MULTIOBJECTIVE GENETIC ALGORITHM APPROACH BASED ON ADAPTIVE PROBABILITIES APPLIED TO CONTRAST ENHANCEMENT AND INTENSITY PRESERVATION FOR GRAY-LEVEL MEDICAL IMAGES

Leandro dos Santos Coelho, leandro.coelho@pucpr.br
Industrial and Systems Engineering Graduate Program, PPGEPS

Teodoro Cardoso Bora, teodoro.bora@pucpr.br
Undergraduate course of Mechatronics Engineering

Marcelo Rudek, marcelo.rudek@pucpr.br
Osiris Canciglieri Junior, osiris.canciglieri@pucpr.br
Industrial and Systems Engineering Graduate Program, PPGEPS
Pontifical Catholic University of Parana, PUCPR
Imaculada Conceição, 1155, Zip code 80215-901, Curitiba, Parana, Brazil

Abstract. *Tailored prosthesis design must to be done in as accurately as possible way to fit particular patient requirements. Aiming this intent, some techniques based on image processing have been being studied. In this context, the image quality is highly important and decisive in the accuracy, or even feasibility, of these methodologies. To do so, the image treatment is done through the gamma correction technique, which must accomplish two as important as objectives: contrast enhancement and intensity preservation. To solve this multi-objective problem, a classic and so spread in literature technique the Non-Dominated Sorting Genetic Algorithm - version II (NSGA-II) is applied, and besides, an adaptive version. In this work, these algorithms were applied to some medical images, and the final results showed that the adaptive techniques used in modified NSGA-II are not only feasible, but also improves the final solutions.*

Keywords*: medical images, prosthesis, optimization, multiobjective genetic algorithm.*

1. INTRODUCTION

It is clear that there exist many situations in practical optimization problems in which optimization of several measures of performance (multi-objective problems, MOPs) or criteria at once is unavoidable and these measures may conflict with each other. In MOPs, instead of one optimal solution, a set of optimal solutions (the Pareto-optimal set) occur due to the presence of multiple objectives. No improvement for each solution in the Pareto-optimal set can be succeeded in any objective without degradation in at least one of the others. One Pareto-optimal solution cannot be declared as better than another unless extra information is available. In order to make a better final decision, a good way is usually to find as many Pareto-optimal solutions as possible.

Nowadays, the use of evolutionary algorithms (EAs) to solve MOPs is a common practice due to their competitive performance on complex search spaces. EAs are well known for their ability to deal with nonlinear and complex optimization problems. The primary advantage of EAs over other numerical methods is that they just require the objective function values, while properties such as differentiability and continuity are not necessary. In terms of EAs, genetic algorithms (GAs) are numerical search tools, which operate according to procedures that resemble the principles of natural selection and genetics. Because of their flexibility, global perspective, and non-reliance on differential information for their operation, GAs have been successfully used in a wide variety of problems in several engineering and computation fields, e.g. Santarelli *et al.* (2006), Dong *et al.* (2007), Ishibuchi *et al.* (1997), Wang and Cui (2009), Qiu *et al.* (2009) and Coelho and Pessôa (2009).

On other hand, the contrast enhancement and intensity preservation of gray-level digital images are used in a relevant research theme in medical applications, e.g. Jiang *et al.* (2004), Qian *et al.* (2000) and Lin and Kao (2000). Since there is always a trade-off between the requirements for the enhancement of contrast and preservation of intensity, a multi-objective GA approach is proposed to resolve this contradiction, making use of its robust and efficient optimization structure. The effectiveness of the proposed multi-objective genetic algorithm approach based on adaptive probabilities of mutation and crossover is illustrated by a number of images of medical applications related to human prosthesis design.

After this view, is important also to attempt to the necessity of this optimization procedure to medical images. It arises from the fact that, the growing image-based CAD programs need well contrasted and intensified images to be able to, at least with some well performance, apply image processing or numerical methods to accomplish its tasks. In this particular case, based on the work of Junior *et al.* (2009), where some of these authors developed an image-based CAD methodology for geometric modeling of tailored prosthesis, the final intent is to provide a well and feasible technique for these images pre-processing.

The remainder of this paper is organized as follows. The section 2 presents the definitions, modeling and metrics for the contrast enhancement and intensity preservation in gray-level images problem. Section 3 gives an overview in the classic Non-Dominated Sorting Genetic Algorithm – version II (NSGA-II) and the adaptive procedure implemented in the original formulation. In section 4 the tests are formally presented and measured for the further conclusions around it in section 5.

