High-Quality Image Enhancement Algorithm Using Kinetic Gas Molecular Optimized (KGMO) Hyperbolic Tangent Function

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Abstract

One of the main steps in various digital image-based applications such as classification, segmentation and prediction etc., is to improve the visibility of digital images. In order to improve the visual efficiency of images, contrast enhancement (CE) is an important preprocessing technique. Depending on the capturing environment, the quality of the image varies, and CE is an important approach to improve the image quality. However, excessive CE resulting in loss of detail and an unnatural appearance of the target image. This paper proposes a new CE using the Kinetic Gas Molecular Optimized Hyperbolic Tangent Function (KGMO-HTF). This is used here to optimize the brightness of the picture α and the sensitivity parameter of the brightness esteems β with hyperbolic tangent (tanh) function. Different parameters such as Enhancement Mean Error (EME), Absolute Mean Brightness Error (AMBE) and Discrete Entropy (DE) are measured to evaluate efficiency of proposed method. Experimental findings are illustrated by CE-KGMO-HTF methods that perform better than conventional methods of CE.

Key words: *Kinetic Gas Molecular Optimization, Hyperbolic tangent function, Gamma Correction, Contrast Enhancement.*

Introduction

Human perception of image background is too dark or too light due to the limitations of the bit resolution and the ability of the image processing equipment, the details of the digital images can change. Researchers have therefore proposed several algorithms to improve the human image perception [1]. As per individuals desire to get top-notch pictures and vendors push to give a high caliber of experience, various picture improving procedures have been effectively examined. One of the best approaches to enhancing images is to apply the CE method, thinking about the fact that contrast is an integral factor in the human understanding of image quality [2]. CE techniques are extensively organized into two sets: direct and indirect. In a direct approach, image contrast is determined based on a human visual system, such as Weber Fechner’s rule or Retinex's theory, and improved by optimization the parameters using various nonlinear functions. These direct methods have few image information enhancement preferences and needs elevated computational complexity and introduces "halo" objects, around strong edges, particularly. Although recent direct methods for alleviating these problems have been proposed [3], using sigmoidal function. Different strength transformations such as the histogram equalization (HE) are implemented by old-style techniques to enhance image quality. To construct a changing job, worldwide HE uses the entire image statistics, thus neglecting to protect better subtleties and mean-brightness of

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the image. On the other hand, local HE takes into account the nearby statistics of the image. However, there are substantial computational costs, and the worldwide presence is distorted in the general histogram adjustment structure. Initially, histogram matching is performed to demonstrate better knowledge based on the reassignment of probability distribution and then to apply S-molded transfer mapping. In separate motion let change and difference restricted versatile HE is joined for independent improvement of low and high-frequency components. In any case, these approaches require the observational setting of multiple parameters and thus suffer the negative consequences of computational difficulty. Non-parametric altered histogram equalization efficiently controls the histogram spikes without experimental parameter alteration and decreases the mutilation [4]. The proposed work has two parameters, for instance α and β. Right now, investigate the impact of these parameters on the resultant pictures to programmed parameter estimation technique. Initially, by differentiating between 0.3 and 0.7 with increments of 0.2, the test images acquired while maintaining β as 2.0. And thus, the wide-ranging experiments were set to demonstrate the effects of β on the output images by varying with increments of 0.5 from 1.0 to 3.0. By assessing the steepness of the transformation function, the enhancement degree is controlled by β. If too little, the success of the proposed process is unsatisfactory for enhancement [5]. On either hand, if too wide, the conversion mechanism has a steep slope, causing enormous misfortune in detail in dull and splendid areas.

This paper is prepared as follows: Section I explains the introduction to CE process in detail. Section II describes the literature survey about the proposed system. Section III describes the proposed method; the parameters of the future method are used. Finally, in Section IV, the results and discussion of this article is presented, and Section V will conclude.

