Analysis of the Image Quality in a Multiobjective Context based on PSO-CLAHE

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Abstract

Contrast enhancement in grayscale images is a technique which highlights useful information therein. A widespread technique for enhancement is CLAHE, nevertheless it presents a challenge in selecting optimal parameters, which may vary for each instance or image, in addition to the appropriate selection of metrics to evaluate the results.

An experiment is proposed in this work, using different metrics available to select which of them will be used in a purely multiobjective optimization process, based on a correlation study. A metaheuristic based on particle swarm (Speed-constrained Multi-objective Particle Swarm Optimization - SMPSO) is applied as optimizer, which tunes CLAHE (Contrast Limited Adaptive Histogram Equalization) parameters.

Comparisons were made using local and global metric pairs to measure the correlation between them. Results show that Local Entropy and SSIM (Structural Similarity Index) have a high negative correlation so the problem must be addressed in a purely multiobjective context. It is also noteworthy that SMPSO is a feasible metaheuristic for the calculation of non-dominated solutions on which the decision maker will choose the most appropriate image based on the work context.

Keywords: Contrast enhacement, Optimization, CLAHE, SMPSO, Entropy, Local Entropy, SSIM, LTG.

1 Introduction

Digital images are exposed to experience several types of distortions during processing, compression, storage, transmission and reproduction, and any of them can result in degradation of visual quality [1]. The main objective of image enhancement techniques is to process an image to make it more suitable than the original for a specific application.

Although the field of digital image processing is based on mathematical and probabilistic formulations, intuition and human analysis play a central role in the choice of one technique over another, and this choice is often

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based on visual subjective judgments. Therefore, it needs to get quantitative measures that can automatically assess the quality of the perceived image.

Image Histogram Equalization (HE) [2] is a broadly adopted technique for improving contrast. However, this and most other contrast enhancement methods can produce images of unnatural appearance and the images obtained by these methods are not desirable. There are approaches to global and local improvement, if we use only global information, a good contrast enhancement is not achieved, because the global techniques could cause a saturation effect of intensities; meanwhile in local approaches local windows for each pixel are considered, and new intensity values are calculated based on local histograms, therefore all pixels in a local window also contribute to the calculation of the new value of the central pixel being considered, solving the problem that could present global approaches [3]. There are several techniques of contrast enhancements based on histogram equalization, using optimization techniques through the use of Genetic Algorithms [4], Fuzzy Logic [5], Particle Swarm Optimization with CLAHE parameters (PSO-CLAHE) [6].

Local improvement approaches appear to be extremely useful when highlighting details in images is needed. Medical images are particularly challenging because preservation of fine details are a must. There are several proposals focusing on enhancing the contrast in X-rays [7, 8, 9]. An adequate metric selection criteria is needed, based in statistical analysis. As a result in this proposal, quality metrics pairs are analyzed, making a correlation comparison between them, to identify the most suitable metric for a multiobjective optimization of contrast enhancement of an image.

Metaheuristic optimization will be used to tune the input parameters of the algorithm of contrast enhancements, in order to obtain a group of contrasted images, which will be evaluated in terms of the information provided and distortion introduced by the equalizer.

The rest of the paper is organized as follows: In section 2 the evaluation metrics are shown; in section 3 the problem to be solved is formally posed; in section 4 the implementation of correlation between the selected metrics is shown; in section 5 results are discussed, and finally in section 6 corresponding conclusions are detailed.

2 Evaluation Metrics

The metrics are selected from the need to find those that provide the best balance of contrast enhancement and distortion. In this section we present the four metrics selected for analysis and correlation comparisons between them. These are the Entropy and Local Entropy as contrast enhancement measures, the Structural Similarity Index and Local Tuned Global model as distortion image measures.

2.1 Entropy

Information Entropy is a measure of randomness present in a set of data, like an image [15], where higher values indicate rich detail images and therefore have high contrast. Image Entropy can be defined as:

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

Where $\mathcal{P}_i$ it is the probability of gray level i occurrence in histogram and L is the highest gray level that can be used to represent the image. This is an interesting metric because it is strongly associated with the average brightness of the image [16]; this coefficient helps us to see how much the contrast increases as a result of image transformation.

