# **New Bioinspired Filter of DICOM Images**

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Abstract: The article refers to a new model of genetic algorithm. The method used has finality of optimize the filtering of artifacts in DICOM images in two-steps. The first step is constituted by filterings with BM4D, 3d median filter and ellipsoid filter. The second step is formed by the application of operators of simple mutations in the previously recovered image, for that was used: intensity change, gaussian filter and mean filter. As a result, a better performance filter was obtained and which provides an improvement in diagnosis, in diseases assessment and in decisions making by the professional.

# **1** INTRODUCTION

Digital images have been used for various purposes, from just storing remembrances until accurate exams in medicine (James and Dasarathy, 2014). Over the years, the use and popularization of the digital image made it possible the great increase of the volume of images, just like it's over by to make available new advances and challenges in its use. As example there is an introduction of images processing solutions in industrial environment for visual inspection in environments at risk for a physical integrity of employees (Gonalves et al., 2014).

Despite of various technological advances, during the captation process and posteriorly the transmission of the digital images can acquire artifacts in innumerable ways.

Each artifacts filter model adapts differently to each noise, thus forming its advantages and disadvantages in relation to a determined type of noise.

As an example, there is the image in figure 1, here white (Gaussian) noise has been added. This type of noise is quite common in communications.

The white noise it comes from the stirring of the electrons in the metallic conductors. Its level is in function of the temperature, being evenly distributed in all the frequencies of the spectrum.

The challenge of suppressing or attenuating has provided the search of enhancement of techniques



Figure 1: Image increased Gaussian noise.

to reduce imperfections, in way to preserve important information of the image such as corners, borders and textures. In the literature, the BM3D (Dabov et al., 2006) noises attenuation technique was intensively researched and tested on real problems such as suppress artifacts in images of ultrasonography (Gan et al., 2015), however, there is no solution available to completely solve the problem.

Genetic Algorithms (GA) are metaheuristics based on the theory of evolution of the species of Charles Darwin, where by natural selection the fittest individual tends to survive and reproduce descendants (Barbosa, 2014). In this context, the individual is a representation of the solution of the problem.

This work proposes and analyzes a 3D hybrid genetic algorithm (HGA3D) for noise attenuation in DI-COM medical images, integrates genetic algorithm to

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some literature attenuation methods: BM4D (Maggioni et al., 2013), 3D median filter (Jiang and Crookes, 2006) and ellipsoid (Yang et al., 2008).

Each individual of the population corresponds to an image initially restored by one of these three methods and the others individuals of the population are created through the application of different mutation operators in the initial image. HGA3D evolves the entire population during a determined amount of time and at the end the best individual is returned as the restored image.

The hypothesis of the work is that the proposed genetic algorithm model be able to find quality solutions when compared to other methods present in the literature for the smoothing of artifacts in DICOM images.

Thus, the article starts with the state of the art, a review of evaluation methods used, explains the methodology, it is made to exhibition of results and a discussion of the results.

# 2 STATE OF ART

Different solution methods for the noise attenuation problem were proposed. The BM4D (Maggioni et al., 2013) method for example, use sliding voxels cubes in a first stage for the stacking of similar cubes, in a second phase each cube is filtered by a Wiener type filter (Gonzalez and Woods, 2006). At the end, the image is reconstructed using adaptive weights for each cube added in its original position.

The proposed BM4D algorithm proved to be effective for gaussians noise and its performance is remarkable in PSNR statistics generated during the author's tests.

Approaches based on the 3D median filter (Jiang and Crookes, 2006) were also suggested. Widely applied in images processing, this filter is known for its edge conservation nature. The filter demonstrated in this paper uses a median calculation of a window with sliding mask size NxNxN voxels. Results demonstrate its efficiency for removal of splashes in 3D medical images, in addition to having low computational cost.

In addition to the previously cited methods, there is also the ellipsoidal filter (Yang et al., 2008). In this paper the author proposes a three-dimensional median filtering method and then an adaptive ellipsoidal Gaussian filtering method for local preservation of the image characteristics. According to the research the filter is ideal in the meaning it reduces the magnitude spatial of the high frequency in an image. There are also methods based on genetic algorithm of great relevance currently, as the hybrid genetic algorithm for noises suppression in images proposed in Paiva's thesis (Paiva, 2016). It is proposed the combination of a genetic algorithm with various algorithms for the removal of artifacts from images found in the literature.

