Sensor Network , Digital image processing

Prakash Chandra Joshi[3] [M.Tech Computer science and engineering, DBIT Dehradun][B.E Computer science and engineering, Nagpur University] Research area , Digital image processing , Graph database , Wireless Sensor Network.

ISSN: 2278 – 1323