2.2 Local Entropy

Local Entropy [17] represents the difference between two probability distributions in the same space. Is related to the variation of gray levels of a pixel's neighborhood. Local Entropy divides the image into separate regions and then analyzes each region as a separate information source. A small neighborhood image is defined as Ω_k with $M_k \times N_k$ size, then Ω_k entropy is defined as :

$$\mathscr{E}(\Omega_k) = \sum_{j=0}^{G-1} \mathcal{P}_j log_2(\frac{1}{P_j}) \tag{2}$$

where $\mathcal{P}_j = \frac{n_j}{M_k \times N_k}$ indicates the gray level probability of j in Ω_k neighborhood, n_j is the number of pixels with j gray level in Ω_k and $\mathscr{E}$ (Ω_k), is Ω_k local entropy.

2.3 Structural Similarity Index (SSIM)

Structural Similarity Index (SSIM) [18] is a useful metric which gives a measure coefficient for distortion degree of a resulting image T as a result of applying a contrast enhancement to an original image I. SSIM measures the similarities by using three elements of both images: luminance, contrast and structure. SSIM is computed by blocks, so two windows I_x and T_y are defined for the original and resulting images, respectively. SSIM index value varies in the interval [0,1]. SSIM is defined as shown below:

$$SSIM(I,T) = \frac{(2\mu_{I_x}\mu_{T_y}+C_1)(2\sigma_{I_xT_y}+C_2)}{(\mu_{I_x}^2+\mu_{T_y}^2+C_1)(\sigma_{I_x}^2+\sigma_{T_y}^2+C_2)} \quad SSIM \in [0,1] \tag{3}$$

Where μ_{I_x} is the average of intensities of I_x; μ_{T_y} is the average of intensities of T_y; $\sigma_{I_x}^2$ y $\sigma_{T_y}^2$ are the variances of intensities of I_x and T_y, respectively;

$\sigma_{I_x T_y}$ is the covariance between I_x and T_y; $C_1 = (K_1 L^2)$, L is the dynamic range of pixel intensities (256 for a 8-bit grayscale image) and $K_1 \ll 1$ is a constant; $C_2 = (K_2 L)^2$, and $K_2 \ll 1$; so C_1 y C_2 are constants used to stabilize the division if the denominator tend to zero.

2.4 Local Tuned Global Model (LTG)

Local Tuned Global (LTG) is based on the metric IQA (Image Quality Assessment) [19], under the supposition that the human visual perception to image quality depends on salient local distortion and global quality degradation [19].

LTG is a gradient's image based approach [20], because it is very sensitive to distortions of it. The metric first extracts luminance and chrominance information from the input original and distorted images, then measure salient local distortions and global quality degradation in luminance information as well as compares the differences of chrominance information, thus deriving the overall image quality score [19].

GM is defined by:

$$G = \sqrt{G_h^2 + G_v^2} \tag{4}$$

Where:

- G_h and G_v are the image partial derivatives along the horizontal and vertical directions using Scharr operator [10].

$$LTG(x, y) = \frac{\Phi(G_s^{\theta_1})}{\Phi(G_m^{\theta_2})} \Phi(I_m^{\theta_3} . Q_m^{\theta_3}) \tag{5}$$

Where:

- G_m = original and distorted image mean gradient.
- G_s = pixels with S% higher values in G_m.
- I_m and Q_m = images chrominance information.

3 Formulation of the Problem Posed

The problem addressed here is metric's correct selection to obtain satisfactory results. The wrong selection of metrics gives unsatisfactory solutions. It is needed to find a couple of metrics with the most negative correlation possible, which indicates that the two metrics are highly contradictory.

3.1 Contrast Limited Adaptive Histogram Equalization (CLAHE)

This contrast enhancement approach presented in [11] is an extension of the original algorithm Adaptive Histogram Equalization (AHE) [12]; both methods implement a local histogram equalization approach based on *Contextual Regions*, representing image sections, with dimensions defined by $(\mathcal{R}_x, \mathcal{R}_y)$, for equalization by sector image. Inconsistencies between border sections of the image are corrected by applying a bilinear interpolation scheme.

The CLAHE algorithm was originally developed to work with medical images and satisfactory results are achieved in the task of enhancing low-contrast images [13, 14].

The ability to control contrast enhancement degree of contrast enhancement by manipulating its parameters, makes it a useful technique to achieve better results for images with contrasts problems [6].

