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Particle swarm optimized multi-objective histogram equalization for image enhancement

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ABSTRACT

Histogram Equalization (HE) is a simple and effective technique for enhancing the contrast of the input image. However, it fails to preserve the brightness while enhancing the contrast due to the abrupt mean shift during the process of equalization. Many HE based methods have been developed to overcome the problem of mean shift. But, they suffered from over-enhancement. In this paper, a multi-objective HE model has been proposed in order to enhance the contrast as well as to preserve the brightness. The central idea of this technique is to first segment the histogram of the input image into two using Otsu's threshold. A set of optimized weighing constraints are formulated and applied on both the sub-images. Then, the sub-images are equalized independently and their union produces the contrast enhanced, brightness preserved output image. Here, Particle Swarm Optimization (PSO) is employed to find the optimal constraints. This technique is proved to have an edge over the other contemporary methods in terms of entropy and contrast improvement index.

1. Introduction

Contrast enhancement techniques are used in image and video processing to achieve better visual interpretation. In general, histogram equalization based contrast enhancement is attained through the redistribution of intensity values of an input image. Histogram modification is the underlying strategy for most of the contrast enhancement techniques. Histogram Equalization (HE) is one of the most widely used techniques to achieve contrast enhancement, due to its simplicity and effectiveness [1]. The HE techniques use linear cumulative histogram of an input image and distribute its pixel values over its dynamic intensity range. HE based enhancement finds applications in medical image processing, speech recognition, texture synthesis, satellite image processing, etc.

HE methods can be categorized into two as global and local. Global HE methods improve the quality of image by normalizing the distribution of intensities over the dynamic range, using the histogram of the entire image. Histogram Equalization (HE) is an ideal example of this approach that is widely used for contrast enhancement [1]. It is achieved by manipulating the intensity distribution using its cumulative distribution function (CDF) so that the resultant image may have a linear distribution of intensities. As HE modifies the mean of the original image, it tends to introduce washed-out effect in the output image.

Local Histogram Equalization (LHE) methods use the histogram intensity statistics of the neighborhood pixels of an image for equalization. These techniques usually divide the original image into several non-overlapped sub-blocks and perform histogram equalization on the individual sub-blocks. The resultant image is produced by merging the sub-blocks using the bilinear interpolation method. The major drawback of these methods is the introduction of checkerboard effect which appears near the boundaries of the sub-blocks. Histogram Specification (HS) [1] is an another enhancement method in which the expected output of image histogram can be controlled by specifying the desired output histogram. However, specifying the output histogram pattern is not a simple task as it varies with the images.

In this paper, particle swarm optimized Multi-Objective Histogram Equalization (MOHE) is proposed that uses Otsu's method to perform histogram thresholding. A set of weighing constraints are formulated and applied to the sub-histograms before equalizing them independently. The weighing constraints are optimized using Particle Swarm Optimization (PSO), which is a population-based optimization technique. MOHE is proved to exhibit better brightness preservation and contrast enhancement.

In Section 2, the traditional HE and a few recently proposed HE based methods are described. Section 3 presents the principle of the proposed technique, MOHE, various image enhancement measures and the PSO algorithm. In Section 4, the results are discussed and in Section 5, the conclusion is given.

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2. Review of histogram equalization methods

The traditional histogram equalization technique [1] is described below

Consider the input image, $F(i, j)$ with a total number of 'n' pixels in the gray level range $[X_0, X_{N-1}]$. The probability density function $P(r_k)$ for the level r_k is given by

$$P(r_k) = \frac{n_k}{n} \tag{1}$$

where n_k represents the frequency of occurrence of the level r_k in the input image, n is the total number of pixels in the image and $k=0, 1,\ldots,N-1$. A plot of n_k against r_k is known as histogram of the image F. Based on Eq. (1), the cumulative density function is calculated as

$$C(r_k) = \sum_{i=0}^{k} P(r_i) \tag{2}$$

HE maps an image into the entire dynamic range, $[X_0, X_{N-1}]$ using the cumulative density function which is given as:

$$f(X) = X_0 + (X_{N-1} - X_0) \times C(X) \tag{3}$$

Thus, HE flattens the histogram of an image resulting a significant change in the brightness.