2. FUNDAMENTALS OF CONTRAST ENHANCEMENT AND INTENSITY PRESERVATION IN GRAY-LEVEL IMAGES

This section is based in the Kwok *et al.* (2009) work. Thus it is a so complete one, because discuss some approaches for contrast enhancement and also proposes a new one, which is already used here. In general the objective is to get contrast enhancement maintaining the mean image intensity.

For the contrast enhancement, Kwok *et al.* (2009) discussed the histogram transformation technique for some benchmark images. The result showed that the enhanced images had a change in the mean image intensity, which is defined in Eq. (1).

$$M = Z^{-1}\sum_{u=1}^{U}\sum_{v=1}^{V} I_{u,v} \tag{1}$$

where $Z = U \cdot V$, U and V are the image´s width and height and $I_{u,v}$ is the gray-level intensity in the pixel located at (u, v). In this context, this change in the M for the benchmark implies that the histogram transformation even though enhanced the contrast, became the viewing inconsistent.

Another point presented in the basis work is that the image should also be characterized for its amount of information conveyed to the viewer. Intuitively it means that a gray-level image is better if it conveys the maximum allowed gray-levels in a captured scene. This measure is done through a so used mathematical expression in the information theory, the called entropy given in Eq. (2).

$$\mathcal{H} = -\sum_{i=1}^{L} p_i \log_2(p_i)\ bits \tag{2}$$

where L is the feasible representative gray-levels (256 gray-levels for instance) and p_i is the probability of a *i*th gray-level $(i = 1,2, \dots, L)$. To the benchmarks, the final image resultant of the transformation method had been reduced in the entropy (information contained).

To avoid these undesirable features, Kwok *et al.* (2009) proposed a modified transformation, called continuous transformation. This method, which intents to maximize the entropy, is presented as follows. Given an gray-level image matrix denoted by ℓ, such that $\ell = \{I_{u,v} \in [0, L-1]\}$. At first, this image in put into a vector as given in Eq. (3) i.e. $\mathcal{I}$ is built taking the matrix´s columns one below the other.

$$\mathcal{I} = \{J_k \in [0, L-1] | k = u + (v-1)U, u = 1, \dots, U, v = 1, \dots, V\} \tag{3}$$

In the next step, $\mathcal{I}$ is sorted in ascending order, and a second vector is created as a linear gray-level vector as in Eq.(3).

$$\mathcal{E} = \left\{\mathcal{E}_m \in [0, L-1] | \mathcal{E}_m = round\left[(L-1) - \frac{(L-1)}{UV-1}m\right], \forall m \in \mathbb{N} \cup \{0\} | \mathcal{E}_m \geq 0\right\} \tag{4}$$

In the next, this vector $\mathcal{E}$ is remapped, following the sorting process done to the vector $\mathcal{I}$ to rebuild the original gray-level image matrix. The result is an image with intensities uniformly distributed, given a maximum entropy. On the other hand, the mean is changed.

To avoid this problem, Kwok *et al.* (2009) studied three techniques: i) Truncated Histogram Transformation, ii) Bi-Histogram Transformation and iii) Gamma-Correction. This last one was chosen because its better results and degrees of freedom.

The gamma-correction is widely adopted in modern devices and discussed is sequence. Consider the procedure done for the continuous correction. It is absolute the same, instead of the fact for the gamma-correction the vector $\mathcal{E}$ is not constructed in a linear form, it is built following an exponential. The mathematical representation is presented in Eq.(5).

$$\mathcal{E} = \left\{ \mathcal{E}_m \in [0, L-1] | \mathcal{E}_m = round\left[255 \left(1 - \frac{1}{UV-1} m \right)^{\gamma} \right], \forall m \in \mathbb{N} \cup \{0\} | \mathcal{E}_m \geq 0 \right\} \quad (5)$$

where the γ factor must be adjusted in such way that the mean intensity is preserved and the entropy is maximized. These two objectives are given by Eqs.(6) and (7),

$$min(|M - M^*|) \quad (6)$$

$$max(\mathcal{H}) \quad (7)$$

where M^* is the original gray-scale image mean. After this exposure, the problem becomes clear end can be summed up as: It is necessary to choose a γ value such that both the original image's mean is maintained and the entropy of the corrected image is maximized. To solve this multi-objective task the NSGA-II and an adaptive variation are presented in next section.

