Blind Image Deconvolution Technique for Image Restoration using Ant Colony Optimization

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ABSTRACT

Image Restoration is a field of Image Processing which deals with recovering an original and sharp image from a degraded image. Blind Image Deconvolution (BID) is a restoration technique where degraded image is restored in the absence of knowledge about the source of degradation of the image. It is very crucial part of image restoration to recover image without the knowledge of the reason of its degradation. Here, an estimate is done about the unknown degradation function and using that, an estimate of the original image is produced. This paper proposes a method that deals with restoration of degraded images which have been blurred by an unknown degradation function using Ant Colony Optimization (ACO) technique for detecting the blurred edges and removing the ringing effect from the detected edges. Ant Colony Optimization is a nature inspired methodology which is based on the foraging behavior of the real ant colonies.

Keywords

Improved binary product unit neural network, Improved binary pi-sigma neural network, Boolean function, principle conjunctive normal form, principle disjunctive normal form , hamming distance.

1. INTRODUCTION

Image restoration is to improve the quality of the degraded image. It is used to recover an image from distortions to its original image. It is an objective process which removes the effects of sensing environment. It is the process of recovering the original scene image from a degraded or observed image using knowledge about its nature. There are two broad categories of image restoration such as Image Deconvolution and Blind Image Deconvolution. Image Deconvolution is a linear image restoration problem where the parameters of the true image are estimated using the observed or degraded image and a known Point Spread Function (PSF).

Blind Image Deconvolution is a more difficult image restoration method where image recovery is performed with little or no prior knowledge of the degrading PSF. The advantages of Deconvolution are higher resolution and better quality. The main aim of Blind Image Deconvolution(BID) is to recover the original image from a degraded image which is blurred by an unknown degradation function, commonly by a Point Spread Function (PSF).This Technique allows the reconstruction of original images from degraded images even when we have very little or no knowledge about PSF.

This paper is structured as follows: Section II describes the image degradation and restoration model. Section III represents ACO based Edge Detection approach describing ACO, its procedure for edge detection and edge taper function. Section IV describes the overall architecture of proposed work. Section V describes experimental results for deblured images using our proposed algorithm. Section VI describes conclusion and future work.

2. IMAGE DEGRADATION / RESTORATION MODEL

In degradation model, original image is blurred using degradation function and additive noise. The degraded image is described as follows:

$$g = h * f + n \tag{1}$$

In equation (1), 'g' is the degraded image, 'h' is the degradation function, 'f' is an original image and 'n' is the additive noise.

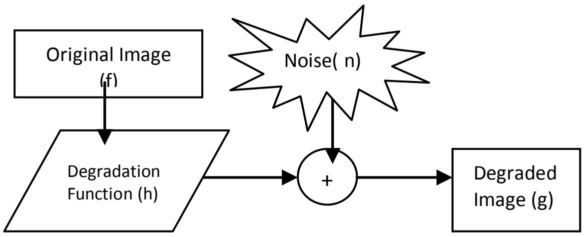

Fig. 1: Degradation Model

Restoration Model

In Restoration model, the degraded image is reconstructed using restoration filters. It performs the inverse process of degradation by removing additive noise and blur factor. We get an estimate of the original image as a result of restoration. The closer the estimated image is to the original image the more efficient is our restoration filter.

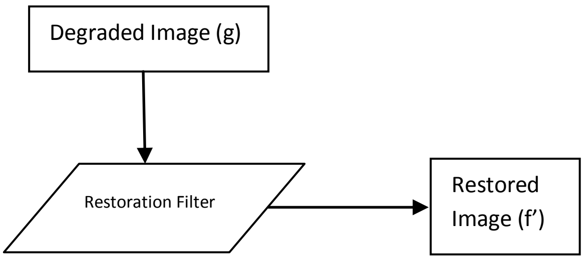

Fig. 2: Restoration Model

3. 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 pheromone on the ground to mark paths between a food source and their colony, which should be followed by other members of the colony. With time, pheromone trails evaporate. The longer it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. Shorter and thus, favorable paths get marched over faster and receive greater compensation for pheromone evaporation. 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.

a) Ant Colony Optimization for Edge detection

During the deconvolution process, high frequency drop-off at the edges of images can occur due to the debluring functions. This high frequency drop-off can create an effect called boundary related ringing in deblured images. For avoiding this ringing effect at the edges of the image, we have to detect the edges of an image. There are various edge detection methods available to detect an edge of the image such as Sobel, Prewitt, Roberts, and Canny. The edges can be detected effectively using Ant colony Optimization method. Edge provides a number of derivative (of the intensity is larger than threshold) estimators. The edge can be detected for checking whether there exists ringing effect in an input image or not.

b) Procedure for ACO-based edge detection

ACO-based image edge detection approach utilizes a number of ants to move on an image for constructing a pheromone matrix. Each entry of pheromone matrix represents the edge information at each pixel location of the image. The movements of the ants are steered by the local variation of the image's intensity values. The whole procedure is divided into following five processes:

- Initialization Process
- Construction Process
- Update Process
- Decision Process

It starts from the *initialization process* and then runs for N iterations to construct the pheromone matrix by iteratively performing both the *construction process* and the *update process*. Finally, the *decision process* is performed to determine the edge. Each of these processes is presented in detail as follows, respectively.

