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Edge Detection of an Image based on Bi-Level Histogram Equalization and Ant Colony Optimization Technique

H. Kavitha[1+] , Dr. M. V Sudhamani[2]

[1]Asst. Prof., Dept. of ISE, Siddaganga Institute of Technology, Tumkur - 572 103

[2]Prof. & Head, Dept. of ISE, R N S Institute of Technology, Bangalore - 560 098

Abstract: This paper describes a novel approach for edge detection of an image which is based on Ant Colony Optimization (ACO), Bi-Level histogram equalization and also Brightness Preserving Dynamic Fuzzy Histogram Equalization. The query image is taken in gray scale form and the Bi-Level Histogram Equalization is applied for enhancing the contrast of the image. This is done since the contrast enhancement gives the better distinction between the brightness of background and the foreground of objects especially in low contrast images. Then ACO is used for edge detection of a Bi-Level Histogram Equalized image. The performance of the proposed approach is demonstrated with the help of experimental results. The results show that our approach is better than other techniques.

Keywords: ACO, Bi-Level Histogram Equalization, Brightness Preserving Dynamic Fuzzy Histogram Equalization, Contrast enhancement, edge detection.

1. Introduction

Image enhancement is one of the main areas in digital image processing. Image enhancement is a process that improves the pixel's intensity of the input image, so that the output image looks subjectively better. Image enhancement aims at improving the visual interpretability of information contained in the images. Image enhancement can also be used to provide a better input for other automated image processing systems. Contrast enhancement plays a significant role in image processing for both human and computer vision. It is used as a preprocessing step in medical image processing, speech recognition, texture synthesis and many other image/video processing applications.

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 [1], [2], which is motivated by the natural phenomenon of ants. The ants deposit pheromone on the ground to denote the shortest path that is to be followed by other members in the colony. The ACO algorithm is first referred as Ant System, proposed by [3]. Many algorithms have been developed on ACO [4] like Max-Min ant system [5] and the Ant Colony System [6]. In this paper, ACO is used for image edge detection. The aim of ACO is to extract the edge information of the image, as it plays a crucial role to comprehend the image's content. The proposed approach exploits the movement of the number of ants on the image which is based on the local variation in the intensity value of the image. This information is used to establish a pheromone matrix, which gives the edge information of the image.

The remainder of the paper is organized as follows: in Section II, an introduction to histogram equalization and details of Contrast Limited Adaptive Histogram Equalization are discussed. In Section III,

[+] Corresponding author.
*E-mail address:*kavitha.halappa@gmail.com, mvsudha_raj@hotmail.com

Bi-Level Histogram Equalization (BLHE) and ACO approaches are discussed. Experimental results are given in Section IV and conclusions and future works are given in Section V.

2. Histogram Equalization

A digital image is nothing but the binary representation of a 2D image. The digital representation of an image is denoted by an array of picture elements named as pixels. These pixels represent the gray level value of that image. Histogram specifies the estimation of the probability distribution of a particular type of data. A histogram of an image is the graphical representation of the gray values of an image. The image histogram analysis tells us the frequency of occurrence of the different gray levels within an image. Histogram Equalization (HE) is a technique to spread out the intensity values among the total range of gray levels in an image, in order to get better contrast. HE is especially applicable when both the background and foreground of the images are in close contrast that is either both background or foreground is bright or dark. There are various classic HE techniques being proposed, few of them are discussed below.

2.1 Bi-histogram Equalization

Bi-histogram equalization [2] technique partitions the histograms into two sub-histograms and equalizes them independently. This technique has been proposed to minimize the change in mean image brightness after histogram equalization. Several image parameters such as median, mean gray level or some sort of automatically selected grayscale threshold are used for partitioning of the histogram. In the proposed method Bi-histogram equalization has been adopted.

2.2 Multi-histogram Equalization

Multi-histogram equalization techniques partition histograms in multiple sub-histograms and equalize them independently. This technique has been proposed to further improve the mean image brightness preserving capabilities of the histogram equalized image. Several histogram features as local peak or valley points act as markers for partitioning of the histogram. Thus valley portions between two consecutive peaks or peaks between two consecutive valley points are taken from the sub-histograms for equalization.

