PARAMETER TUNING OF CLAHE BASED ON MULTI-OBJECTIVE OPTIMIZATION TO ACHIEVE DIFFERENT CONTRAST LEVELS IN MEDICAL IMAGES

Luis G. Moré, Marcos A. Brizuela, Horacio Legal Ayala, Diego P. Pinto-Roa, José Luis Vázquez Noguera

Facultad Politécnica - Universidad Nacional de Asunción

ABSTRACT

In certain medical images, it is possible to achieve contrast enhancement at different levels, in order to highlight different structures present therein. This could be useful to medical specialists to perform more specific diagnoses, in chest radiographs and mammograms, where it is possible to highlight different details when contrast is enhanced. Parameter tuning for Contrast Limited Adaptive Histogram Equalization (CLAHE) using a multi-objective meta-heuristic (SMPSO) is proposed, where the objective functions are the maximization of the amount of information available (via Entropy) and minimization of distortion in the resulting images (Structural Similarity Index, SSIM) simultaneously. The results show that our approach calculates a set of non-dominated solutions or Pareto Set, which represents images with different contrast levels and different levels of commitment between Entropy and Structural Similarity Index. Particularly, these objective functions are contradictory. These enhanced images provide useful information for decision making of specialists.

***Index Terms*—** SMPSO, CLAHE, Entropy, SSIM, Contrast Enhancement, Multi-objective Optimization.

1. INTRODUCTION

Improve contrast of medical images is a very important task in order to emphasize and maintain the features present within them. Radiographs show particular contrast features, such as in chest radiography and mammograms, because there might be notorious contrast differences because of the attenuation characteristics of X-Rays [1].

Important efforts are devoted to achieve Contrast Enhancement and automatically assess the quality of the results [2, 3, 4, 5]. Local improvement approaches prove to be extremely useful when enhancing details in medical images, and there are various proposals focused on improving radiography contrast [6, 7, 8]. In our proposal a meta-heuristic for optimization will be used, in order to tune input parameters of the contrast enhancement algorithm described in section 2; in this context, we will get groups of images with different contrast levels, which will be evaluated assessing the provided information gain and distortion introduced by the equalization process (section 3). Obtained images show different relationships between contrast and distortion, in order to highlight different features of the test images, which is useful for analysis performed by the specialist. The literature shows several proposals for improvement based on meta-heuristics, as shown in [9], where a Genetic Algorithm is used; in [10] a similar approach to ours is used, although it focuses on a single objective and only one result is obtained for each original image; or in [11] a multi-objective meta-heuristic based on weighted sums is also used; the main difference is that our proposal is implemented more effectively in medical imaging because CLAHE shows satisfactory results in this type of images [12, 8], and we obtain a set of non-dominated solutions, which leads to a pure multi-objective optimization approach.

The rest of the paper is organized as follows: In section 2 the adopted contrast enhancement algorithm is described briefly; in section 3 it is shown the metrics for evaluating results; section 4 formally poses the problem being solved; section 5 shows how the optimization approach is applied to the contrast enhancement algorithm; then in the section 6, the results are discussed, and finally in section 7 the corresponding conclusions are detailed.

2. CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION - CLAHE

This contrast enhancement approach presented in [13] is an extension of the original Adaptive Histogram Equalization (AHE) algorithm [14]; both methods implement equalization based on Contextual Regions whose dimensions are defined by $(\mathscr{R}_x, \mathscr{R}_y)$ to perform equalization in several areas of the image. Inconsistencies between borders are corrected using bilinear interpolation. AHE presents problems of noise amplification, so in CLAHE a limitation is implemented in the contrast through limiting the number of pixels that can achieve certain grayscales within the local histogram; here the *Clip Limit* coefficient $\mathscr{C}$ is defined as a factor that is closely related to the contents of the histogram.

3. EVALUATION METRICS

In order to evaluate the performance of CLAHE, metrics are needed to measure the quality of the resulting images; two coefficients were adopted that are important for comparisons between different results: *Entropy* as a contrast enhancement measure, and *Structural Similarity Index* as a measure of image distortion.

