Particle Swarm Optimization applied to parameter tuning of CLAHE based on Entropy and Structural Similarity Index

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Abstract

Contrast enhancement is fundamental in image processing, as a preprocessing step for other high level applications. Capturing images sometimes results in poor details of the scene. Transforming the image to improve details is essential to any contrast enhancement operation. Contrast enhancement can be divided into two approaches: global and local. In global approach, a transformation function is applied to the image at once, while in local approach a function is applied to blocks of pixels. Contrast Limited Adaptive Histogram Equalization(CLAHE) is an algorithm that improves image contrast locally, but requires 2 parameters to be determined; to address this complex tuning problem, we propose a method to find optimal parameters using PSO, evaluating two metrics: Entropy, which maximizes the amount of information, and SSIM, which evaluates the image distortion level of the resultant image. Experimental results show that CLAHE gives a good level of contrast enhancement for general images and the parameters are not the same for each one.

Keywords: Contrast enhancement, particle swarm optimization, structural similarity index, entropy, contrast limited adaptive histogram equalization.

1. INTRODUCTION

Images captured by any device may not reflect properly the fine details of the captured scene because they may contain some areas brighter than others or shadows that hides image details [1]. Contrast Enhancement is a technique which tries to reveal hidden or barely perceptible details. It consists in the expansion of the range of gray levels by modifying the histogram of the image [2]. Besides providing a better view of the details of the image, contrast enhancement is normally used as a form of preprocessing, serving as an input to more complex applications (e.g. feature detection, pattern recognition, monitoring images, medical images, and others) [3].

One contrast enhancement method is the Histogram Equalization (HE), which consists in transforming the distribution of gray levels. HE is very popular due to its simplicity and effectiveness [4]. However, it often does not give the best visual results. Various techniques have been developed based in HE [5], [6], [7]. For our work, we have chosen a technique called Contrast Limited Adaptive Histogram Equalization (CLAHE) [9]. This algorithm is an extension of the Adaptive Histogram Equalization (AHE) [8]. Also, we will use Particle Swarm Optimization (PSO) algorithm in order to find the appropriate parameters for CLAHE. To assess the quality of the solutions, we will use two evaluation metrics: Entropy, and Structural Similarity Index (SSIM)[12]. In [11] a method is proposed, which finds the optimal parameters of CLAHE, but unlike our approach, the image degradation is not taken into account as a metric for evaluation. We compare our results with the results of this method and we noted that the use of the image degradation as a metric marked a noticeable difference between the results.

The rest of the paper is organized as follows: Section 2 describes the Histogram Equalization. The CLAHE algorithm is briefly described in Section 3. In Section 4 we define the evaluation metrics. Section 5 presents the PSO applied in this work; while in Section 6 the obtained results are presented and discussed. Finally, Section 7 states our conclusion.

2. HISTOGRAM EQUALIZATION

The Histogram is a distribution of the gray levels of an image. Histogram Equalization(HE) consists in applying a transformation function of the cumulative distribution of gray levels in order to obtain a new distribution that approximates an uniform distribution, this is, the same amount of pixels for each gray level. However, HE has some drawbacks, such as noise amplification, contrast over-stretching, or it can change the overall brightness [4], [11], [14]. For these reasons, HE based methods are divided into two major categories: global and local methods [15] to be explained in the next section.

2.1. Global Histogram Equalization

Global HE uses the histogram information of the entire input image in its transformation function [15]. In this approach, the contrast stretching is limited to the gray levels with high frequencies. That is, the high frequency gray levels dominate the low frequency gray levels. In this situation, the global approach transforms the gray levels and the dominating gray levels that have higher frequency gain contrast stretching, which causes a significant contrast loss for the gray levels with less occurrence. Additionally, in most cases, the neighboring pixels may not get captured and transformed with precision.