Initialization Process

Here total K ants are randomly assigned on an image I of size M1 × M2, each pixel of which can be viewed as a node. The initial value of each component of the pheromone matrix $\boldsymbol{\tau}$ (0) is set to be a constant $\boldsymbol{\tau}_{init}$=0.0001.

$$K = \left\lfloor \sqrt{M1 * M2} \right\rfloor \qquad (2)$$

Construction Process

At the n^{th} construction-step, one ant is randomly selected from the above-mentioned total K ants and this ant will consecutively move on the image for L movement-steps. This ant moves from the node (l,m) to its neighboring node (i, j) according to a transition probability that is defined as:

$$p^{(n)}_{(l,m),(i,j)} = \frac{(\tau_{i,j}^{(n-1)})^{\alpha}(\eta_{i,j})^{\beta}}{\sum_{(i,j)\in\Omega(l,m)}(\tau_{i,j}^{(n-1)})^{\alpha}(\eta_{i,j})^{\beta}} \qquad (3)$$

where $\tau_{i,j}^{(n-1)}$ 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. Various parameters of equation (3) are set as follows:

α = 1: weighing factor of pheromone information.

B =0.1: weighing factor of heuristic information.

L = 40: total number of ant's movement-steps within each construction-step.

N = 4: total number of construction-steps.

Ω= 8: connectivity neighborhood as shown in figure below:

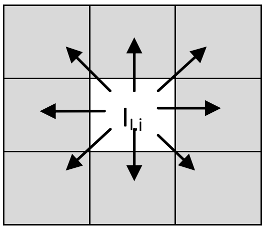

Fig.3:8 connectivity neighborhood for pixel $I_{i,j}$

Update Process

The proposed approach performs two updates operations for updating the pheromone matrix:

a) 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:

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho).\tau_{i,j}^{(n-1)} + \rho.\Delta_{i,j}^{(k)}, & if\ (i,j) is\ visited\ by\ the\ current\ k-th\ ant; \\ \tau_{i,j}^{(n-1)},\ otherwise \end{cases} \qquad (4)$$

where, ρ is the evaporation rate= 0.1, $\Delta_{i,j}^{(k)}$ is determined by heuristic matrix = $\eta_{i,j}$

b) The second update is carried out after the movement of all ants within each construction-step according to:

$$\tau^{(n)} = (1-\Psi).\tau^{(n-1)} + \Psi.\tau^{(0)} \qquad (5)$$

where, Ψ is pheromone decay coefficient =0.05.

Decision Process

In this step, a binary decision is made at each pixel location to determine whether it is edge or not, by applying a threshold T on the final pheromone matrix $\boldsymbol{\tau}^{(N)}$.

$$E_{i,j} = \begin{cases} 1,\ if\ \tau_{i,j}^{(n)} \geq T; \\ 0,\ otherwise \end{cases} \qquad (6)$$

The initial threshold T(0) is selected as the mean value of the pheromone matrix. Next, 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. The above process is repeated until the threshold value does not change any more.

Summary of ACO-based edge detection

The whole process of the proposed approach for edge detection using ACO is summarized as shown in figure below:

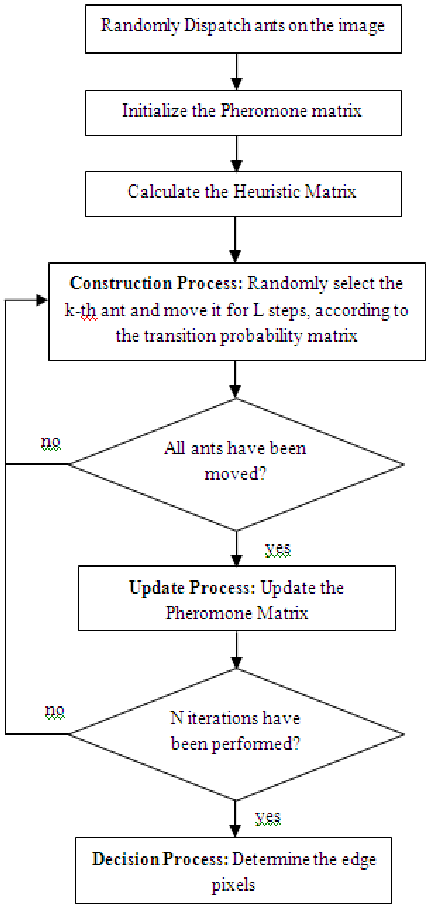

Fig.4: Summary of ACO based edge detection

c) Edge taper for Ringing Effect

The ringing effect can be avoided using edge taper function. Edge taper function is used to preprocess our image before passing it to the debluring functions. It removes the high frequency drop-off at the edge of an image by blurring the entire image & then replacing the center pixels of the blurred image with the original image.