3.1. Entropy

The *Information Entropy* is a measure of randomness of the image [15]. Entropy of the image is defined as:

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

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

3.2. Structural Similarity Index

The *Structural Similarity Index (SSIM)* [17] is a coefficient that measures the degree of distortion in a resulting image T as a result of applying contrast enhancement to an original image I. *SSIM* is calculated by blocks, so given two image windows I_x and T_y for the original and resulting images, respectively, the *SSIM* is defined as shown below:

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

Where μ_{I_x} is the intensity average of I_x; μ_{T_y} is the intensity average of T_y; $\sigma_{I_x}^2$ and $\sigma_{T_y}^2$ are the intensity variances for I_x and T_y, respectively; $\sigma_{I_xT_y}$ is the covariance between I_x and T_y; $C_1 = (K_1L^2)$, L is the dynamic range of intensities of the pixels (256 for a grayscale image of 8 bits) and $K_1 \ll 1$ is a small constant; $C_2 = (K_2L)^2$, and $K_2 \ll 1$; both C_1 y C_2 are constants that are used to stabilize the division in case the denominator approaches zero.

4. FORMULATION OF THE PROBLEM POSED

Given an input image I with $M \times N$ pixels, and a vector $\overrightarrow{x} = (\mathscr{R}_x, \mathscr{R}_y, \mathscr{C})$, where $\mathscr{R}_x$ and $\mathscr{R}_y$ are contextual regions and $\mathscr{C}$ is the *Clip Limit*, it is needed to calculate a set of non-dominated solutions $\mathscr{X}$, which simultaneously maximize the objective functions f_1 and f_2, as shown below:

$$f(I,\overrightarrow{x}) = [f_1(I,\overrightarrow{x}), f_2(I,\overrightarrow{x})]; \qquad f_1, f_2 \in [0,1] \quad (3)$$

where:

- T is the image enhanced by *CLAHE* using the parameters $\overrightarrow{x}$ applied to I; this is $T = CLAHE(\overrightarrow{x}, I)$.
- $f_1(I,\overrightarrow{x}) = \frac{\mathscr{H}(T)}{log_2 L}$ is the normalized Entropy of image T.
- $f_2(I,\overrightarrow{x}) = SSIM(I,T)$ is the *SSIM* between I and T.

Bounded to:

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

5. PROPOSAL

The *SMPSO* [18] meta-heuristic is used to calculate the potential solutions $\overrightarrow{x} = (\mathscr{R}_x, \mathscr{R}_y, \mathscr{C})$ at each generation. *SMPSO* hands a set of solutions Ω called *swarm*, which contains *particles* that represent potential solutions. Each particle $\overrightarrow{x_i}$ is updated at each generation t according to the following equation:

$$\overrightarrow{x_i}^t = \overrightarrow{x_i}^{(t-1)} + \overrightarrow{v_i}^t \quad (4)$$

where the element $\overrightarrow{v_i}$ is the velocity and is given by:

$$\overrightarrow{v_i}^t = \omega \cdot \overrightarrow{v_i}^{(t-1)} + c_1 \cdot r_1 \cdot (\overrightarrow{x_{p_i}} - \overrightarrow{x_i}) + c_2 \cdot r_2 \cdot (\overrightarrow{x_{g_i}} - \overrightarrow{x_i}) \quad (5)$$

Here, $\overrightarrow{x_{p_i}}$ is the best solution viewed by $\overrightarrow{x_i}$, $\overrightarrow{x_{g_i}}$ is the best particle (also known as the *leader*) found by the whole swarm. ω is the inertia weight of the particle, r_1 y r_2 are two random numbers, c_1 and c_2 are parameters which control the effect of the local and global particles. If a particle is better than other, it is said that the first *dominates* the second one; and this is defined as follows: $\overrightarrow{x_a} \succ \overrightarrow{x_b}$ if and only if

$$\begin{cases} f_i(I,\overrightarrow{x_a}) \geq f_i(I,\overrightarrow{b}) \forall i \in \{1,2\} \\ f_i(I,\overrightarrow{x_a}) > f_i(I,\overrightarrow{b}) \exists i \in \{1,2\} \end{cases} \quad (6)$$

The *Pareto Set* is the group of non-dominated solutions $\mathscr{X}$, and its image in the objective functions space is the *Pareto Front*.