2.2. Local Histogram Equalization

Local HE tries to resolve the issues associated with global HE. It divides the image into sub images and equalizes them independently. There are many ways to divide an image into blocks of windows. One simple way is by dividing the image in two windows. Another way is to slide the window pixel by pixel on the entire image sequentially, but only the pixels that fall into the window are considered for the equalization. This gives an equalization centered in the window and only the gray levels within the window are allowed to get better enhancement of the portion of the image that is hidden or difficult to visualize with a global equalization. However, local HE is computationally expensive, and sometimes causes over-enhancement.

To address the issues showed before, one of the local methods, Contrast Limited AHE (CLAHE) will be explained on the next section.

3. CONTRAST LIMITED AHE

The natural behavior of the human eye is to assess the information contained in an image, based on its local components. Hence, it might be relevant to perform a contrast enhancement based on the local region approach. For AHE, it is implemented by optimizing contrast within rectangular regions of the image, so called *contextual regions* [9], with the region dimensions defined as $(\mathcal{R}_x, \mathcal{R}_y)$. Then, the histogram equalization is performed within the contextual regions.A bi-linear interpolation function is executed on contextual regions boundaries to correct inconsistencies between them. One of the characteristics of AHE is that is capable to enhance contrast information of the image[10].

AHE is associated with noise amplification, particularly visible in areas where there are homogeneous gray levels. This problem can be solved by limiting the contrast enhancement in such areas. The idea behind CLAHE is to limit the amount of pixels that can reach a certain gray level, thus correcting the gray level peak associated to the homogeneous regions. The pixels are redistributed in order to clip the peak, and are equally redistributed across the histogram of the contextual region. We can define the clip limit $\mathscr{C}$

as a factor associated with the average of the histogram contents. When we define a low coefficient, the local histograms will not show heights associated to homogeneous areas, thus giving a narrow enhancement. When we choose a higher $\mathscr{C}$, we get a behavior of CLAHE that turns out to be equivalent to the AHE algorithm. In Figures 1(a) and 1(b), we see an example of directly applying CLAHE using arbitrary parameters: contextual region $(\mathcal{R}_x, \mathcal{R}_y) = (8, 8)$ and $\mathscr{C} = 3$.

(a) Original image (b) After applying CLAHE

Figure 1: An example of applying CLAHE.

We need to define certain comparison metrics in order to determine the quality of the results obtained. Those metrics are described briefly in the subsequent section.

4. COMPARISON METRICS

4.1. Entropy

Information entropy is a coefficient that gives a quantitative measure of the randomness found within the signal carried by the image[16]. When we measure entropy of two qualitatively similar images, we have in our hands an instrument to evaluate if there is an improvement in the amount of information carried by the images. The information found within gray scale images is defined as a coefficient which shows how much of the enabled gray levels are effectively used to construct the image [17].

In order to formulate the information entropy, it is fundamental to define the histogram of an image, as shown in (1):

$$\mathcal{H} = \{h_i \in [0...N] \mid i = 0, 1, ..., L-1\} \tag{1}$$

where h_i is the counting of occurrences of the $i-th$ gray level composing in the image; N is the total number of pixels of the image, note that $N = \sum_{i=0}^{L-1} h_i$; L is the maximum gray level defined to represent gray scales of the image. For a 8-bit scale, the maximum gray level is $2^8 = 256$ possible gray levels. Then, the normal distribution of the gray scales of the histogram is defined as:

$$\mathcal{P}_i = \frac{h_i}{N} \tag{2}$$

finally, we can formulate the entropy of a given image as (3):

$$\mathscr{H} = -\sum_{i=0}^{L-1} \mathcal{P}_i log_2(\mathcal{P}_i)[bits] \tag{3}$$

It is desirable to measure the entropy of an image because it is directly related to the brightness homogeneity [18]. Another important feature is that it is directly related to an efficient usage of the available gray levels of the image.

For the preservation of the structural characteristics of the enhanced image, the SSIM is defined in the next section.