3. NON-DOMINATED SORTING GENETIC ALGORITHM – II (NSGA-II) AND ADAPTIVE PROCEDURES

The Non-dominated Sorting Genetic Algorithm – version II (NSGA-II) was firstly proposed in Deb *et al.* (2002). This algorithm is from the GAs family, where the objective is to mimic the nature behavior given by the genetic dynamic and characteristics assigned by its combinations. Summing up, the idea is to generate a computer model to simulate the Darwin's species evolution theory. The basic concept is based in create individuals (solutions) formed by a vector of genes (parameters) and some consequently fitness characteristics (objective values). Given that, crossover and mutation operations are carried out, natural selection is simulated such that only the fittest solutions should be part of the next generation.

In this context, the NSGA-II is a so classic algorithm, which has as great features his elitist characteristic without loss diversification. These two features are reached through both the fast non-dominated sorting and crowding distance assignment algorithms. The first implements the elitism mechanism through the assignment of ranking based in a dominance concept. The second one assigns a quantitative measure to determine how much spread the solution is.

The selection is done through a simple mechanism. After the parents (chosen from the population with a Tournament selection for instance) are joined with their offspring the resulting population has the double size that originally it had. At this point the ranks are assigned and, for each one, the solutions crowding distance are calculated. The next generation population is then build taken the firsts rank till this procedure is not possible anymore, i.e. there is not slot in the final population for the entire rank. Then this rank is cropped in such way that the more spread solutions are taken from to be part of the population. The NSGA-II pseudocode is presented in Figure 1.

$P_1 \leftarrow$ Population initialization using uniform distribution
$P_1 \leftarrow Evaluate\ the\ fitness\ (P_1)$
$[P_1, F] \leftarrow Fast\ non-dominated\ sort\ (P_1)$
$P_1 \leftarrow Crowding\ distance\ assignment\ (P_1, F)$
$P_1 \leftarrow Tournament\ selection\ (P_1)$
$Q_1 \leftarrow Generate\ new\ offsprings\ (P_1)$
$Q_1 \leftarrow Evaluate\ the\ fitness\ (Q_1)$
$For\ t = 1 : Number\ of\ generations$
  $R_t = P_t \cup Q_t$
  $[R_t, F] \leftarrow Fast\ non-dominated\ sort\ (R_t)$
  $P_{t+1} = \emptyset\ and\ i = 1$
  $While\ |P_{t+1}| + |F_i| \leq Number\ of\ individuals$
    $R_t(F_i) \leftarrow Crowding\ distance\ assignment\ (R_t(F_i))$
    $P_{t+1} = P_{t+1} \cup R_t(F_i)$
    $i = i + 1$
  $End\ While$
  $F_i \leftarrow Crowding\ distance\ sorting\ in\ descending\ order(F_i)$
  $P_{t+1} = P_{t+1} \cup R_t\left(F_i(1: |Number\ of\ individuals - |P_{t+1}|)\right)$
  $P_{t+1} \leftarrow Tournament\ selection\ (P_{t+1})$
  $Q_{t+1} \leftarrow Make\ new\ offsprings\ (P_{t+1})$
  $Q_{t+1} \leftarrow Evaluate\ fitness\ (Q_{t+1})$
  $t = t + 1$
$End\ For$

Figure 1: Pseudocode of the NSGA-II.

There are 4 parameters, when NSGA-II is in its classical formulation that must be chosen before the run. They are crossover and mutation indexes and probabilities. The indexes are from the Simulated Binary Crossover (SBX) and Polynomial Mutation that can be seen with more details in Deb *et al.* (2001). The final Pareto front is highly dependent of these parameters, as is formally proved for the No Free Lunch Theorem (NFL) for optimization given in Wolpert and Macready (1996).

Another point is the clear necessity in choose these parameters to speed up the convergence without stop in local minima or even loss diversity. This tuning task, as can be seen, is not exactly an easy one. After all, find good sets of parameters to reach all this objectives is some empirical procedure is so time spending and, in some cases, even impossible given time variance of the problem. To try dodge this last difficult and improve the NSGA-II performance, and adaptive procedure is discussed in sequence.