The HGA was tested on images corrupted by a gaussian additive noise with different levels of standard deviation. At the end of the work, the effectiveness of the proposed method is demonstrated by means of statistical and visual data, showing better results in several cases in relation to literature methods.

In addition to all the methods already mentioned above, a search was made in the literature for other approaches of great current impact in the research area, for this was considered the google scholar metrics option. Initially a work was used available in '*IEEE Transactions on Image Processing*' whose index is the same.

In the work proposed in (Moore and Lopes, 1999) is proposed a general methodology to create and optimize a wide group of algorithms for the destruction of a mixed artifact between poisson noise and gaussian noise. To remove of the artifact is demonstrated, an algorithm denominated *PURE-LET* where in particular the best results are obtained. With the tests in images and posteriorly the comparison between this proposed method and other competing methods it is verified the effectiveness of the restoration of several textures present in the image.

In (Danielyan et al., 2012) is proposed an analysis and synthesis for the family of BM3D algorithms aiming to develop new iterative algorithms of debluring. The BM3D is a non-local modeling technique based on adaptive models, it is divided into three steps where initially, similar image blocks are collected in groups, then the obtained groups spectra are filtered, and lastly the filtered spectra are inverted providing estimates of blocks that were returned to their original positions and finally occurs the image recostruction.

Based on the researchs carried out and described, a genetic algorithm based on BM4D, 3D median and ellipsoid was developed.

# 3 METRIC METHODS OF EVALUATION

The image filtering search aims to reduce the number of artifacts to represent an image, removing the noises, as much as possible. The ideal is to get the resulting image it's close to the original image. One of the ways to quantify is given by the measurement of proximity with the Mean Square Error (MSE) can be defined mathematically by equation 1 (Talbi et al., 2015).

$$MSE = \frac{1}{mn} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (I(x,y) - K(x,y))^2 \qquad (1)$$

In this equation I represents the original image and K the final image to be compared. The x and y are two matrices of size MxN, respectively representing the original x-channel and the y-channel to be compared (after filtering).

Another way to compare the quality of the images is the Peak Signal to Noise Ratio (PSNR) what is usually a measure of image quality and can be represented by equation 2 (Fedorov and Rodyhin, 2016). The PSNR ideal of comparison presents an optimum value the higher its is your value.

$$PSNR = 10\log\left(\frac{MAX^2}{MSE}\right) = 20\log\frac{MAX}{MSE^{\frac{1}{2}}} \qquad (2)$$

In which, MAX represents the maximum possible value of the pixel in the image and MSE is the value resulting from equation 1.

The MSE may present problems when used to compare similarity. The main from them is that large distances between pixel intensities do not necessarily mean that the content of the images be dramatically different. It is important to note that a value of 0 for MSE indicates perfect similarity. A value greater than 1 implies smaller similarity and will continue to grow as the mean difference between pixel intensities increases as well.

In order to remedy some of the problems associated with MSE for image comparison, one has the Structural Similarity Index (SSIM). The SSIM Is observed by equation 3.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(\sigma_{xy} + c_1)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$
(3)

In the equation 3 o  $\mu$  represents the mean, the  $\sigma$  symbolizes the standard deviation and  $\sigma_{xy}$  the covariance. And  $c_1$  with  $c_2$  represent constants that avoid the instability of values.

Unlike MSE, the SSIM value can range from -1 to 1, where 1 indicates perfect likeness.

The essence of SSIM is to model the perceived change in the structural information of the image, while the MSE is actually estimating the perceived errors. There is a subtle difference between the two, but the results can be great.

In addition, the SSIM is used to analyze small subsamples instead of the entire image as in MSE. The parameters used are the mean of the pixel intensities, the variance of the intensities, together with the covariance. In this way, a more robust approach is obtained capable of explaining the changes in the structure of the image, instead of just the perceived change.