4.2. Structural Similarity Index

Structural Similarity Index (SSIM) is a coefficient that is capable of assessing the structural information changes, giving a good measure of the image distortion. SSIM lies on the idea that there is a strong dependency between pixels that are close to each other [12]. Traditional methods like Peak Signal to Noise Ratio (PSNR), and Mean Squared Error (MSE), are inconsistent with human eye perception[13]. SSIM is calculated across several windows that are defined within the image.

Let x and y be two windows at equal cartesian coordinates, for the original image and the resultant image, respectively; then, we can formulate SSIM as in (4):

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{4}$$

where μ_x is the average of x; μ_y is the average of y; σ_x^2 is the variance of x; σ_y^2 is the variance of y; σ_{xy} is the covariance of x and y; $c_1 = (K_1 L)^2$ where L is the dynamic range for the pixel values (255 for a 8 bit grayscale image) and $K_1 \ll 1$ is a small constant; $c_2 = (K_2 L)^2$, and $K_2 \ll 1$. c_1 and c_2 are constants to stabilize the division when the denominator tends to zero.

When it comes into practice, a single coefficient is taken to assess the entire resultant image quality, hence the Mean of SSIM (MSSIM) is defined as measuring the image quality as a whole. It is defined in (5):

$$MMSIM(x, y) = \frac{1}{M} \sum_{j=1}^{M} SSIM(x_j, y_j) \tag{5}$$

where x and y are the original and resultant images respectively; x_j and y_j are the image pixels at the $j-th$ window; and M stands for the total of windows that where used to process the original image.

5. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a metaheuristic which has been applied successfully in several optimization problems, in a broad range of scientific research fields[19].We define PSO as follows[20]: Let i be a complete cycle of execution of the algorithm, denominated *iteration*, and a $\mathcal{D}$-dimensional search space; then, each particle of the swarm is composed by a series of vectors, where $\overrightarrow{x_i}$ is the current position of a particle within the search space; $\overrightarrow{p_i}$ is its previous best position, and $\overrightarrow{v_i}$ is its velocity. We can describe $\overrightarrow{x_i}$ as an array of coordinates, in which a point of the solution space is completely defined. When a particle evaluates this solution against the best solution it has found so far, the solution is stored in $\overrightarrow{p_i}$; symilarly, the best position achieved by the whole swarm is stored in $\overrightarrow{p_g}$. A single particle moves towards a new point to the next evaluation, adding $\overrightarrow{v_i}$ coordinates to $\overrightarrow{x_i}$, and the algorithm adjusts a new $\overrightarrow{v_i}$, which can be seen as a movement pace. Taking this description into account, we might be able to formulate the PSO algorithm as showed in (6):

$$\begin{cases} \overrightarrow{v_i} = \omega \overrightarrow{v_i} + U(0, \phi_1) \bigotimes (\overrightarrow{p_i} - \overrightarrow{x_i}) + U(0, \phi_2) \bigotimes (\overrightarrow{p_g} - \overrightarrow{x_i}), \\ \overrightarrow{x_i} = \overrightarrow{v_i} + \overrightarrow{x_i} \end{cases} \tag{6}$$

where ω is the *inertia weight*; $\overrightarrow{U}(0, \phi_i)$ represents a function of random numbers between $[0, \phi_i]$, generated on every iteration for each particle, and $\otimes$ is a scalar-vector multiplication. In Algorithm 1, the PSO-CLAHE pseudocode used in this work is shown.