Prior Work

Different works have been carried out to improve the efficiency of the CE method. The enhancement is done using both direct pixel approaches and indirect pixel techniques. In [6] Introduced image enhancement and extraction of functionality depend on satellite data. The application of texture estimates and transformation properties based on the visual intensity obtains high-resolution satellite imagery while using different image enhancement systems is primarily discussed. A new automatic Histogram Equalization (HE) algorithm which is based on Bi-Histogram Equalization (BHE) is suggested in and argues that this method retains a light and improves intensity. Also, the study describes a technique that calculates the average intensity for selecting thresholds to maintain a strategic distance from excessive exposure and increases the complexity of the threshold and limits the histogram to a specific average trough to be extracted into small details. The same information and the average brightness of the output are guaranteed. In [7] propose a powerful method that makes Contract Enhancement (CE) without critical contortion in both the first and second-order statistics of the enhanced image. The detail of an improvement issue utilizing a variation of the notable Total Variation (TV) standard image rebuilding plan. Examinations show that the calculation successfully conquers the first and second-order statistics-based finders without misfortune in the quality of the enhanced image. In [8] given the low visual acuity and severity of mammography X-rays, they need to be improved to achieve a beautiful and attractive appearance. There are numerous tunable parameters and improved wave control methods for multi-scale functions in the newly developed strategy of incorporating multidirectional geometric data. First, a measure of the order of the lightness error is suggested for objective access to the preservation of naturalness. Second, a luminance pass-through filter is suggested to separate the image from the reflection and brightness, which determines the details and authenticity of the image, respectively. In [9] they have emphasized neuro physiologically assisted connecting synapses.

The use of single peaks, as real neurons do, allows synaptic calculations to include temporal and spatial data. The rationale behind enhancing an image is to improve a person's visual perception, and improvement is important when the difference in the image is invisible or noticeable. Area change methods can be improved by increasing the number of recurring subgroup ratios or by increasing the measured visual acuity. In [10] it was suggested to introduce an effective method to enhance remote sensing images using improved world variations and nearby subtleties. This method involves an observation method using a regularized histogram equation and to enhance the image quality using Discrete Cosine Transforms. Introduced a global approach by changing the input histogram to increase variance. To create a circulatory function for the input image, this method uses a sigmoid function and a histogram.

a) Using KGMO for optimal α and β
b) Using a hyperbolic tangent function for KGMO instead of a sigmoid function
c) KGMO can be controlled by adjusting the scaling parameter of the hyperbolic tangent function

Proposed Method

The brightness of the image and the sensitivity parameter of the image brightness esteems are evaluated utilizing α and β. Also, additionally the led broad tests are performed to examine the impacts of β on the output pictures by changing β value from 1.0 to 3.0 with augmentations of 0.5. By determining the sharpness of the transformation element, β regulates the enhancement degree.

A. Block Diagram of Proposed Method

A low-contrast image is provided as an input image and then the three-color components of the images such as component R, component G, and component B are extracted and these values are passed directly into the optimized hyperbolic tangent (tanh) function called CE-KGMO-HTF. Fig 1 shows that the output from these components will be combined and an improved picture will be generated as the output of the merger.

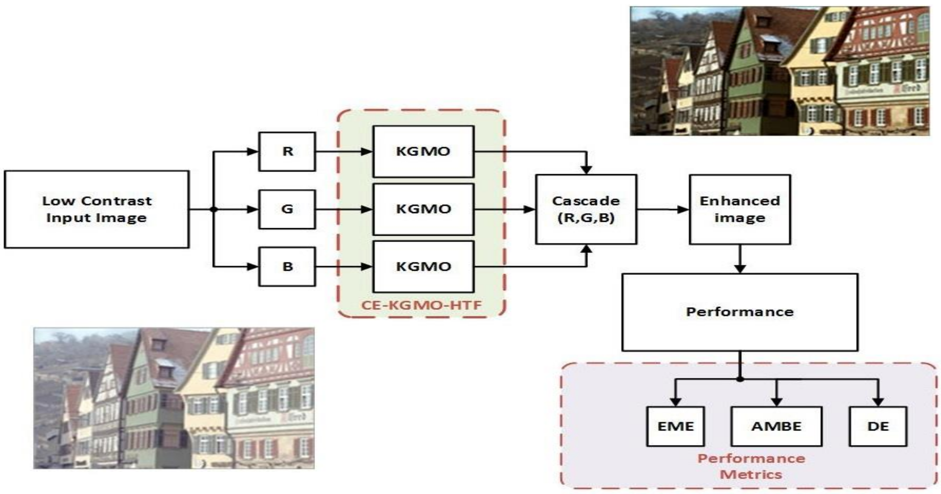

Figure 1. Block diagram of the proposed method

If the result for this value is low, this means that the average input image brightness is effectively saved by the appropriate enhancement process [11].