3.1. Adaptive procedure

And adaptive procedure to crossover (p_c) and mutation (p_m) probabilities was proposed by Srinivas *et al.* (1994) and will be implemented in sequence in the NSGA-II. In their formulation, the probabilities are given as in Eqs. (8) and (9), adapted to minimization.

$$p_c = \begin{cases} \dfrac{k_1(f_{min} - f')}{(f_{min} - \bar{f})}, f' \geq \bar{f} \\ p_c = k_3, f' < \bar{f} \end{cases} \tag{8}$$

$$p_m = \begin{cases} \dfrac{k_2(f_{min} - f)}{(f_{min} - \bar{f})}, f' \geq \bar{f} \\ p_m = k_4, f < \bar{f} \end{cases} \tag{9}$$

where $k_1, k_2, k_3, k_4 \leq 1.0$ are constants, f_{min} is the minimum of some objective value in the population, f' is the best function value between the two parents and f the solution objective (under mutation). This formulation is done for single-objective, for a multi-objective problem it is expected to p_c and p_m becomes vector with length equal to the number of objectives. So, to get only one probability value it is proposed to use the average of these components.

The main concept of these procedures is make the mutation parameter be changed when is perceived a loss of diversity. The same idea is extended to the crossover parameter despite of de convergence rate.

4. RESULTS

To analyze the effectiveness of the described algorithms, 30 runs were done to give statistical relevance. It was used a population size of 100 and 250 generations. For the classic NSGA-II, the crossover and mutation probabilities were 0.9 and 0.1, respectively. Both algorithms are real codded, then it was used the SBX operator and Polynomial Mutation. In this context these indices were set as $\eta_c = \eta_m = 20$.

Besides, the tomography images must be changed as few as possible. In this context, it was decided to choose the minimum mean deviation in preference. Despite of this fact, the Pareto frontier of both algorithms is shown in Figure 2. A first qualitative analysis of this image shows that the adaptive NSGA-II to the gamma correction problems tends to be more spread.

In Table 1, both algorithms are statically analyzed. For each run the minimal mean deviation solution is chosen, and after, between all good ones, a best solution is chosen. These solutions are a quantitative indicator that the supposed spread characteristic, discussed earlier above, is true. Note that the mean and deviation of both objectives of the Adaptive NSGA-II are bigger than the classic one. Besides, the best solution of the adaptive one is better than the classic for both objectives, minimizing the mean and maximizing the entropy.

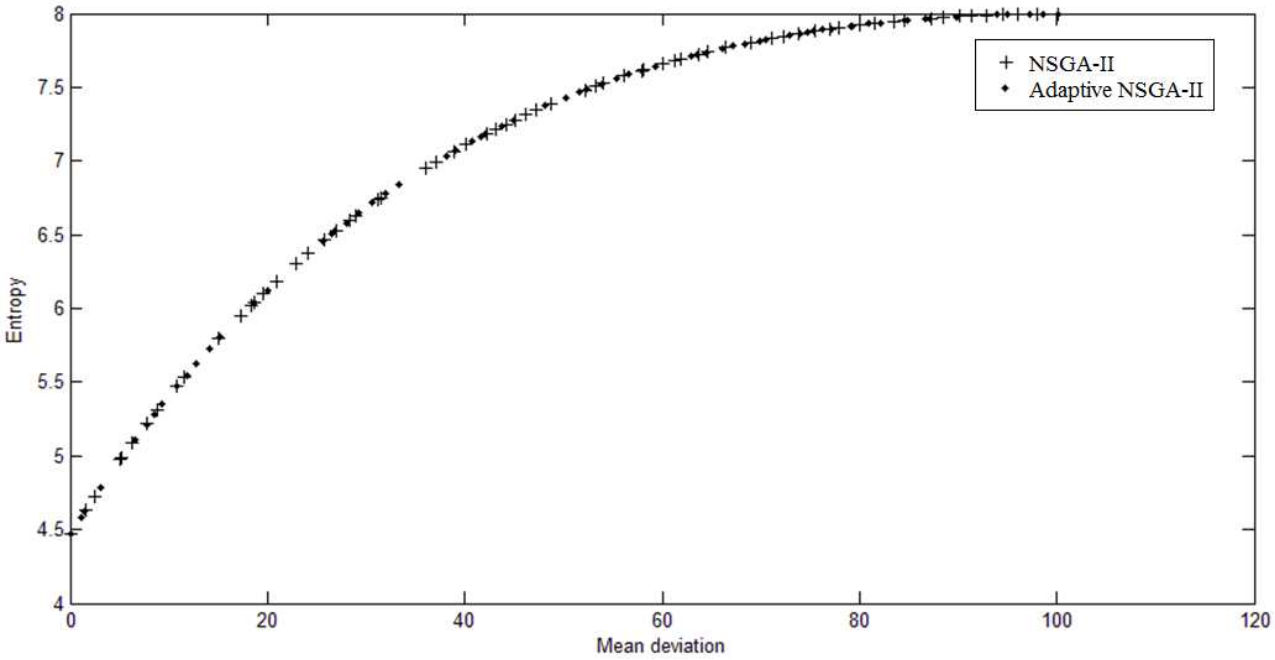
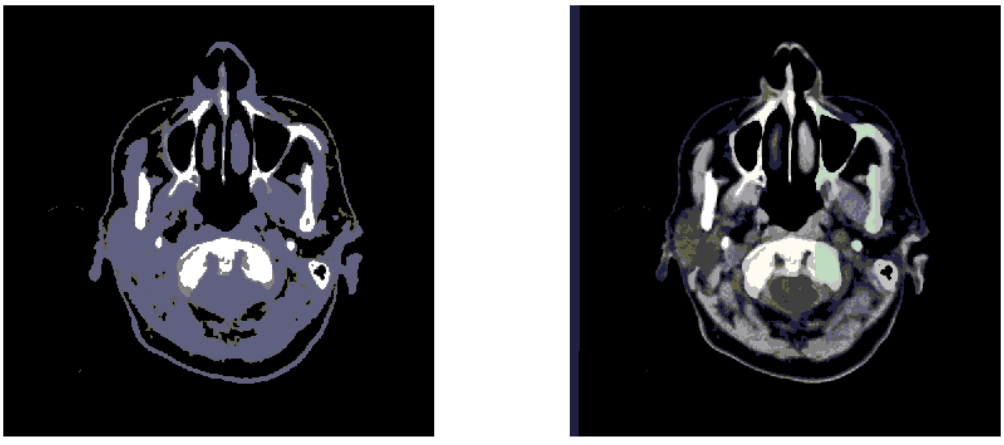


