

# Chapter 4

## Multi-Thresholded Histogram Equalization Based on Parameterless Artificial Bee Colony

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### ABSTRACT

*This chapter presents a novel variant of histogram equalization (HE) method called multi-thresholded histogram equalization (MTHE), depending on entropy-based multi-level thresholding-based segmentation. It is reported that proper segmentation of the histogram significantly assists the HE variants to maintain the original brightness of the image, which is one of the main criterion of the consumer electronics field. Multi-separation-based HE variants are also very effective for multi-modal histogram-based images. But, proper multi-separation of the histogram increases the computational time of the corresponding HE variants. In order to overcome that problem, one novel parameterless artificial bee colony (ABC) algorithm is employed to solve the multi-level thresholding problem. Experimental results prove that proposed parameterless ABC helps to reduce the computational time significantly and the proposed MTHE outperforms several existing HE variants in brightness preserving histopathological image enhancement domain.*

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## **INTRODUCTION**

Contrast enhancement methods have been applied for better visual interpretation. Histogram Equalization (HE) is one of the most simple and widely used method for contrast enhancement (Gonzalez, R.C., Woods, R.E. (2002)). Basically HE computes linear cumulative histogram of the original image and dispenses intensity values over its dynamic intensity range. HE based techniques have been used in medical image processing, satellite image processing etc. The method of Traditional Histogram Equalization (Gonzalez, R.C., Woods, R.E. (2002)) is described below:

The method of Traditional Histogram Equalization (Chen, S. D., Ramli, A. R. (2004)) has the following steps:

If the original image  $f(i, j)$  has total  $W$  number of pixels within the dynamic range  $[X_0, X_{L-1}]$ , where  $L$  is the number of discrete gray levels, then the probability density function  $H1(X_k)$  of intensity level  $X_k$  of the image is given by:

$$H1(X_k) = \frac{n_k}{W} \text{ for } 0 \leq k \leq L - 1 \quad (1)$$

Where,  $n_k$  is the total number of pixels with intensity level  $X_k$ . The plot of  $X_k$  vs.  $n_k$  is the histogram of image  $f$ . the cumulative density function is defined as (Chen, S. D., Ramli, A. R. (2004)):

$$CDF(X_k) = \sum_{i=0}^k H1(X_i) \quad (2)$$

Traditional HE maps the corresponding image into the total dynamic range  $[X_0, X_{L-1}]$  with the help of the CDF as given below:

$$f(X) = X_0 + (X_{L-1} - X_0).CDF(X) \quad (3)$$

In the HE procedure the entire gray levels are distributed uniformly, HE improves the image contrast and maximizes the image entropy and also change the mean brightness of the output image to the middle of the gray level regardless of the input image's mean (Chen, S. D., Ramli, A. R. (2004), Kim, Y.T. (1997)). The equation of mean or statistical expectation  $E(\cdot)$  of the output image  $G$  is given below:

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