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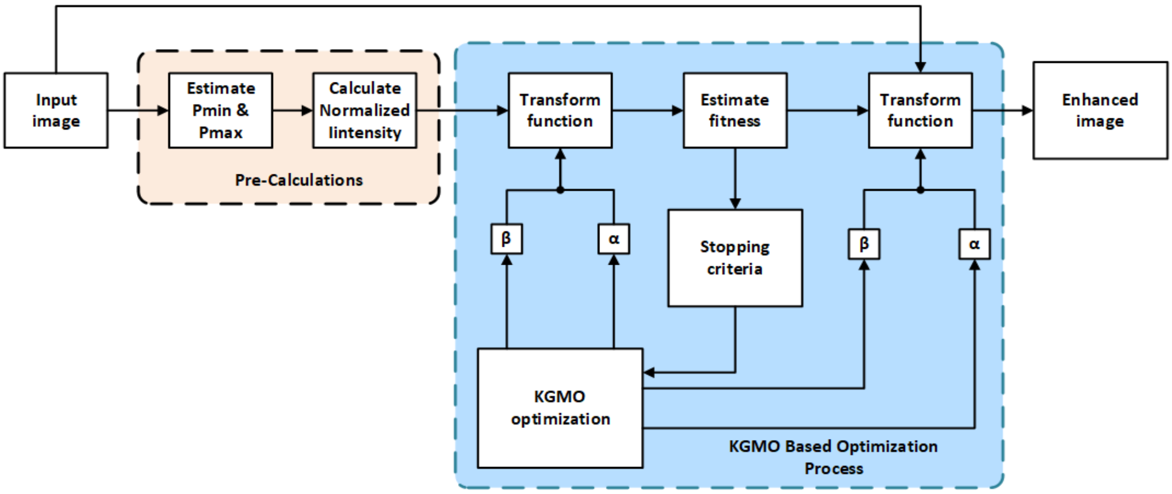

Figure 2. Block diagram KGMO optimization process

Finally, the sum of information represented in the image is the distinctive entropy of an image. The higher the discrete entropy value, the more data the image offers. KGMO based optimization method of the input image is illustrated in Fig 2. The image is sent to the pre-calculation process where the P_{min} and P_{max} values are estimated.

Next, the image is normalized and given to the KGMO optimization process. Inside the KGMO, the first process is the transformation function it will take all the normalized value for calculating the best fitness value. KGMO will change the parameters α, β by performing iterations, and the result is sent to estimate the fitness until the stopping criteria are satisfied. This process is repeated until the best result is evaluated. The enhancement of the image is done by using the hyperbolic tangent function and the equation for the function is given as follows.

$$\tanh(x) = 1 - \frac{2}{e^{2x}+1} = \alpha\sigma(2x) - \beta \tag{1}$$

B. *KGMO Optimization*

In this optimization method, gas molecules are the operators. For assessing more efficiency, dynamic energy is used. Every gas atom (operator) has four pieces of information in Kinetic Gas Molecular Optimization: location, kinetic energy, speed, and mass. Each gas atom's kinetic energy determines its velocity and location. First, consider a structure that has operators with N (gas atoms). The position of the m^{th} operator is determined by the equation given as

$$P_m = P_m^1, \dots P_m^c \dots, P_m^z for\ (i = 1,2, \dots . K) \tag{2}$$

The pace of the i^{th} agent can be obtained by

$$v_m = v_m^1, \dots v_m^c \dots, v_m^z for\ (m = 1,2, \dots . K) \tag{3}$$

Where v_m^cdenotes the rate of the m^{th}negotiator in the c^{th}dimension. The kinetic energy is described in the equation given by

$$K_{E}{}_m^c(u) = {}^3/_2 \left(K_y U_m^c(u), j_m = (j_m^1, \dots j_m^c, \dots, j_m^z), for\ (i = 1,2,3 \dots . z)\right) \tag{4}$$

$$v_m^c(u+1) = U_m^c(u)\omega v_m^c(u) + l1r(u)\left(e_{best}^c - A_m^c(u)\right)$$
$$+l2r(u)\left(\left(\frac{(F_{best}^c(u) + F_{best}^c(u-1) + F_{best}^c(U-2))}{K_E}\right) - A_m^c(u)\right) \tag{5}$$

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WhereU_m^cthis decrease exponentially overtime for the converging molecules and is measured as

$$U_m^c = 0.95A\left(U_m^c(u-1)\right) \tag{6}$$

The best position in the history of the i^{th} gas atom is detected, and the best position in the holder among the entirety of the particles is$ebest_m = (ebest_m^1, ebest_m^2, \ldots\ldots ebest_m^z,)$. Where m represents the complete number of past best taken for averaging. Here, $[-vmin, vmax]$are utilized as the cutoff points of the gas atom's speed.