2.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

The main difference between CLAHE and the ordinary adaptive histogram equalization is its contrast limiting. This feature when applied to global histogram equalization, gives rise to contrast-limited histogram equalization (CLHE). In CLAHE, the contrast limiting procedure is applied for each neighborhood from which a transformation function is derived. The main aim of CLAHE is to prevent the over amplification of noise that is due to adaptive histogram equalization. This is done by limiting the contrast enhancement of Adaptive Histogram Equalization (AHE).

3. Proposed Approach

Here, we have proposed a Bi Level Histogram Equalization (BLHE) technique and ACO technique [11]. The results of the above two methods are compared with Brightness Preserving Dynamic Fuzzy Histogram Equalization [10] (BPDFHE).

3.1 Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE)

The BPDFHE technique manipulates the image histogram in such a way that no remapping of the histogram peaks takes place, while only redistribution of the gray-level values in the valley portions between two consecutive peaks takes place. The BPDFHE technique consists of following operational steps:

Step 1: Fuzzy Histogram Computation

Fuzzy histogram $h(v)$ is the frequency of occurrence of gray levels *'around v'*. For an image F with the pixel gray value $F(x,y)$ at location (x,y) the fuzzy histogram is computed as given by the formula.

$$h(v),\ v \in \{0,1,\dots,L-1\}$$

$$h(v) \leftarrow h(v) + \sum_i \sum_j \xi_{\tilde{F}(i,j),v}$$

$$\xi_{\tilde{F}(i,j),v} = max\left[0,1 - \frac{|F(i,j) - v|}{\alpha}\right]$$

Where $\xi_{\tilde{F}(x,y),v}$ is the fuzzy membership function defining membership of F(x,y) to the set of pixels with grayscale-value *v*. Fuzzy statistics of the digital images is used to effectively handle inexactness of the image data and to obtain a smooth histogram.

Step 2: Histogram Partitioning

The fuzzy histogram now obtained is partitioned to obtain sub histograms which are to be dynamically equalized. The histogram partitioning involves two steps:

- Local maxima detection: located using the first and second order derivatives of the histogram
- Creating partitions: Each valley portion between two consecutive local maxima is considered as a partition.

Let $\{m_1, m_2, \cdots m_n\}$ be the n local maxima points detected. Then for a histogram with spread $[F_{min}, F_{max}]$ the $n+1$ sub-histograms obtained after partitioning are $\{[F_{min}, m_1], [m_1, m_2], \cdots [m_n, F_{max}]\}$

Step 3: Dynamic Equalization of Sub-histograms

The sub histograms obtained are individually equalized by DHE technique. The step involves two operations.

- Dynamic range mapping of sub-histograms: In this step the output dynamic range for individual partitions is computed using input dynamic range and number of pixels in the partition With output dynamic range of all the sub-histograms available, smallest and largest gray levels for all partitions are computed.
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$$Range_k = \frac{(L-1)\times (high_k - low_k)\times log_{10}P_k}{\sum_{i=1}^{n+1}(high_i - low_i)\times log_{10}P_i}$$

$$Start_k = \sum_{i=1}^{k-1} Range_i + 1 \quad Stop_k = \sum_{i=1}^{k} Range_i$$

- Histogram equalization of sub-histograms: Equalization technique used is similar to that used for HE. For gray level value *v* in input image *F*, the corresponding new gray value *v'* in equalized image is obtained as

$$v' = Start_k + Range_k \times \sum_{i=Start_k}^{v} \frac{h(i)}{P_k}$$

$$where\ k = n | v \in [m_{n-1}, m_n - 1]$$

Step 4: Normalization of Image Brightness

The output image obtained after DHE of each sub histogram has mean brightness slightly different than that of the input image. If $\mu_{\tilde{F}}$ and μ_F are the mean brightness of the input and DHEed output images then the brightness normalized output image *G* is obtained as

$$G = \frac{\mu_F}{\mu_{\tilde{F}}} \times \tilde{F}$$

3.2 Bi Level Histogram Equalization (BLHE)

The proposed method, BLHE combines the advantages of image inversion and HE based adaptive histogram equalization technique. The intensity of the input image is first inversed; then equalized using CLAHE technique mentioned earlier and then the output is re-inversed. The re-inversed image is again subjected to histogram equalization. Now the generated output image contrast is enhanced and histogram equalized. The steps descriptions are given below:

1. Read an input image.
2. Inversing an image reveres its grayscale; it is also referred to as gray scale inversion. Inverting the image does not reverse the color map or look-up-table (LUT) but computes the new image data. For the numeric arrays the formula given below is used for computing the inverse:
   invIm = (maxVal + minVal) – im
3. The contrast of images is enhanced in CLAHE by transforming the values in the intensity of the input image. Unlike HE, CLAHE operates on the small data regions, other than the entire image. Each tile's contrast is enhanced, so has the histogram of the output region approximately matches the specified histogram. Bilinear interpolation is used to combine the neighboring tiles to eliminate the artificially induced boundaries. The contrast, especially in the homogeneous areas, could be limited to avoid the amplifying noise which might be present in the image.

4. The obtained output is subjected to image inversion for getting the original visual outlook of the image.
5. Finally, the inversed image so obtained is subjected to CLAHE which produces the good visual clarity of the image. This output image is better histogram equalized, at the same time there is a clear distinction between the brightness of foreground and background of the objects in the image.

3.3 Ant Colony Optimization

In the proposed ACO method the edge of an image is detected by constructing the pheromone matrix, which is obtained by the movement of the number of ants on a 2-D image. Every entry of the pheromone matrix represents the edge information for each pixel location in the image. The local variation of the image intensity value determines the movement of the ants.

The ACO starts with the initialization process and further runs for N number of iterations to build the pheromone matrix. This is an iterative process which consists of the two processes: construction process followed by the update process. The last process is the decision process which is used to determine the edge. All the above mentioned processes are presented in detail below.

- Initialization Process

In this process for an image I of size $M_1 \times M2$ randomly K ants are assigned and each pixel of the image is viewed as a node. The constant $\boldsymbol{\tau_{init}}$ is assigned to each $\boldsymbol{\tau^{(0)}}$, which is the initial value of every component of the pheromone matrix.

- Construction Process

In the n^{th} step of construction, randomly an ant is selected from the K total ants, and consecutively this ant will move for L steps on the image. The selected ant will move from the (l,m) node to (i, j) node which is its neighboring node, has specified by the transition probability that is discussed below:

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

Here $\tau^{(n-1)}_{i,j}$ denotes the pheromone value at the node (i, j) and $\Omega_{(l,m)}$ denotes the neighborhood nodes of the node (l,m), $\eta_{i,j}$ denotes the heuristic information at the node (i, j). The constants α shows the influence of the pheromone matrix and constant β denotes the influence of the heuristic matrix.

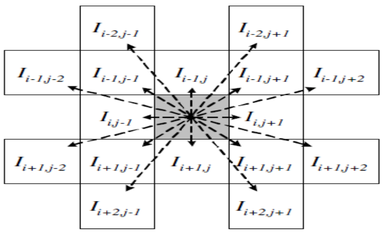

Fig. 1. A local configuration at the pixel position $I_{i,j}$ for computing the variation $V_c\left(I_{i,j}\right)$. The pixel $I_{i,j}$ is marked as Gray Square.

The two crucial issues of the construction process are:

1) The determination of the heuristic information $\eta_{i,j}$ is discussed in (9). It is found at the pixel position (i, j) by using the local statistics as given below:

$$\eta_{i,j} = \frac{1}{Z} V_c\left(I_{i,j}\right)$$

Here Z is the normalization factor. The $I_{i,j}$ intensity value specifies the intensity value of the pixel at position (i, j) of an image I and is found as given below:

$$Z = \sum_{i=1:M_1} \sum_{j=1:M_2} V_c\left(I_{i,j}\right)$$

Here $V_c\left(I_{i,j}\right)$ denotes the function of a local group of pixels c which is called clique. The Fig. 1 shows the local configuration at the pixel position $I_{i,j}$ for computing the variation $V_c\left(I_{i,j}\right)$. The pixel $I_{i,j}$ is marked as Gray Square. Its value is based on the variation of the intensity values in the clique. To be more specifying, if the pixel under consideration is $I_{i,j}$ its function $V_c\left(I_{i,j}\right)$ is determined as given below:

$$V_c\left(I_{i,j}\right) = \mathrm{f}\,(\left|I_{i-2,j-1} - I_{i+2,j+1}\right| + \left|I_{i-2,j+1} - I_{i+2,j-1}\right| + \left|I_{i-1,j-2} - I_{i+1,j+2}\right| + \left|I_{i-1,j-1} - I_{i+1,j+1}\right|$$

$$+\left|I_{i-1,j}-I_{i+1,j}\right|+\left|I_{i-1,j+1}-I_{i-1,j-1}\right|$$
$$+\left|I_{i-1,j+2}-I_{i-1,j-2}\right|+\left|I_{i,j-1}-I_{i,j+1}\right|)$$

The function f (·) is determined by the given below four functions:

$$f(x) = \lambda x, \text{ for } x \geq 0,$$
$$f(x) = \lambda x^2, \text{ for } x \geq 0,$$
$$f(x) = \begin{cases} \sin\left\{\frac{\Pi x}{2\lambda}\right\} & 0 \leq x \leq \lambda; \\ 0 & else \end{cases}$$
$$f(x) = \begin{cases} \frac{\Pi x \sin\left\{\frac{\Pi x}{2\lambda}\right\}}{\lambda} & 0 \leq x \leq \lambda; \\ 0 & else \end{cases}$$

The functions shape is determined by adjusting the value of the parameter λ.

2) The latter issue is about the determination of the permissible range of the ant's movement (i.e., Ω(l,m)) at the position (l,m). The ants at any position (l, m) can move in either the 4-connectivity neighborhood or the 8-connectivity neighborhood as shown in Fig. 2.

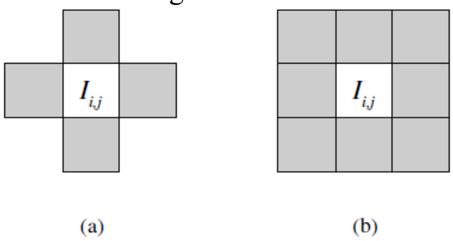

Fig. 2 Various neighborhoods of the pixel $I_{i,j}$: (a) 4-connectivity neighborhood; and (b) 8-connectivity neighborhood

- Update Process

In the update process the pheromone matrix is updated after the two update operations as specified below:

In the first update each update is based on the movement of each ant in each construction step and the entry in the pheromone matrix is updated has given below:

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

After the ants have moved in all the construction steps the second update is performed has given below:

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

- Decision Process

In the decision process a binary decision is taken at every pixel to determine if it's an edge are not. This is done by applying the threshold τ on the final pheromone matrix τ(N). The threshold τ chosen here is adaptively computed. Mean value of the pheromone matrix is selected as the initial threshold τ(0). The other entries of the pheromone matrix belongs to two categories based on its value is lower than τ(0) or greater than τ(0). The average mean value of the above mentioned two categories is computed and that forms the new threshold. The above steps are repeated till a constant threshold is found.

The values for the various parameters are set as follows:

- $K = \sqrt{M1 \times M2}$: represents the total number of ants.
- τ_{init} = 0.0001: represents the initial value of each component in the pheromone matrix.
- α = 1: denotes weighting factor of the pheromone information.
- β = 0.1: denotes weighting factor of the heuristic information.
- Ω = 8-connectivity neighborhood: denotes the permissible ant's movement range.
- λ = 1: denotes the adjusting factor of the functions.
- ρ = 0.1: denotes the evaporation rate.
- L = 40: denotes the total number of ant's movement in each construction step.
- ψ = 0.05: denotes the pheromone decay coefficient.
- ∈ = 0.1: denotes the user-defined tolerance value used in the decision process.