Given an input image I, a contrast enhancement algorithm $PSO - CLAHE(\overrightarrow{x}, I)$ with parameters $\overrightarrow{x} = (\mathcal{R}_x, \mathcal{R}_y, \mathcal{C})$ applied to I, where $\mathcal{R}_x$ and $\mathcal{R}_y$ are contextual regions and $\mathscr{C}$ is $ClipLimit$, a solution set $\mathscr{X}$ is calculated to determine the combination of objectives f_A y f_B, such that:

$$min(\rho_{f_A f_B}) \tag{6}$$

where:

- ρ is the correlation between f_A y f_B
- $f_A, f_B \in [\mathcal{H}, \mathcal{E}, SSIM, LTG]$

subject to:

- $\mathcal{R}_x \in [2, .., M]$ in $\mathbb{N}$ numbers.
- $\mathcal{R}_y \in [2, .., N]$ in $\mathbb{N}$ numbers.
- $\mathscr{C} \in (0, 1]$ in $\mathbb{R}$ numbers.

This means that $\mathcal{R}$ values can only take positive integer values between $(2, 2)$ and (M, N) and $\mathscr{C}$ can take a greater than zero and less than or equal to 1 values.

4 Proposal

Multi-objective optimization is performed for each test image, taking metrics f_A and f_B during the process. Then Pearson correlation tests [21] are performed - whose index is used to measure the degree of relationship or covariance of two different metrics linearly related, as long as both are

quantitative - the relationship strength between metrics f_A and f_B is defined, where potential solutions ρ_{xy} are called correlation coefficients of the variables x and y (where $x = f_A$ and $y = f_B$). The correlation index value varies in the interval [-1,1], then:

$$-1 < \rho_{xy} < 1 \tag{7}$$

Where:

- If $\rho = 1$, is a perfect positive correlation. It means that there is a direct relation between the two variables when one increases, so does the other in constant proportion.
- If $0 < \rho < 1$, there is a positive correlation.
- If $\rho = 0$, there is no linear relation.
- If $-1 < \rho < 0$, there is a negative correlation.
- If $\rho = -1$, is a perfect negative correlation. The index indicates that there is an inverse relation between the two variables: when one increases, the other decreases at a constant rate.

The metaheuristic chosen $SMPSO$ [22] is applied to $CLAHE$ algorithm, where the potencial solutions are defined as $\overrightarrow{x} = (\mathcal{R}_x, \mathcal{R}_y, \mathcal{C})$; these are called *particles* and the set of particles Ω is called *swarm*. Each particle $\overrightarrow{x_i}$ is updated in each t generation according to the following equation:

$$\overrightarrow{x_i}^t = \overrightarrow{x_i}^{(t-1)} + \overrightarrow{v_i}^t \tag{8}$$

where the factor $\overrightarrow{v_i}$ is known as velocity and is given by:

$$\overrightarrow{v_i}^t = \omega \cdot \overrightarrow{v_i}^{(t-1)} + C_1 \cdot r_1 \cdot (\overrightarrow{x_{p_i}} - \overrightarrow{x_i}) + C_2 \cdot r_2 \cdot (\overrightarrow{x_{g_i}} - \overrightarrow{x_i}) \tag{9}$$

Here, $\overrightarrow{x_{p_i}}$ is the best solution found by $\overrightarrow{x_i}$, $\overrightarrow{x_{g_i}}$ is the best particle (also known as a *leader*) that was found throughout the swarm, ω is the weight of the particle inertia, r_1 and r_2 are two aleatory numbers, and C_1 and C_2 are parameters that control the effect of local and global particles. If a particle is better than another, it is said that *dominates*, and dominance is defined as follows: $\overrightarrow{x_{g_i}} \succ \overrightarrow{x_i}$ if and only if

$$\begin{cases} f_i(I, \overrightarrow{x_g}) \geq f_i(I, \overrightarrow{x}) \forall i \in \{1, 2\} \\ f_i(I, \overrightarrow{x_g}) > f_i(I, \overrightarrow{x}) \exists i \in \{1, 2\} \end{cases} \tag{10}$$

The *Pareto Set* is the set of solutions $\mathscr{X}$, and the target image in space is the *Pareto Front* Γ.

The resulting images are evaluated according to metrics Entropy (1) or Local Entropy (2) and SSIM (3) or LTG (5), and the best results obtained

based on these metrics make the pareto set Γ. The set is a series of images with different contrast levels, so as to highlight particular features of it.

Finally the ρ_I coefficients on f_A and f_B of the I_Γ images that conform the set Γ are measured; each value obtained is averaged and compared between them thus obtaining the pair of metrics whose ρ_I coefficient is the lowest for the image being analyzed, which indicates which pair of metric is more appropriate for the optimization process.

