CONTRAST ENHANCEMENT IN GRAYSCALE AND COLOR IMAGES BY HOMOMORPHIC FILTERING AND CLUSTER-CHAOTIC OPTIMIZATION (CCO)

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Abstract

Image contrast enhancement is a technique used in image processing to extract more information from an image, which can be used in complex image analysis systems. This study proposes a new approach to enhance image contrast using homomorphic filtering (HF) and the cluster-chaotic optimization metaheuristic algorithm, an alternative to conventional methods. Chaotic algorithms are based on chaos theory, which defines chaos as the behavior of nonlinear systems that are unstable and nonperiodic. HF is a technique that enhances images with non-uniform lighting and removes multiplicative noise. Unlike histogram equalization, commonly used in conventional methods, HF uses generalized superposition. To evaluate the effectiveness of this approach, we conducted several tests.

1. Introduction

Digital image processing is a field of computer vision that has gained much attention over the years. Many techniques have been developed to improve image quality for further analysis, and one of the most essential is Image Contrast Enhancement (ICE)[1]. One common technique used in ICE is Histogram Equalization (HE) [2], which spreads out the most frequent intensity values within the image range. However, HE can lead to noise in the image and information loss. Recently, evolutionary algorithms have been used to improve ICE techniques [3]. These algorithms were inspired by the genetic material exchange in cellular organisms and were first developed in the early 1960s by John H. Holland, who created the Genetic Algorithm (GA). Nowadays, there are various types of evolutionary algorithms, including bioinspired algorithms like Particle Swarm Optimization (PSO), Cuckoo Search (CS), Artificial Bee Colony (ABC), and Firefly Algorithm (FA) [4 - 7], as well as other methodologies based on physical phenomena, like the Harmonic Algorithm or Gravitational Search Algorithm (HA, GSA) [8, 9], and mathematical principles, like the Cluster Chaotic Optimization Algorithm (CCO) [10]. In this study, we propose a new method for image contrast enhancement that utilizes the CCO algorithm and homomorphic filtering technique. The CCO algorithm uses chaos theory to arrive at the global optimum of a given function. The strategy presents a promising alternative to conventional ICE methods and can improve image quality for further analysis.

2. Preliminary Concepts

2.1. Image Contrast Enhancement (ICE)

Contrast enhancement is a technique used to improve the visual quality of an image, making it easier for humans to interpret and for further image analysis procedures to be performed [11] The two conventional strategies used for contrast enhancement are pixel-by-pixel exchange and histogram optimization. The former approach provides a quick "decompression" of the image with fewer resources [12], but it can also increase the noise level in the original image. The latter technique allows for the adjustment of the image histogram to distribute the gray levels more evenly.

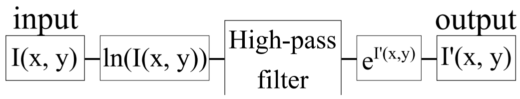
However, the approach differs from these conventional methods by utilizing the concept of the generalized superposition [13, 14]. This approach involves nonlinear mapping in a different domain, applying linear filtering techniques before returning to the original domain through a different mapping. This method provides a more effective and efficient way to enhance image contrast than the conventional strategies mentioned above.

2.2. Homomorphic Filtering (HF)

Homomorphic filtering is a technic that presents an image as a problem composed of an illumination-reflectance model representing that the intensity of each pixel reflected by a point in the image is the product of illumination and reflectance in the scene [15]. HF is one of the most common ICE methods for non-uniform lighting correction [13, 14], [16]. It can also attenuate the noise simultaneously. HF consists of three essential parts, shown in Figure 1. At first, the input image must be changed into a logarithmic scale, then the application of the high-pass filter, and finally, the shift in an exponential scale to cancel the first conversion and thus return to natural values.