In addition, a restriction for $\overrightarrow{v}$ is performed for each component $j \in \overrightarrow{x}$, according to the following equation:

$$v_{i,j}^t = \begin{cases} delta_j & \text{if } v_{i,j}^t > delta_j \\ -delta_j & \text{if } -delta_j \\ v_{i,j}^t & otherwise \end{cases} \quad (7)$$

where:

$$delta_j = \frac{upper\_limit_j - lower\_limit_j}{2} \quad (8)$$

The **Algorithm 1** shows how Multi-objective PSO-CLAHE (MOPSO-CLAHE) based on SMPSO is implemented to tune the parameters of CLAHE. The resulting images are evaluated according to the metrics (1) and (2), and the best results measured by these form a Pareto set. The front shows different contrast levels of images, so as to highlight particular features within. The interaction among particle, *CLAHE* and objective functions evaluation is shown in **Fig. 1**. The parameters received by *CLAHE* are stored by a particle $(\mathscr{R}_x, \mathscr{R}_y, \mathscr{C})$, and for the original image I, and the processed image T, Entropy $\mathscr{H}$ and *SSIM* are calculated. The non-dominated solutions are stored in the Pareto set. $MOPSO-CLAHE$ process is repeated until a stop criterion is reached. More details of *SMPSO*'s optimization process can be found in [18].

Algorithm 1 MOPSO-CLAHE

Require: Input image I, amount of particles Ω, iterations t_{max}
Initialize ω, c_1, c_2, $t = 0$, $lower\_limit_1$, $lower\_limit_2$, $lower\_limit_3$, $upper\_limit_1$, $upper\_limit_2$, $upper\_limit_3$, $\mathscr{X}$
while $t < t_{max}$ **do**
  for every i-th particle **do**
    Calculate new velocity $\overrightarrow{v_i}^t$ of the particle using equations (5) and (7)
    Calculate new particle position $\overrightarrow{x_i}^t$ using expression (4)
    T = CLAHE($\overrightarrow{x_i}^t$, I)
    $f_i^t = f(I, \overrightarrow{x_i}^t)$
    if $\overrightarrow{x_i} \succ \overrightarrow{x_{p_i}}$ **then**
      replace $\overrightarrow{x}_{p_i}$ by $\overrightarrow{x_i}^t$
    end if
    if $\overrightarrow{x_i} \succ \overrightarrow{x_{g_i}}$ **then**
      Update the Pareto set $\mathscr{X}$
    end if
    $t = t + 1$
  end for
end while
Ensure: $\mathscr{X}$

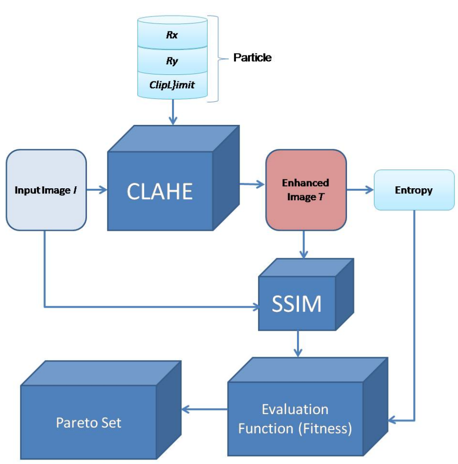


Fig. 1: Interaction among *CLAHE*, *MOPSO* particle and objective functions evaluation.

6. RESULTS AND DISCUSSION

Tests were performed using 16 images of chest radiographs and mammography, in order to assess the effectiveness of this proposal; they were downloaded from http://openi.nlm.nih.gov/. *SMPSO* implementation is available at [19], meanwhile the corresponding implementations of *CLAHE*, $\mathscr{H}$ and *SSIM* are available at [20]. The initial parameters chosen for MOPSO-CLAHE are listed in **Table 1**.

Table 1: Initial parameters for MOPSO-CLAHE.