C. KGMO Based Parameter Optimization

Steven's power law when compared with KGMO optimization law, it is an effective model that transforms a wide variety of atmospheres. The perceived brightness $R(P)$ will be determined by KGMO optimization law by

$$\mathrm{R(P)} = P^k \tag{7}$$

Here the exponent k will depend on the simulation type. The difference from the eqn. (7) will be reworked as follows

$$\frac{1}{R}dR = k\frac{1}{P}dP \tag{8}$$

As appeared in eqn.(8), k is a sensitivity parameter deciding just how quickly the consciousness develops as per the boost force increments. K is anticipated as consistent for various kinds of sensations, bringing about the normal bend.

$$\mathrm{K(P)} = \alpha\beta^{-log_e(\mathrm{p})} \tag{9}$$

Where α and β are parameters that determine K(P)'s greatest value and steepness, in the resulting eqn.(10) by substituting eqn.(7) in eqn.(9)

$$\mathrm{R(P)} = 255 \times \bar{P}^{\alpha\beta - log_e(\mathrm{p})} \tag{10}$$

The pixel strength of the range [0, 255] is P in (9) and the $\bar{P}$ of the pixel is normalized to [0,1] and this will be obtained by using (10)

$$\bar{P} = \frac{P - Pmin}{Pmax - Pmin} \tag{11}$$

In eqn.(11), the proposed work has two parameters, α, and β. Exactly now, analyze the effect of these parameters on the resulting images and implement a new automated method of parameter estimation. Initially, the output images acquired by differentiating between 0.3 and 0.7 with increases of 0.2, while preserving β as 2.0. The output image becomes darker as α increases.

$$R(P_{mean}) = 255 \times \bar{P}_{mean}{}^{\alpha\beta^{-log_e(P_{mean})}} = P_{mean} \tag{12}$$

Where $\bar{P}$mean is the normalized input image's mean intensity level and by solving the eqn. (12) and the optimized α for mean brightness and this will be denoted by using the eqn. (13)

$$\alpha = \frac{log_e\left(\frac{P_{mean}}{255}\right)}{log_e(\bar{P}_{mean})} \times \beta^{log_e(\bar{P}_{mean})} \tag{13}$$

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$$E(\alpha,\beta) = \frac{1}{M(M-1)} \sum_{m=1}^{M} \sum_{n=1}^{M} H_0(m)H_0(n)(n-1) \tag{14}$$

Fig. 3 shows the presence of different impacts of the parameters used in this work. Furthermore, by fluctuating the parameter β from 1.0 to 3.0 with additions of 0.5, more iterations are performed to separate the impacts of β on the output images. Set α using equation (13) for these analyses. The parameter β regulates the degree of enhancement by assessing the sharpness of the alteration work for color image due to more probability of color combination, it is very difficult to find out proper α and β values. By using KGMO, as stated in the above section, there is the correct solution with a lower number of iterations.