For the quantitative comparison of the filtering methods in this article, the objective metrics evaluation methods MSE, PSNR and SSIM were used. Such methods are known as full reference, because they consider the original image as a reference.

These methods are applied over a DICOM image. Being that, in this work MatLab software was used to manipulation of the presented algorithms and the visualization of the results.

### 4 METHODOLOGY

The hybrid genetic algorithm (HGA) of this work is based on the genetic algorithm (GA) proposed by Toleto (Toledo et al., 2013) and in the method proposed by Paiva (Paiva, 2016), where each individual of the population is an image itself, represented by a set of pixels whose values are integers in the range of 0 to 255. In a similar way to this method starts the proposed algorithm, where a noisy image is used as input for the method and the other individuals in the population are created from applied mutation operators.

Based on the analysis and results demonstrated in (Paiva, 2016), it was decided that the same parameters already tested by the author were used as standard values in the model proposed here. In the step by step of choosing the best parameters by the author is demonstrated the effectiveness of each change in metric data PSNR and SSIM, in addition a whole argumentation of each result is provided.

According to Paiva (Paiva, 2016), during the choice of tournament size the worst case of tournament size 3 tends to be better than the worst case of the others. However the test of the different local search rates, although all the results were very close, the value rate 0.6 was the one that reached the best results compared to the others. The differences between the results with different population sizes showed up clearer in their 2D approach, however, there is a superiority of size 15 population where it obtained good results in about 70 % of cases in both PSNR and SSIM. Also is demonstrated the effectiveness of two other parameters, beta whose best value was 1.5 and execution time equal to 20 minutes.

The proposed algorithm combines the GA method approach (Toledo et al., 2013), with noises smoothing techniques in 3d images. In which, the pseudocode is described in Algorithm 1. Algorithm 1: Hybrid Genetic Algorithm for Dicom (HGA3D).

!th				
1:	function HGA3D(Dicom path)			
2:	<i>images</i> $\leftarrow$ ReadingPath(path)			
3:	<i>Population</i> ← createPopulation(images)			
4:	<i>best</i> $\leftarrow$ Population.best			
5:	while elapsedTime < maxTime do			
6:	$cont \leftarrow 0$			
7:	while <i>cont</i> < <i>maxIter</i> do			
8:	IntermPop $\leftarrow$ Population			
9:	for $i \leftarrow 1$ to Population.size do			
10:	<i>ind</i> 1 $\leftarrow$ Parents(Population)			
11:	<i>ind</i> $2 \leftarrow$ Parents(Population)			
12:	$ind3 \leftarrow Crossover(ind1,ind2)$			
13:	if $(\Lambda \in [0,1]) \leq \text{LocalSearchRate}$			
	then			
14:	<i>localSearch</i> (ind3)			
15:	end if			
16:	IntermPop.append(ind3)			
17:	end for			
18:	Sort(IntermPop)			
19:	<i>Population</i> ←IntermPop[1Popula-			
	tion.size]			
20:	if ( <i>best</i> =Population.best) then			
21:	$cont \leftarrow cont + 1$			
22:	else			
23:	$cont \leftarrow 0$			
24:	end if			
25:	end while			
26:	end while			
27:	end function			

The beginning of the HGA consists of creating the initial population in two steps: first, the image with noise is used as input for three methods of noises smoothing. Thus, at the end of the first stage, the population has three individuals. Next are cited the techniques used:

- BM4D (Maggioni et al., 2013)
- 3D median filter (Jiang and Crookes, 2006)
- Ellipsoid (Yang et al., 2008)

After the first stage, one of the outputs of these techniques is chosen randomly. Then it is passed by a mutation operator, also in a random way and changes are realized in the image initially recovered by one of the initial methods. As Mutation operators was used three types:

• Intensity change: is a linear operation that consists of multiplying all the pixels of the image by the same numerical factor.

- Gaussian filter: the filter that has the effect of smoothing the image artifact through a Gaussian function.
- Average filter: the technique that allows the smoothing of noises in images by means of calculating the average of all the filters of a given vicinity for each pixel of the original image.