5 Results and Discussions

For the implementation of the optimization process, the following hardware settings were used: A desktop computer with Intel Core i5 quad-core processor with 8 GB of RAM, and Windows 7 64-bit operating system. A desktop computer with Intel Core i5 quad-core processor with 4 GB of RAM, and Windows 7 64-bit operating system.

Tests were performed using 23 previously digitized radiological images of the torax and mammograms from https://openi.nlm.nih.gov/. They were selected based on the lot of details they have, representing a suitable challenge for contrast enhancement.

The inverse relationship between metrics is shown in the obtained results. From **Figure 1(c)** it is observed that as the LTG metric approximates to 1, the results are more similar to the original image **Figure 1(a)**, in terms of contrast and visibility of details; however, while Local Entropy increases, a better distinction is observed in the details not visible because of the low contrast **Figure1(b)**. The images that are included in the pareto set highlight different details when the objectives' coefficients vary; this is achieved because an appropiate metric set selection is performed, based in the analysis described above.

It is important to emphasize that the best inverse proportion is for the case of Local Entropy/SSIM combination. This is consistent with **Figure 2** where a good inverse proportion between them is observed.

During the previous optimization process, 30 executions for each test image were performed. About 300 images pareto solutions were obtained for each of them, which were filtered once again when the whole executions were finished. **Figure 1** shows two of the solutions found in the Pareto set for metrics Local Entropy/LTG, and **Figure 2** shows two of the solutions found in the Pareto set for metrics Local Entropy/SSIM, plus the original images as a visual reference. **Table 1** shows correlations between pairs of metrics used; the bold marked numbers for each row represent the lowest correlation index found for every test image. It is noticeable that an inverse relationship is present, indicating that these pairs of metric are complementary to maintain the compromise between contrast enhancement and minimize distortion. The Pearson correlation coefficient obtained through the coefficients of the

objective functions during testing, shows the behavior in terms of how one metric affects each other because of the contrast enhancement process.

6 Conclusions and Future work

In this paper 4 pairs of metrics were presented: Entropy/SSIM, Local Entropy/SSIM, Entropy/LTG and Local Entropy/LTG, used by a metaheuristic algorithm and the algorithm CLAHE, aiming to obtain metrics that maximize contrast and minimize image distortion simultaneously. The experimental results obtained in **Table 2** show that the pair of metrics Local Entropy/SSIM are the most contradictory according to the correlation used for the experiment.

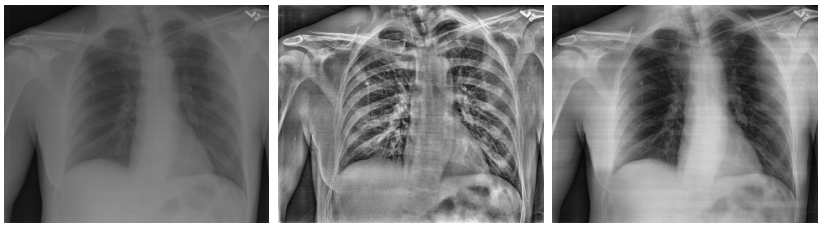
As future work it may be useful to use PSO-CLAHE implementation with more quality assessment metrics, find another correlation indexes and compare them with the one used in this work and do more experiments in order to determine how related are the local metrics with the size of the neighborhood.

	Entropy/SSIM	Local Entropy/SSIM	Entropy/LTG	Local Entropy/LTG
Image 1	-0.9719	**-0.9906**	-0.9525	-0.9718
Image 2	-0.9614	**-0.9892**	-0.9459	-0.9752
Image 3	-0.9659	**-0.9826**	-0.9696	-0.9667
Image 4	-0.9083	-0.9869	-0.7653	**-0.9899**
Image 5	-0.9500	-0.9884	-0.9005	**-0.9888**
Image 6	-0.8783	**-0.9867**	-0.9581	-0.9588
Image 7	-0.9568	**-0.9937**	-0.9415	-0.9681
Image 8	-0.9464	**-0.9867**	-0.9399	-0.9799
Image 9	-0.9409	**-0.9851**	-0.9190	-0.9811
Image 10	-0.9776	**-0.9942**	-0.9537	-0.9921
Image 11	-0.9669	**-0.9814**	-0.8767	-0.9685
Image 12	-0.9539	**-0.9859**	-0.9365	-0.9758
Image 13	-0.9644	**-0.9817**	-0.9485	-0.9754
Image 14	-0.9762	**-0.9832**	-0.9582	-0.9703
Image 15	-0.9606	**-0.9889**	-0.9204	-0.9807
Image 16	-0.9524	**-0.9896**	-0.9393	-0.9327
Image 17	-0.9627	**-0.9844**	-0.9533	-0.9530
Image 18	-0.9777	**-0.9838**	-0.9269	-0.9713
Image 19	-0.9709	**-0.9848**	-0.9501	-0.9689
Image 20	-0.9591	**-0.9854**	-0.9232	-0.9756
Image 21	-0.9550	**-0.9843**	-0.9456	-0.9729
Image 22	-0.9841	**-0.9889**	-0.9818	-0.9800
Image 23	-0.9340	**-0.9938**	-0.9273	-0.9841
Image 24	-0.9563	**-0.9850**	-0.8845	-0.9747
Image 25	-0.9375	**-0.9807**	-0.9516	-0.9725