In HF, a digital image can be defined as the product of two non-separable components, as shown in (1):

FIGURE 1:
Homomorphic filtering



$$I(x,y) = I_l(x,y).I_r(x,y) \quad (1)$$

The illumination and the reflectance components can be separated applying the transformation to logarithmic scale. This is represented by:

$$ln\{f(x,y)\} = ln\{f_l(x,y).f_l(x,y)\} \quad (2)$$

Then, the Fourier transform is applied for use the frequency domain:

$$F(u,v) = F_i(u,v) + F_r(u,v) \quad (3)$$

Filtered output in the frequency domain is given by:

$$S(u,v) = H(u,v)\left(F_i(u,v) + F_r(u,v)\right) \quad (4)$$

Where $S(u,v)$ is frequency domain filtered output, $H(u,v)$ is the high-pass filter response in frequency domain, and $F(u,v)$ is the frequency domain image. Fourier transform is applied to get spatial domain image as in (5):

$$s(x,y) = IFT\left(H(u,v)F_i(u,v) + H(u,v)F_r(u,v)\right) \quad (5)$$

Finally, the exponential is applied to reconstruct the enhanced image as in equation (6)

$$g(x,y) = e^{\{s(x,y)\}} \quad (6)$$

2.3. Difference of Gaussians filter (DoG filter)

Despite the advantages of the HF, it presents complications due to its parameter calibration stage. Under such circumstances, extensive experimentation is usually conducted to tune the filter's parameters. Under such circumstances, HF needs a robust filter to obtain good results. Therefore, this project uses the Difference of Gaussian filter (DoG) to support improving the HF process.

The DoG filter is a technique that removes noise from an image through the difference between two Gaussian filters with different blur values so that the result is a smoothed image [17]. DoG filtering is an effective technique for finding image edges and delimiting image regions. In DoG filtering, there are two values; namely σ_1 and σ_2, which are responsible for delimiting the inner and outer edges of the regions, respectively:

$$G(x,y) = \frac{1}{\sqrt{2\pi}}\left(e^{(-\alpha)} - e^{(-\beta)}\right) \quad (7)$$

where:

$$\alpha = \frac{(x+y)^2}{2\sigma_1^2}, \qquad \beta = \frac{(x+y)^2}{2\sigma_2^2} \quad (7.1)$$

A smaller value in σ_2 will result in a denser separation (thicker edges). However, different experiments have shown that σ_1 can be smaller if the image object is light and has a dark background.

2.4. Cluster-Chaotic Optimization (CCO)

Cluster-Chaotic Optimization (CCO) is an evolutionary algorithm based on the chaos theory applied in a clustering algorithm [10]. Clustering aims to identify the most suitable essentials for the evolution process. The CCO algorithm assumes that potential solutions are found in clusters of all individuals in the population. The algorithm establishes a search strategy where the association of individuals is considered necessary for the optimization process [18].

Most of the ICE methods do not consider the spatial associations of solutions. However, CCO contemplate spatial relationship among solutions to find areas where it is more likely to find the global optimum by using the chaotic schemes to perform random perturbations. By substituting chaotic numbers instead of random numbers, it has been possible to obtain better results. The pseudocode of the CCO algorithm is shown in table 1.

TABLE 1
Pseudocode of the CCO

Input $\mathrm{N_D}, \mathrm{gen}, \mathrm{k} = 0$
$\mathrm{D^k} \leftarrow$ initialize $(\mathrm{N_D})$
While k<=gen do
$\mathrm{d_B^k} \leftarrow$ **Select best particle** $(\mathrm{D^k})$
$[\mathrm{C_q^k}, \mathrm{g}] \leftarrow$ **Clustering**$(\mathrm{D^k})$
$\alpha \leftarrow$ **Calculate Perturbation**(gen)
For (1=1; 1<=g; q++)
$\mathrm{d_b^k} \leftarrow$ **best Element Cluster**$(\mathrm{C_q^k})$
$\mathrm{d_l^{k+1}} \leftarrow$ **Local attraction** $(\mathrm{C_q^k})$
$\mathrm{d_l^{k+1}} \leftarrow$ **Local perturbation** $(\mathrm{d_l^{k+1}})$
End for
For (all best cluster elements of $\mathrm{C_q^k}$)
$\mathrm{d_b^{k+1}} \leftarrow$ **Global attraction** $(\mathrm{d_b^k})$
$\mathrm{d_b^{k+1}} \leftarrow$ **GLobal perturbation** $(\mathrm{d_b^{k+1}})$
End for
k=k+1
end while
Output: $\mathrm{d_B^k}$