Parameter	Value	Parameter	Value
$lower\_limit_{\mathscr{R}_x}$	2	$upper\_limit_{\mathscr{R}_x}$	$M/2$
$lower\_limit_{\mathscr{R}_y}$	2	$upper\_limit_{\mathscr{R}_y}$	$N/2$
$lower\_limit_{\mathscr{C}}$	0	$upper\_limit_{\mathscr{C}}$	0.5
Ω	100	t_{max}	100
$c_1\ min$	1.5	$c_1\ max$	2.5
$c_2\ min$	1.5	$c_2\ max$	2.5
$r_1\ min$	0.0	$r_1\ max$	1.0
$r_2\ min$	0.0	$r_2\ max$	1.0

For every test image, 30 executions of MOPSO-CLAHE were performed. Approximately 300 non-dominated solutions were obtained for every image, which represents a wide group of images at different levels of contrast and distortion, thereby facilitating further analysis. In **Fig. 2,3,4** there are 2 non-dominated solutions in order to visually assess how contrast varies considering the original image as reference. In **Fig. 2a,3a,4a** are exposed the original images. The Pareto set are showed in **Fig. 2c,3c,4c** where is noteworthy that there is an inverse relationship between objective functions; i.e, when $\mathscr{H}$ is increased, the *SSIM* coefficient decreases. This means that both metrics are complementary in order to maintain the compromise between contrast enhancement and distortion minimization. From the Pareto set it is possible to obtain images which allow to visualize different details while the contrast changes. It is also remarkable that the soft tissues are better seen in chest radiographs when certain contrast is reached (see **Fig. 2b,4b**). A similar effect is achieved in mammograms (see **Fig. 3b**), in which potential injuries are more visible, but the fine details are preserved successfully. In this proposal, a significant amount of resulting images are obtained, with different relations between contrast and distortion, in an automatic manner, which represents an advantage because it can lead to better diagnoses.

7. CONCLUSIONS

A multi-objective meta-heuristic algorithm is presented which maximizes simultaneously contrast by means of Entropy and Structural Similarity Index; with the latter it is possible to minimize image distortion, in medical images context, specifically in chest radiographs and mammograms. Experimental results show a set of solutions at different contrast levels, and allowing to highlight different structures. This would allow medical specialists to handle different visualization options automatically, which is useful for diagnostics.

The authors are still executing tests with several images found in the search engine. As future work it might be useful to adopt new meta-heuristics, such as Multi-Objective Evolutionary Algorithms (MOEA)[21], and take into account metrics based on high order statistics, as seen in [5], and local saliency maps based metrics, as in [2].

8. REFERENCES

[1] D.-C. Chang and W.-R. Wu, "Image contrast enhancement based on a histogram transformation of local standard deviation," *Medical Imaging, IEEE Transactions on*, vol. 17, no. 4, pp. 518–531, 1998.

[2] K. Gu, G. Zhai, X. Yang, and W. Zhang, "An efficient color image quality metric with local-tuned-global model," in *Image Processing (ICIP), 2014 IEEE International Conference on*, pp. 506–510, Oct 2014.

[3] K. Gu, G. Zhai, X. Yang, W. Zhang, and C. Chen, "Automatic contrast enhancement technology with saliency preservation," *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. PP, no. 99, pp. 1–1, 2014.

[4] Z. Chen, B. Abidi, D. Page, and M. Abidi, "Gray-level grouping (glg): an automatic method for optimized image contrast enhancement - part ii: the variations," *Image Processing, IEEE Transactions on*, vol. 15, pp. 2303–2314, Aug 2006.

[5] K. Gu, G. Zhai, W. Lin, and M. Liu, "The analysis of image contrast: From quality assessment to automatic enhancement," *Cybernetics, IEEE Transactions on*, vol. PP, no. 99, pp. 1–1, 2015.

[6] I. Frosio and N. Borghese, "Real time enhancement of cephalometric radiographies," in *Biomedical Imaging: Nano to Macro, 2006. 3rd IEEE International Symposium on*, pp. 972–975, April 2006.

[7] X. Mou and M. Zhang, "Nonlinear multi-scale contrast enhancement for chest radiograph," in *Image Processing, 2008. ICIP 2008. 15th IEEE International Conference on*, pp. 3184–3187, Oct 2008.

[8] N. Parveen and M. Sathik, "Enhancement of bone fracture images by equalization methods," in *Computer Technology and Development, 2009. ICCTD '09. International Conference on*, vol. 2, pp. 391–394, Nov 2009.