Table 1: Results of Pearson correlation using Entropy, Local Entropy, SSIM and LTG

Metrics	Correlation
Entropy/SSIM	-0.9548
Local Entropy/SSIM	**-0.9866**
Entropy/LTG	-0.9308
Local Entropy/LTG	-0.9732

Table 2: Average Pearson Correlation

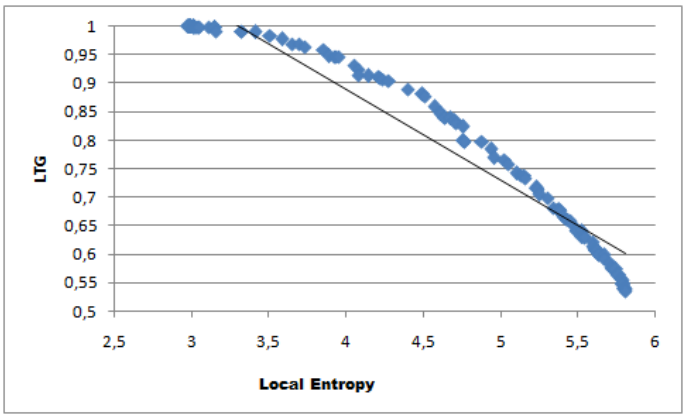


(a) (b) $LTG = 0.7512$ $\mathscr{E} = 4.9449$ (c) $LTG = 0.9144$ $\mathscr{E} = 4.0753$

Figure 1: Multiobjective PSO-CLAHE results. Local Entropy/LTG. 2(a) Original image, with $\mathcal{R}_x = 9, \mathcal{R}_y = 55, \mathcal{C} = 0.033391$ values and 2(c) with $\mathcal{R}_x = 108, \mathcal{R}_y = 2, \mathcal{C} = 0.0088699$ values, resulting images.

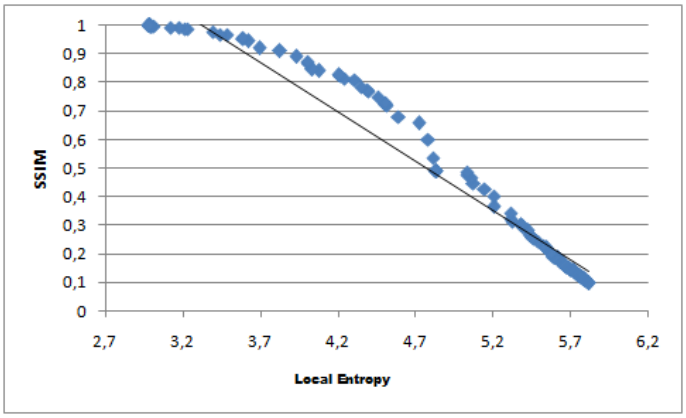
(a) (b) $SSIM = 0.4675$ $\mathscr{E} = 5.0595$ (c) $SSIM = 0.6820$ $\mathscr{E} = 4.5598$

Figure 2: Multiobjective PSO-CLAHE results. Local Entropy/SSIM. 2(a) Original image, 2(b) with $\mathcal{R}_x = 16, \mathcal{R}_y = 32, \mathcal{C} = 0.037273$ values and 2(c) with $\mathcal{R}_x = 45, \mathcal{R}_y = 133, \mathcal{C} = 0$ values, resulting images.



(a)

Figure 3: Pearson's Correlation for Local Entropy/LTG objectives, for image in **Figure 1**



(a)

Figure 4: Pearson's Correlation for Local Entropy/SSIM objectives, for image in **Figure 2**

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