3. The proposed method

The proposed research aims to show a novel image contrast enhancement method called ICE-CCO through CCO and homomorphic filtering. From a computational point of view, contrast enhancement can be considered a complex optimization process due to its discontinuity, high multimodality presence, and inherent nonlinearity nature. Since homomorphic filtering (via DoG filter) has a set of configurable parameters, which can be difficult to calibrate. The proposed approach uses the CCO to find the optimal parameters to obtain the best image quality. The CCO algorithm finds the optimal values to be calibrated within the HF structure. These parameters are named σ_1, and σ_2 the values are obtained from (8). As can be seen, the objective function has two dimensions to find each of the σ values. The proposed method is summarized in Table 2. The proceeding of the CCO is shown in table 1.

$$F(Z) = log\left(log\left(E\left(I(Z)\right)\right)\right) \cdot \frac{ne\left(I(Z)\right)}{PH \cdot PV} \cdot H\left(I(Z)\right) \quad (8)$$

Where: $F(Z)$ Represents the quality of the output image, $E\left(I(Z)\right)$ Is the sum of edge intensities, $ne\ (I(Z))$ Is the number of edges, $H((I(Z)))$ Is the entropy of the output image and finally, PH and PV are the numbers of horizontal and vertical pixels of the image, respectively.

TABLE 2
CCO-ICE Pseudocode

1. **Input** image I
2. **Convert** image to double values
3. **Run** metaheuristic algorithm CCO (contained in TABLE 1)
4. **Output**:d_B^k(2 dimensions)
5. **Assign** σ_1, σ_2 values from d_B^k
6. **Convert** to logarithm scale to separate luminance and reflectance elements ($L(x,y), R(x,y)$ respectively)
7. **FFT**($L(x,y) + R(x,y)$)
8. Difference of gaussians filter(**h**)
9. Convert to high frequency filter (**H**=1-**h**)
10. **IFFT** (Z (x, y))
11. **Convert** to exponential scale (logarithmic-exponential cancellation principle)
12. **IMAGE OUTPUT**

4. Experimental study

In this section, the experimental results of the proposed methodology are discussed. A comparison between similar methods is shown. This comparison evaluates the quality, stability, and accuracy of the images obtained using the proposed method against state-of-the-art and traditional ICE methods. Several datasets are used to evaluate the performance of the proposed approach. These include the TID2013 dataset and the USC SIPI (standard) image dataset. To test the performance of the proposed approach, the metrics considered in the experimental study are the Peak Signal-to-Noise Ratio (PSNR), the Number of edges (N. edges), the Structure Similarity Index Measure (SSIM), the Mean Squared Error (MSE), the Edge Preserve Index (EPI), the Entropy (E) and the colorfulness (C). The set of experiments has been tested on Ryzen 5 1600 processor, 3.2 GHz 6-core, 20Gb DDR4 RAM, 2400MHz, GeForce GTX 1650 Graphic card 4Gb DDR5, Solid state disk barracuda WD 240 Gb, MATLAB 2019a.

4.1. Experimental Study

In this subsection, the comparison of the numerical results of the proposed approach is analyzed. For comparison purposes, popular evolutionary methods are the Genetic Algorithm (GA), and the Artificial Bee Colony (ABC) algorithm.

TABLE 3
PSNR metric from GA, ABC and the proposed method (CCO-ICE)

Image	GA	ABC	CCO-ICE
G1	14.16	23.64	**27.4711**
G2	13.21	12.18	**17.0105**
G3	13.75	17.42	**25.5680**
G4	20.12	20.16	**25.3994**
G5	17.92	**24.84**	16.2187

Table 3 shows the comparison considering the PSNR between methods. As it can be seen, the proposed method preserves the quality with respect to the original image, since the higher the PSNR value, the better the quality of the output image. On the other hand, the G5 image has a better value, and this may be due to the particularities of the image, such as its illumination or the color.