4. OVERALL ARCHITECTURE

The main focus of this proposed work is to restore an original image from a degraded image that has been degraded by some unknown sources. Firstly, an image is degraded using Gaussian blur, then this is image is restored using blind image deconvolution. During the deconvolution process, high frequency drop-off at the edges of images can occur due to the debluring functions. This high frequency drop-off can create an effect called boundary related ringing in deblured images. For avoiding this ringing effect at the edge of image, we have to detect the edges of an image. Ant colony optimization based edge detection is done to find out the ringing effects near the edges of the image. Then this ringing effect is removed using edge taper function and as a result we get an improved quality image. The overall architecture of the proposed approach is explained in figure bellow:

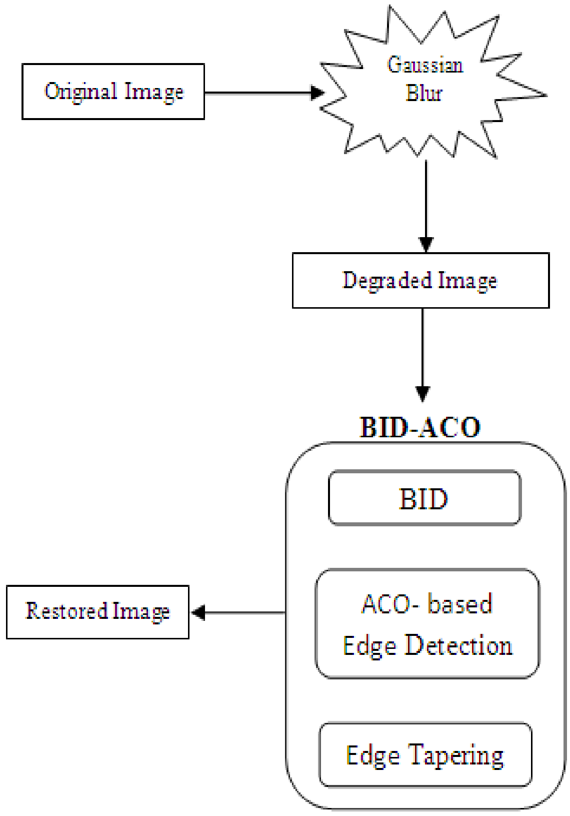

Fig. 5: Overall architecture of BID-ACO

The whole process of Ant Colony Optimization based Blind Image Deconvolution i.e. BID-ACO is described by the following procedure:

1) Read an original input image f(x, y).
2) Degrade the original image with Gaussian Blur function to get a blurred image g(x,y).
3) Now restore the degraded image with deconvblind function to get a restored image having ringing effects at its edges.
4) To remove the ringing effect at edges, ACO based edge detection is done :
   a) Initialize the positions of total K ants, as well as the pheromone matrix $\boldsymbol{\tau}(0)$.
      - For the construction-step index set 'n' = 1 : N,
        - For the ant index set k = 1 : K,
          - Consecutively move the k-th ant for L steps, according to a probabilistic transition matrix **p**(n).
        - Update the pheromone matrix $\boldsymbol{\tau}(n)$.
   b) Make the solution decision according to the final pheromone matrix $\boldsymbol{\tau}(N)$.
5) Apply edge taper function to remove ringing effects at the edges detected using ACO.
6) Finally, we get a restored image f'(x,y).

5. EXPERIMENTAL RESULT

The proposed approach is experimented using a test image 'cameraman.tif' of size 256 x 256.The below images represent the result of degradation model using Gaussian blur.

Fig. 6: Original image

Image shown in Fig.6 represents the original image 'cameraman.tiff' of size 256 x 256.

Fig.7: Blurred Image

Above figure shows the blurred image which is degraded with Gaussian blur.

Fig. 8: ACO edges

Fig. 9 shows the edges of the image detected using ACO based edge detection method.

Fig. 9 : Restored Image

This is final output image of the proposed work i.e BID-ACO.

6. CONCLUSION

We have presented a method for blind image deconvolution using Ant Colony Optimization. The method differs from most other existing methods by using ACO for detecting the edges and ringing effect at the edges of the image. Good estimates of both the image and the blurring operator are reached by initially considering the main image edges. In this paper, an ACO-based image edge detection approach has been successfully developed. The proposed approach yields superior subjective performance to that of the existing edge detection algorithm such as Sobel, Prewitt, Roberts, and Canny. The restoration quality of our method was visually and quantitatively better than those of the other algorithms such as Wiener Filter algorithm, Regularization algorithm and Lucy-Richardson and Blind Image Deconvolution algorithm with which it was compared.The future work of this paper is to implement and experiment BID-ACO on other image formats considering different types of blurs and then comparing the results.

7. REFERENCES

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