[9] S. Hashemi, S. Kiani, N. Noroozi, and M. E. Moghaddam, "An image contrast enhancement method based on genetic algorithm," *Pattern Recognition Letters*, vol. 31, no. 13, pp. 1816 – 1824, 2010. Meta-heuristic Intelligence Based Image Processing.

[10] L. G. Moré, M. A. Brizuela, J. L. Vázquez Noguera, D. P. Pinto-Roa, and H. Legal Ayala, "Particle swarm optimization applied to parameter tuning of clahe based on entropy and structural similarity index," in *Proceedings of the 3rd. Conference of Computational Interdisciplinary Sciences*, Oct 2014.

[11] P. Shanmugavadivu and K. Balasubramanian, "Particle swarm optimized multi-objective histogram equalization for image enhancement," *Optics & Laser Technology*, vol. 57, no. 0, pp. 243 – 251, 2014. Optical Image Processing.

[12] A. Reza, "Realization of the contrast limited adaptive histogram equalization (clahe) for real-time image enhancement," *Journal of VLSI signal processing systems for signal, image and video technology*, vol. 38, no. 1, pp. 35–44, 2004.

[13] K. Zuiderveld, "Graphics gems iv," ch. Contrast Limited Adaptive Histogram Equalization, pp. 474–485, San Diego, CA, USA: Academic Press Professional, Inc., 1994.

[14] S. M. Pizer, E. P. Amburn, J. D. Austin, R. Cromartie, A. Geselowitz, T. Greer, B. ter Haar Romeny, J. B. Zimmerman, and K. Zuiderveld, "Adaptive histogram equalization and its variations," *Computer vision, graphics, and image processing*, vol. 39, no. 3, pp. 355–368, 1987.

[15] D.-Y. Tsai, Y. Lee, and E. Matsuyama, "Information entropy measure for evaluation of image quality," *Journal of digital imaging*, vol. 21, no. 3, pp. 338–347, 2008.

[16] A. Khellaf, A. Beghdadi, and H. Dupoisot, "Entropic contrast enhancement," *Medical Imaging, IEEE Transactions on*, vol. 10, pp. 589–592, Dec 1991.

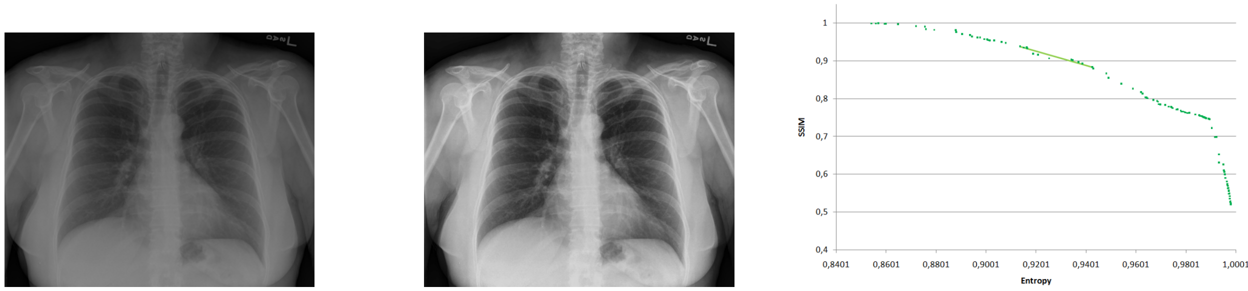
[17] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *Image Processing, IEEE Transactions on*, vol. 13, no. 4, pp. 600–612, 2004.

[18] A. Nebro, J. Durillo, J. Garcia-Nieto, C. Coello Coello, F. Luna, and E. Alba, "SMPSO: A new pso-based metaheuristic for multi-objective optimization," in *Computational intelligence in miulti-criteria decision-making, 2009. mcdm '09. ieee symposium on*, pp. 66–73, March 2009.

[19] J. Durillo, A. Nebro, and E. Alba, "The jmetal framework for multi-objective optimization: Design and architecture," in *Evolutionary Computation (CEC), 2010 IEEE Congress on*, pp. 1–8, July 2010.