initialize $inputImage$, $numIterations$, $numParticles$, w, i, ϕ_1, ϕ_2;
for *each particle* x_i **do**
    initialize x_i randomly and set the velocity $\overrightarrow{v_i}$ to 0;
    $outputImage$ = runCLAHE(x_i, $inputImage$);
    A_i = calculateFitness($outputImage$, $inputImage$);
    set the local best $\overrightarrow{p_i}$ of the particle to its initial position;
    set the global best particle $\overrightarrow{p_g}$ if the current particle is better;
end
while i = *0*, i < *numIterations* **do**
    for *each particle* x_i **do**
        calculate the new velocity $\overrightarrow{v_i}$ according to Eq. (6);
        calculate the new position $\overrightarrow{x_i}$ according to Eq. (6);
        $outputImage$ = runCLAHE(x_i, $inputImage$);
        A_i = calculateFitness($outputImage$, $inputImage$);
        actualize the local best $\overrightarrow{p_i}$ if the current particle is better;
        actualize the global best $\overrightarrow{p_g}$ if the current particle is better;
    end
end
return $\overrightarrow{p_g}$;

Algorithm 1: PSO-CLAHE proposed pseudo-code

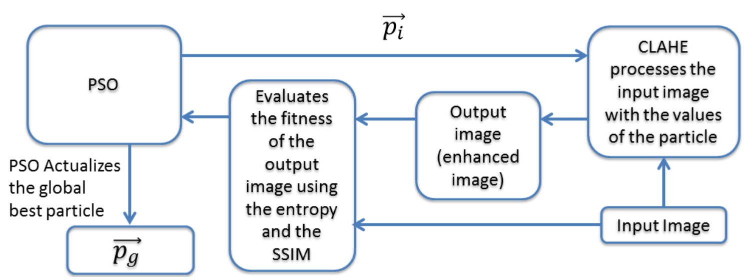


Figure 2: PSO-CLAHE relationship

In the context of the problem being addressed, a particle is composed by the input coefficients for CLAHE, this is $\overrightarrow{x_i} = ((\mathscr{R}_x, \mathscr{R}_y), \mathscr{C})$, where $(\mathscr{R}_x,\mathscr{R}_y)$ is the contextual region in which the local histogram equalization is performed, and $\mathscr{C}$ is the coefficient of clip limit applied by the particle. The inertia weight value ω is set to 0.1, and $\overrightarrow{U}(0, \phi_i)$ takes values between 1.5 and 2.5 for every iteration.

To evaluate the quality of the results achieved by the particle, a fitness function is defined: Let $\mathscr{A}$ be such function, and given Entropy (3) and MSSIM (5) which are obtained from the resultant image, we can formulate $\mathscr{A}$ as showed in (7):

$$\mathscr{A} = \mathscr{H} \times MSSIM \tag{7}$$

PSO stores a new $\overrightarrow{p_i}$ every time $\mathscr{A}_{\overrightarrow{p_i}} < \mathscr{A}_{\overrightarrow{x_i}}$, and stores a new $\overrightarrow{p_g}$ whenever $\mathscr{A}_{\overrightarrow{p_g}} < \mathscr{A}_{\overrightarrow{x_i}}$. This comparison series occurs until a stop criterion is reached. In Figure 2 is presented the relationship between PSO and CLAHE algorithms.

6. RESULTS AND DISCUSSION

Six images were chosen to test the PSO, see Figures 3(a), 3(b), 3(c) and 5(a), 5(b), 5(c). For every image, 10 tests were run; the population was configured with 100 particles and 50 iterations as stop criterion. The best fitness (the best result in terms of gain of entropy and loss of Structural Similarity) from the tests for PSO-CLAHE was taken for every image, and results are listed in Table 1. In Table 2, we show the results we obtained using a state-of-the-art method for Contrast Enhancement [11], for comparison pourposes.