Figure 2: NSGA-II and Adaptive NSGA-II Pareto front.

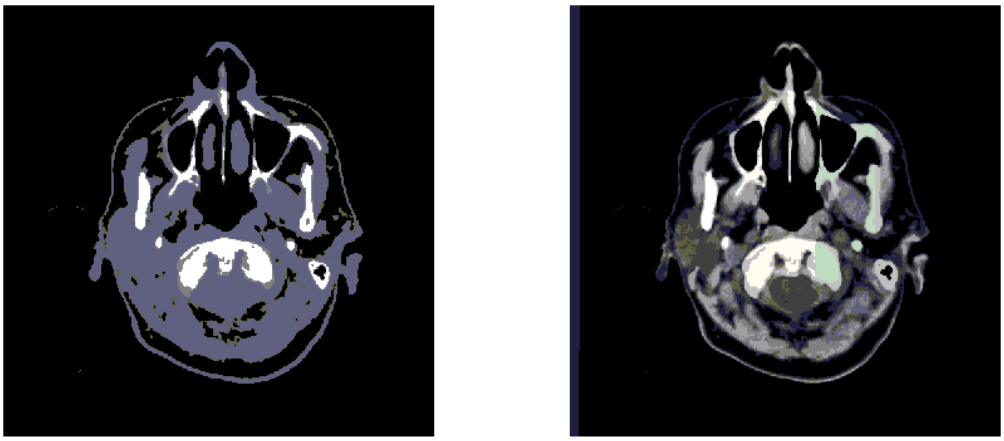
		NSGA-II	Adaptive NSGA-II
Mean Deviation	**Mean**	0.000599	0.002255
	Standard Deviation	0.000563	0.003596
Entropy	**Mean**	4.471093	4.471204
	Standard Deviation	0.000089	0.000435
Best	**Mean Deviation**	0.000004	0.000061
	Entropy	4.471088	4.471083
	Gamma value	8.463340	8.463360

Table 1: Statistical results of both NSGA-II and adaptive NSGA-II for gamma correction in 30 runs.

Figure 3 shows the best solution found gamma correction for a tomography in RGB. Besides, in Figure 4 the same result in jpeg is presented.