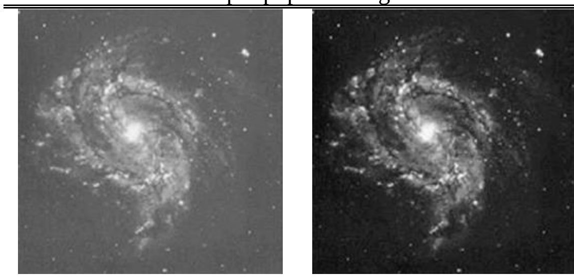
TABLE 4
Comparison of Edges from GA, ABC and the proposed method (CCO-ICE)

Image	GA	ABC	CCO-ICE
G1	1.96E+03	1.33E+03	**2.58E+03**
G2	2.50E+03	2.90E+03	**4.31E+03**
G3	2.88E+03	2.17E+03	**3.88E+03**
G4	3.49E+03	3.53E+03	**8.98E+03**
G5	3.32E+03	2.56E+03	**9.16E+03**

According to Table 4, the CCO-ICE method is able to maintain the number of image edges and prevent their loss in all cases. Unlike other methods that stretch the histogram, this method detects and enhances the image edges. Additionally, the GA method retains its second-place ranking in terms of edge preservation, while the ABC method shows the lowest values. These findings suggest that the GA method is also somewhat effective at preserving image edges, although not as much as the ICE-CCO method.

Figure 2 shows the graphical comparison between the original and sample images obtained from the new method. As can be seen, the quality increases without damaging the image edges, which gives a neat and sharp result. Some information loss is expected in conventional methods, something that does not happen in CCO-ICE. The image does not lose quality, since the image histogram is not directly altered.

FIGURE 2
Comparison between the original image vs the CCO-ICE output popular image



4.2. Comparison with state-of-art methods

Tests performed with state-of-the-art methods demonstrate that this work is capable of using practical proofs and will continue to perform well. Unlike other methods, the image is not abruptly altered, which is demonstrated by the values of the metrics. As shown in Table 5, all of the tests performed resulted in the winner being the CCO-ICE. It is noteworthy that the method with the worst result was precisely the one based on histogram equalization. For a better understanding, it is necessary to see figure 3, which shows the graphical results obtained. The method used allows easy edge enhancement, without the need to use post-processing techniques, such as filters, masks and value compensators.

FIGURE 3
Comparison between the original color image vs the CCO-ICE output color image

TABLE 5
comparison among CLAHE, MSA and CCO with grayscale images

Image	Metric	CLAHE	MSA-ICE	ICE-CCO
	SSIM	0.7651	0.8854	**0.9982**
	MSE	8.87E+03	8.01E+03	**0.0127**
	EPI	0.9874	**1.1247**	0.9980
I_1	E	5.7428	6.7421	**7.1376**
	C	0.2978	0.3341	**0.1388**
	SSIM	0.5832	0.7021	**0.9981**
	MSE	6.75E+03	6.17E+03	**0.0130**
	EPI	0.8941	0.9874	**0.9942**
I_2	E	3.7024	4.8821	**7.0017**
	C	0.2417	0.3011	**0.1634**
	SSIM	0.7104	0.8421	**0.9983**
	MSE	7.93E+03	7.32E+03	**0.0128**
	EPI	0.8621	0.9421	**0.9895**
I_3	E	3.1421	4.1014	**6.8530**
	C	0.2422	0.2987	**0.0453**
	SSIM	0.6931	0.8021	**0.9983**
	MSE	8.84E+03	7.89E+03	**0.0119**
	EPI	0.8654	0.9765	**0.9973**
I_4	E	3.7892	4.5672	**7.1171**
	C	0.1892	0.2893	**0.1497**
	SSIM	0.8122	0.9032	**0.9977**
	MSE	8.58E+03	7.81E+03	**0.0157**
	EPI	0.8840	**0.9902**	0.9870
I_5	E	3.6783	5.0393	**6.6309**
	C	0.2076	0.3678	**0.0721**
	SSIM	0. 8122	0.9032	**0.9985**
	MSE	8.58E+03	7.81E+03	**0.0120**
	EPI	0.8840	0.9902	**0.9947**
I_6	E	3.6783	5.0393	**7.5281**
	C	0.2076	0.3678	**0.0401**

5. Conclusions

Homomorphic filtering is a well-known contrast enhancement technique. Development of a contrast enhancement method based on the cluster-chaotic optimization algorithm and HF was proposed. The values obtained from tests with conventional algorithms prove the quality enhancement of the original images. Future work can be oriented towards this area.

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