- N = 4: denotes total number of construction-steps.

4. Experimental Results

We have carried out experiments to evaluate the performance of the proposed method based on BLHE and detected edges using ant colony optimization. The images from the USC SIPI database are used for the conduction of experiments. The Fig. 3 shows the experimental results after applying the Jing Tian and the proposed method ACO with BLHE on the same images. In Jing Tian method there two hundred construction steps and number of iterations is four and in our work the number of construction steps is reduced to thirty five and number of iterations decreased to two. The clarity of the features is better in our proposed technique compared to Jing Tian method. The results are shown in Fig. 4 informs that the edges are detected better in our proposed technique compared to normal histogram equalization and BPDFHE technique.

5. Conclusion and Future Work

We have proposed an edge detection technique based on Ant Colony Optimization and Bi-level histogram equalization. Our method performs better than the existing edge detection algorithms and it is shown by experimental results. Furthermore, the parallel execution of the ACO algorithm can be exploited so has to reduce the computational load of the proposed algorithm as a part of future research work.

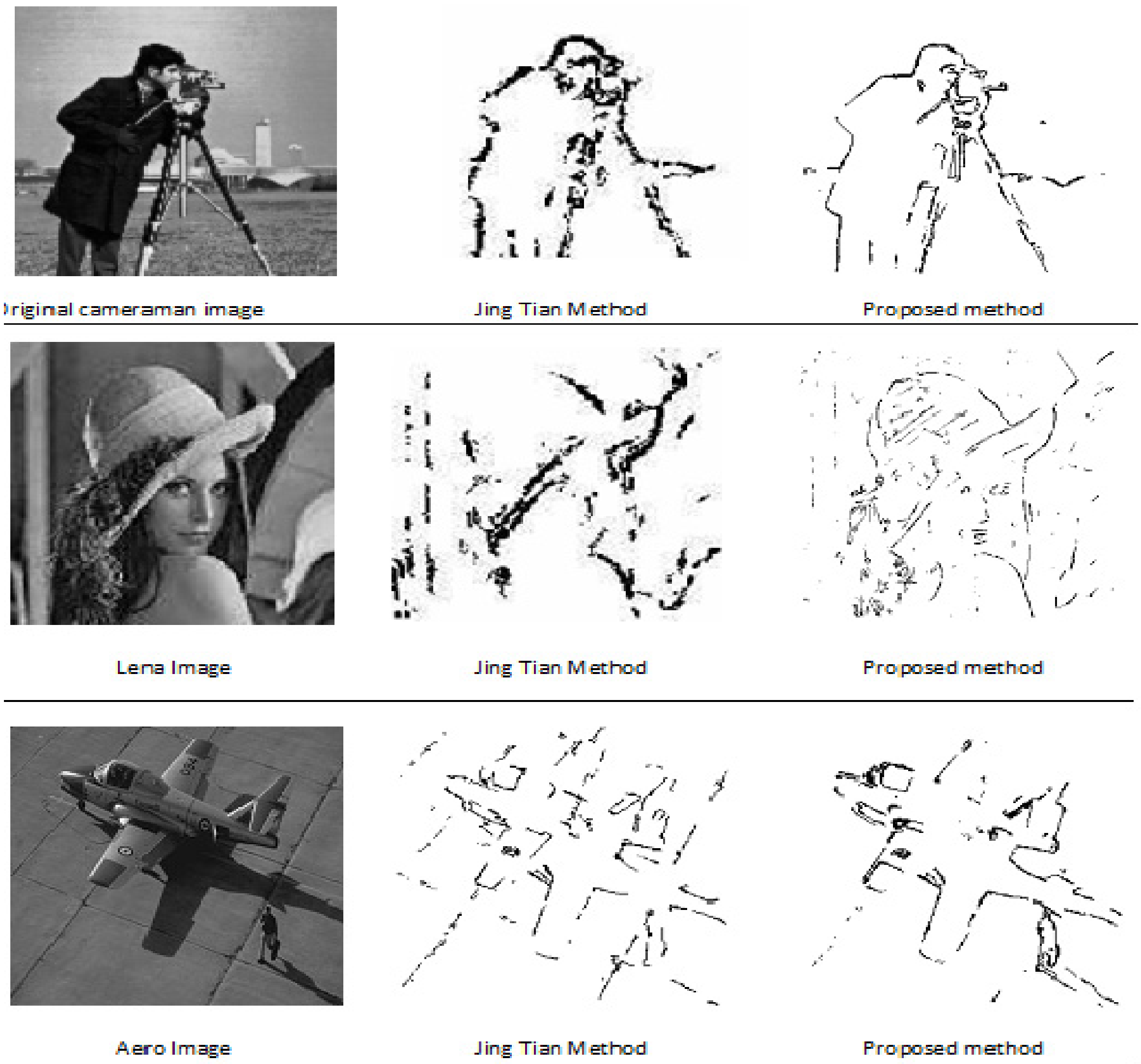

Fig. 3 Comparison of Jing Tian ACO and the proposed ACO method

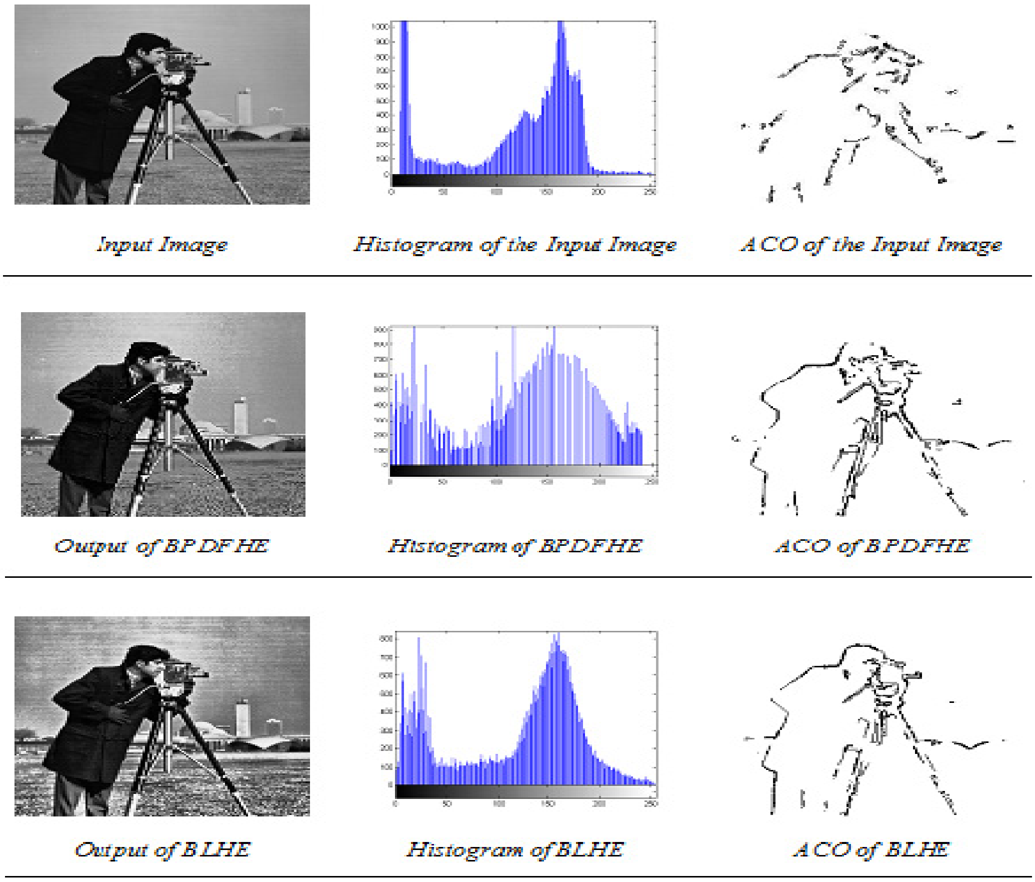

Fig. 4 Comparison of the input image, output of BPDFHE and output of BLHE, their histograms and also the edges detected using the ACO.

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