A new HE based brightness preservation method known as Brightness Preserving Bi-Histogram Equalization (BBHE) was proposed by Kim (1997) [2]. BBHE first segments the histogram of input image into two, based on its mean; the one ranging from minimum gray level to mean and the other from mean to the maximum and then, it equalizes the two histograms independently. It has been clearly proved that BBHE can preserve the original brightness to a certain extent [3]. Wan et al. proposed a method (1999) called equal area Dualistic Sub-Image Histogram Equalization (DSIHE) which is an extension of BBHE [4]. DSIHE differs from BBHE only in the segmentation process. The input image is segmented into two, based on median instead of mean. This method is suitable only for images which are not having uniform intensity distribution. But, the brightness preserving potential of DSIHE is not found to be significant. Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) [5] is also an extension of BBHE (2003) proposed by Chen and Ramli which performs the histogram separation based on the threshold level, which would yield minimum difference between input and output mean, called Absolute Mean Brightness Error (AMBE). This technique is also not free from undesirable effects.

Recursive Mean Separate Histogram Equalization (RMSHE) was proposed by Chen and Ramli (2003) in which the histogram of the given image is partitioned recursively [6]. Each segment is equalized independently and the union of all the segments gives the contrast-enhanced output. This technique has been clearly proved to be a better method among the recursive partitioning approaches [3]. Sim et al. proposed a similar method (2007) called Recursive Sub-Image Histogram Equalization (RSIHE) [7]. This technique has the same characteristics as RMSHE in equalizing an input image, except that it separates the histogram based on gray level with cumulative probability density equal to 0.5, whereas RMSHE uses mean-separation approach. This method is proved to have an edge over RMSHE. However, this recursive procedure increases the computational complexity and the resultant image is very similar to that of original input image as the recursion level increases. Moreover, finding a generic optimal level of recursion, applicable to all types of images is still a challenge for all of these methods.

A fast and effective method for video and image contrast enhancement, known as Weighted Thresholded HE (WTHE) was proposed (2007) [8]. This technique provides an adaptive mechanism to control the enhancement process. WTHE method provides two-fold benefits such as, adaptivity to different images and ease of control, which are difficult to achieve in the GHE-based enhancement methods. In this method, the probability density function of an image is modified by weighing and thresholding prior to HE. A mean adjustment factor is then added to normalize the luminance changes. Two more weighing techniques, Weight Clustering HE (WCHE) [9] and Recursively Separated and Weighted HE (RSWHE) [10] were also developed (2008). Both these techniques use different weighing principles and have proved their own merits. Ibrahim and Kong proposed Sub-Regions Histogram Equalization (SRHE) (2009) [11] which partitions the input image based on Gaussian filtered, smoothed intensity values of it and outputs the sharpened image. Zuo et al. recently developed Range Limited Bi-Histogram Equalization (RLBHE) for image contrast enhancement in which the input image's histogram is divided into two independent sub-histograms by a threshold that minimizes the intra-class variance [15]. Then, the range of the equalized image is calculated to yield minimum absolute mean brightness error between the original image and the equalized one.

Evolutionary soft computing techniques like Fuzzy Logic, Neural Network (NN), Genetic Algorithm (GA), Particle Swarm Optimization (PSO) etc. are used for enhancing the contrast of the input image [17–21]. PSO based algorithms exhibit computational simplicity unlike selection, crossover and mutation operations necessary for GA; framing numerous fuzzy rules as required by fuzzy logic or exploration of supervised or unsupervised learning algorithms of NN. The major advantage of PSO is that it takes less time to converge to better optima [21]. Kwok et al. have developed multi-objective PSO (MPSO) for enhancing the contrast as well as for preserving the intensity of the input images [22]. This MPSO is mainly based on gamma correction where the entropy gain being one of the major objectives. Though entropy gain improves the contrast, sometimes it may cause over-enhancement and brightness degradation of input images.

3. Multi-objective histogram equalization (MOHE)

The proposed MOHE accomplishes the contrast enhancement and brightness of input images in three distinct phases as

Phase I: Segmentation of the input image's histogram based on Otsu's threshold.
Phase II: Development of weighing constraints with respect to the threshold.
Phase III: Optimizing the weighing constraints using PSO.

3.1. Segmentation of the input image's histogram based on Otsu's threshold

Thresholding is an ideal method for image segmentation. A threshold is used to divide the input image's histogram into two parts: the lower gray level of the object and the higher gray level of the background. Then the target region and the background can be equalized separately so that the contrast of target and background can both be effectively improved. From the pattern recognition perspective, the optimal threshold should produce the best performance to separate the target class from the background class. This performance is characterized by intra-class variance. Otsu's method [16] is used to automatically perform thresholding based on the histogram shape of the image. Otsu's method assumes that the image to be thresholded contains two classes of pixels (e.g., foreground and background) and calculates