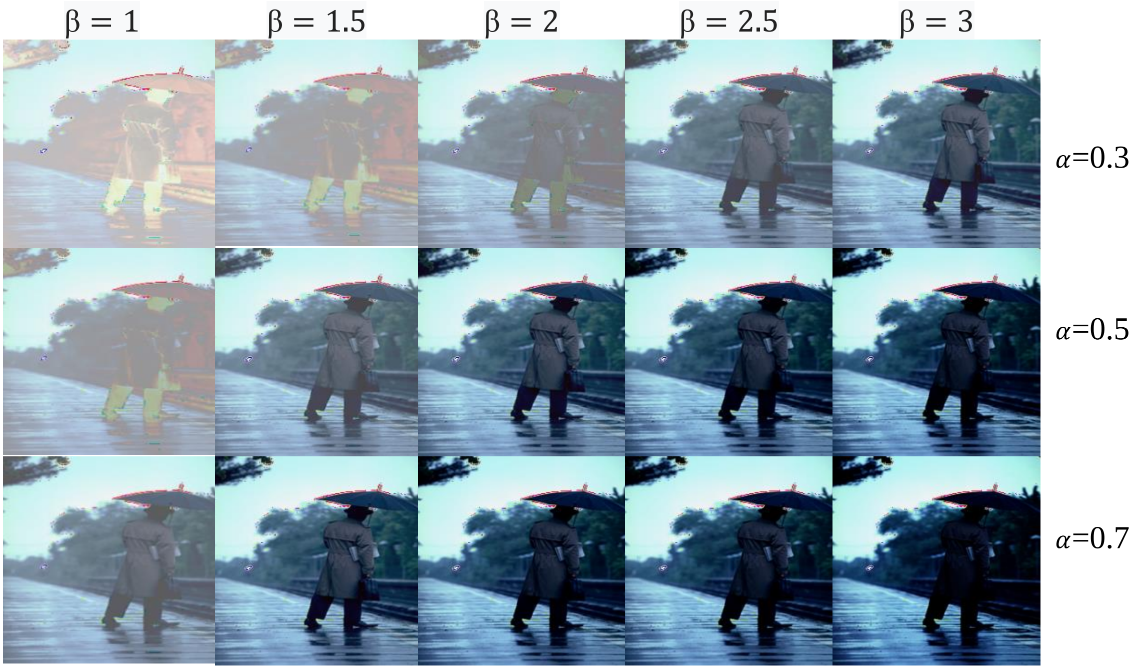

Figure 3. Impacts of the parameter α and β

Results and Discussion

MATLAB 2018a is used for the implementation of the proposed method. Three separate public databases are used in this work to verify the algorithm's accuracy. For analysis purpose, proposed method is compared with the existing methods. The resultant values concerning retrieval performance are given below in Table I. Fig 4 shows the performance analysis of methods such as gamma-corrected sensitivity hyperbolic tangent function and the proposed method has higher performance while comparing other methods.

Input image

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Proposed Work

Figure 4. Performance analysis of different methods

D. Dataset

In the proposed framework, there are three different databases namely, the USC-SIPI database [15], Kodak lossless true image suite [16], and Berkeley image dataset. Various quality evaluation metrics can be shown in the last row of the table.

E. Quality Metrics

Various performance metrics are calculated to evaluate the performance of the proposed techniques. The detailed information is given below.

1) Discrete Entropy (DE)

An image's entropy is the corresponding condition of intensity level that can be adapted to any individual pixel. The Entropy value is used to provide good comparison values of the images. The equation (14) given below is the representation of entropy.

$$H = \sum_{m=1}^{M} \sum_{n=1}^{N} P(X_{m,n})\, log_{10}(P(X_{m,n})) \tag{15}$$

2) Enhancement Mean Error (EME)

For EME, the upgraded X image has been isolated to N sub-squares $X_{m,}n$of size $M \times N$, and the proportion of max to min image degree of each sub-square was determined. At that point, the normal proportion is determined as the last score. EME is calculated using the equation (15) for any image

$$EME(X) = \frac{1}{M * N} \sum_{m=1}^{M} \sum_{n=1}^{N} 20\, In \frac{max(X_{m,n})}{min(X_{m,n}) + \delta} \tag{16}$$

3) Absolute Mean Brightness Error (AMBE)

The main difference between the input images and the enhanced images in mean pixel intensity will be determined by the absolute mean brightness error. Equation (16) shows the representation of AMBE calculated

$$AMBE(I,J) = \frac{1}{M * N} \sum_{m=1}^{M} \sum_{n=1}^{N} |J(m,n) - I(m,n)| \tag{17}$$

where I, J are the input and output image.m, n are the size of the image.

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Table. 1 Performance analysis of different enhancement techniques

Algorithm	**EME**	**AMBE**	**DE**	**Processing Time (MS)**
NPEA [12]	11.51	24.52	7.1992	8526.2
LSCN [13]	77.56	14.56	6.4947	6061.8
RISE [14]	24.10	5.67	7.4926	302.0
Proposed	26.17	4.66	7.1673	5.4

Conclusion

A high-quality color image enhancement algorithm is suggested in this work to increase visual quality and decrease computational complexity. KGMO optimization is employed to optimize the parameter which is used in the hyperbolic tangent (tanh) function. Various rates are set to optimize the parameter value properly to get the correct output and the lesser iteration loop. Various performance evaluation techniques such as AMBE, EME, DE are used to validate visual quality evaluation. Experimental results give that CE-KGMO-HTF reduced computational complexity and also improved the visual quality when compared to conventional image enhancement techniques.

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