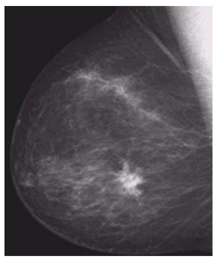
	Normalized Coefficients			Fitness	Parameters applied		
Image Name	Original $\mathscr{H}$	$\mathscr{H}$	$MSSIM$	Best $\mathscr{A}$	$\mathcal{R}_x$	$\mathcal{R}_y$	$\mathscr{C}$
Lenna	0.9306	0.9813	0.9246	0.9073	2	3	1.1604
Flowers	0.8748	0.9201	0.9103	0.8375	42	6	0.5590
Mammogram	0.8217	0.8732	0.9052	0.7904	7	3	1.5883
Giraffe	0.6724	0.8127	0.7984	0.6489	72	5	2.1555
Trees	0.7675	0.8382	0.8187	0.6862	17	17	2.4977
Woman	0.6685	0.9327	0.7296	0.6804	5	2	8.0793

Table 1: Summary of Results for PSO-CLAHE

	Normalized Coeffients			Fitness	Parameters applied		
Image Name	Original $\mathscr{H}$	$\mathscr{H}$	$MSSIM$	Best $\mathscr{A}$	$\mathcal{R}_x$	$\mathcal{R}_y$	$\mathscr{C}$
Lenna	0.9306	0.9948	0.8208	0.7639	2	2	0.030
Flowers	0.8748	0.9906	0.631	0.5519	2	2	0.044
Mammogram	0.8217	0.9564	0.6215	0.5107	2	2	0.051
Giraffe	0.6724	0.9754	0.3169	0.2131	2	2	0.056
Trees	0.7675	0.9842	0.5735	0.4402	2	2	0.063
Woman	0.6685	0.7936	0.5735	0.3834	32	32	0.042

Table 2: Summary of Results for the method proposed on [11]

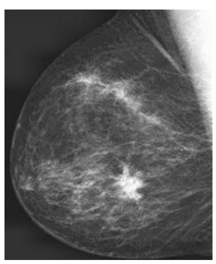
When comparing Table 2 against Table 1, it is seen for all rows that resulting entropy coefficients from the method proposed in [11] are higher for every row listed, than the ones obtained from PSO-CLAHE; this is because in Table 2, entropy was maximized, without setting a explicit constraint that prevents image quality degradation. Therefore, the fitness coefficients resulted lower for every row in Table 2, when compared with the same values in Table 1. Finally, we can state that images obtained with our method show better image quality, and less amplified noise when compared with resultant images obtained from the method in [11].



(a) Original image - Mammogram

(b) Original image - Tree

(c) Original image - Giraffe



(d) Result - Mammogram

(e) Result- Tree

(f) Result - Giraffe

Figure 3: Original images and best solutions for PSO-CLAHE

(a) Result - Lenna

(b) Result - Flowers

(c) Result - Mammogram

Figure 4: Image results for the method proposed on [11]

The enhanced images are shown in Figure 3(d), 3(e), 3(f) and Figure 5(d), 5(e), 5(f). It is remarkable that there was a perceptible enhancement of contrast in every image in Figures 3 and 5, and that there was no amplified noise. In Figures 3(d), 3(f) and 5(f), we obtained better appreciation of image details. Meanwhile, in Figures 5(d) and 5(e), strong contrast was achieved. It is clearly shown that, in Figure 5(d) there is little noise amplification, when comparing with Figure 1(b).

(a) Original image - Lenna (b) Original image - Flowers (c) Original image - Woman

(d) Result - Lenna (e) Result - Flowers (f) Result - Woman

Figure 5: Original images and best solutions for PSO-CLAHE

7. CONCLUSION

This paper states a promissory approach for Contrast Enhancement. We proposed the use of PSO to find the optimal parameters of CLAHE, a local HE method, regardless of the nature and size of the image, based on Entropy and SSIM as the metrics that determine which parameters are optimal. The results indicated that our method can be applied to any type of gray level images, gives good results in terms of visual assessment, and it is not limited to a particular type of image. Using Entropy and SSIM yields images with a good natural appearance, and without amplifying noise, which is a serious drawback of AHE-based techniques. As a future work, it might be interesting to apply PSO-CLAHE in order to perform Contrast Enhancement on HDR images [21] .

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