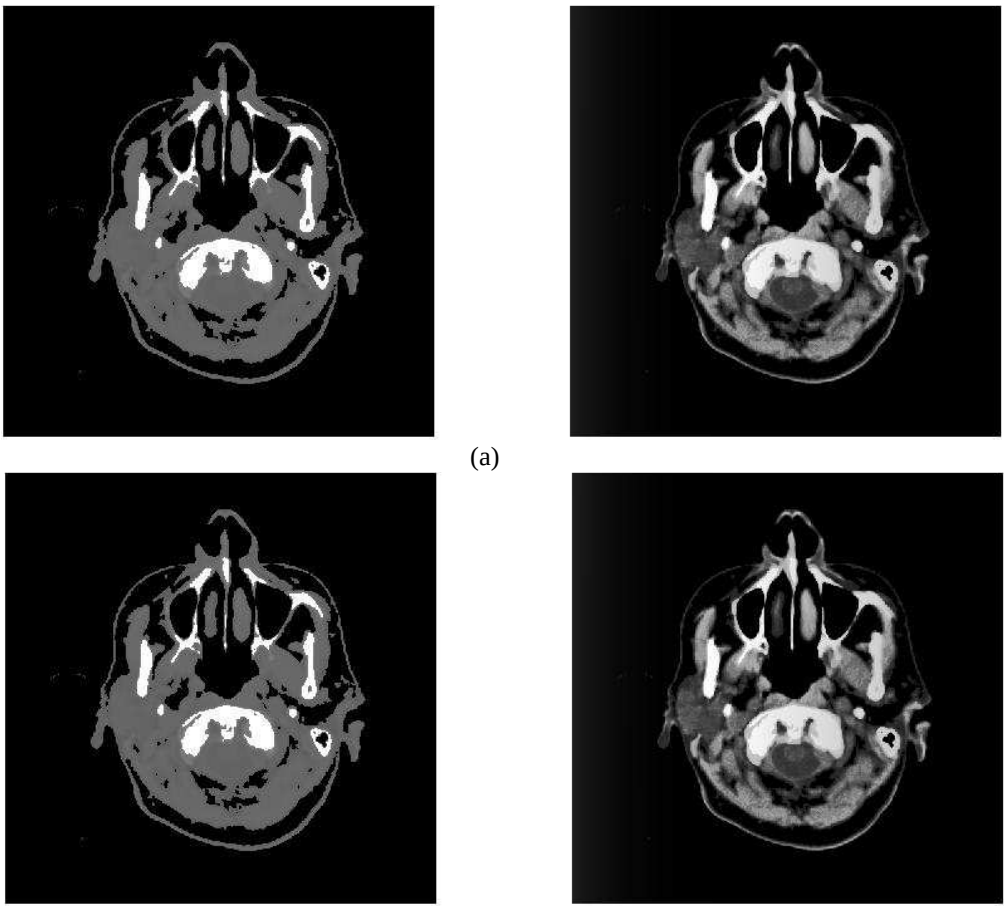


(a)



(b)

Figure 3: Gamma-correction for (a) NSGA-II and (b) Adaptive NSGA-II. RGB images.



(a)

Figure 4: Gamma-correction for (a) NSGA-II and (b) Adaptive NSGA-II. Gray-scale images.

5. CONCLUSION

The advantage of the use of gamma-correction in medical images gets clear in Figures 3 and 4. On the other hand, the parameter tuning could be a time-spending task, and difficult so much to make the method reach good solutions. In this context the exposed in this work leads to conclude that the adaptive NSGA-II not only dodges this tuning difficult but also arrives in best results.

In the gray-scale image it gets clear that the maximization of entropy carries the final image to contain more information about the content that must be characterized by this two dimensional signal. And, even though the values in Table 1 are very close, a qualitative analysis of Figure 4 shows that this little difference could imply in a great impact in final image. In fig 4 is clear that the adaptive NSGA-II is more contrasting than the reached by NSGA-II, but the entropy difference is only of 0.000020. On the other hand the mean of the corrected image must be maintained to a

minimal variance in relation to the original one. That is why the gamma correction could lead to very bigger entropy levels, but it should change the real content. This effect is undesired in any application, but in medical image analysis it could induce to a wrong analysis by software or even for a medic.

Finally, the results presented here are so interesting and appear to be a well possibility to application in medical images. It is clear also the advantage of the use of adaptive NSGA-II, providing best results (a great value of entropy almost without mean deviation) with less parameter configuration, or time spending tuning for other images.

6. ACKNOWLEDGEMENTS

This work was supported by the National Council of Scientific and Technologic Development of Brazil — CNPq — under Grants 303963/2009-3/PQ and 'Fundação Araucária' under Grant 14/2008-416/09-15149. The second author, also, would like to thanks the Pontifical Catholic University of Parana — PUCPR for the financial support provided through the Institutional Program for Scientific Initiation Scholarships — PIBIC.

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