[20] G. Bradski, "Opencv," *Dr. Dobb's Journal of Software Tools*, 2000.

[21] C. A. C. Coello, D. A. Van Veldhuizen, and G. B. Lamont, *Evolutionary algorithms for solving multi-objective problems*, vol. 242. Springer, 2002.

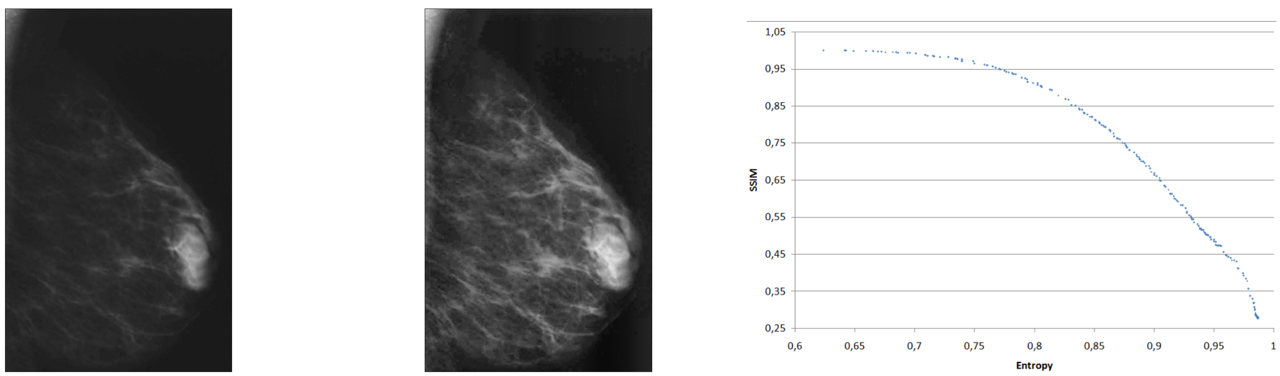


a: Original Image. *SSIM*=1.0 $\mathscr{H}$=0.8536

b: Resultant Image. *SSIM*=0.9688 $\mathscr{H}$=0.7922

c: Pareto front graphic related to this image.

Fig. 2: Results for a chest image.

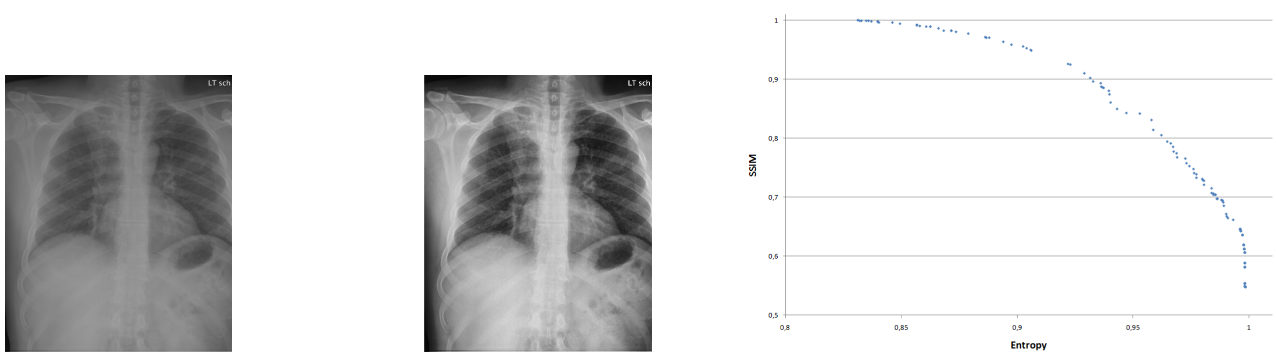


a: Original Image. *SSIM*=1.0 $\mathscr{H}$=0.6235

b: Resultant Image. *SSIM*=0.8032 $\mathscr{H}$=0.8549

c: Pareto front graphic related to this image.

Fig. 3: Results for a mammographic image.



a: Original Image. *SSIM*=1.0 $\mathscr{H}$=0.8309

b: Resultant Image. *SSIM*=0.8423 $\mathscr{H}$=0.9528

c: Pareto front graphic related to this image.

Fig. 4: Results for a chest image.