At the end of this stage the resulting image is added to the population. Then the mutation process is repeated until the population reaches the chosen size. Thus, a hybrid population is formed, constituted of the output of the three methods of suppression of initial noises plus the images that went through the mutation process.

The HGA runs for a fixed time, in which the population continues to evolve while there is no changes in the best individual to a maximum number of interactions. By reaching maximum number of interactions, the entire population is restarted while only the best individual is preserved. Posteriorly the population is created again by the same process already mentioned.

An intermediate population twice the size of the initial population is created during the process of evolution formed by the current population plus the new individuals generated. These new individuals are created through operators crossover where the parents' selection is made via the tournament. Shortly after the parents were chosen, a new operator crossover is randomly selected for the generation of a new individual (son). For this are cited below the three types available for the choice:

- Operator of a line point: randomly choose a line of pixels in the image, then all the pixels above it will come from one parent and the other pixels that are below it will come from the other parent.
- Operator of a column point: approach similar to the first, but the image is divided by a column rather than a line.
- Uniform Operator: each pixel of the image is chosen randomly from one of the parents with 50 % chance of the value chosen to be from either parent.

Once created, the new individual can still be submitted by a local search operator, a process that has purpose improve the final quality of the solution by means of transformations in the individual, case satisfied the condition that a real number generated by the algorithm in the execution that is equal to a value within the range of 0 to 1 in the algorithm be less than the local search rate chosen, it will go through one of the artifact suppression operators already mentioned in the initial step: BM4D, Median Filter or Ellipsoid. With all intermediate population completed, individuals are ordered by fitness, from the first individuals selected in a population of the size chosen at the outset to form the main population of the HGA for the next evolution step, where the algorithm verifies if there are no changes in the best individual of the population during a chosen number of executions of the evolution. Case the best individual does not change after a maximum number of iterations, so this population is restarted. A flow diagram of the execution of the algorithm is shown in figure 2.



Figure 2: Flowchart of the algorithm. Source: Own author.

At the outset they begin to form the main population of the HGA3D for the next evolutionary step, where the algorithm checks if there is no change in the best individual of the population during a chosen number of evolution executions. If the best individual does not change after a maximum number of Iterations, then this population is restarted. A flowchart of the algorithm execution is shown below.

### 5 RESULTS

In this chapter the results of the quantitative analysis of the results will be presented through the evaluation metrics. The comparison established is related to other methods of filtering three-dimensional images: 3D median and ellipsoid. The table 1 refers to the amount of MSE for each image after the filtering, establishing values. In the column 1 shows the percentage of image degradation, in column 2 the noise mean, and columns 3, 4 and 5 the respective MSE values obtained for the filters of the median 3d, ellipsoid and the proposed filtering method HGA3D.

Table 1: Evaluation of the result through MSE.

	Gaussian additive noise			
	Noise (MSE)	Median	Ellipsoid	HGA3D
10%	(0.0062)	0.0102	0.0102	0.0747
20%	(0.0268)	0.0112	0.0189	0.0025
30%	(0.0307)	0.0120	0.0115	0.0747
40%	(0.0336)	0.0145	0.0073	0.0165
	Average	0.0199	0.0119	0.0187

Table 2: Evaluation of the result through PSNR.

	Gaussian additive noise			
	Noise (PSNR)	Median	Ellipsoid	HGA3D
10%	(65.61)	72.58	72.93	73.85
20%	(61.22)	69.83	69.93	72.76
30%	(58.00)	67.07	67.68	71.24
40%	(56.06)	65.16	65.69	69.88
	Average	68.66	69.05	71.93

Table 3: Evaluation of the result through SSIM.

	Gaussian additive noise			
	Noise (SSIM)	Median	Ellipsoid	HGA3D
10%	(0.2651)	0.4810	0.5053	0.8600
20%	(0.1076)	0.2946	0.2428	0.8004
30%	(0.0955)	0.2319	0.2456	0.6303
40%	(0.0887)	0.1826	0.2357	0.5374
	Average	0.2875	0.3773	0.7070

In the tables 2 and 3 are related to the qualitative analysis of PSNR and SSIM. Featuring a *design* similar to table 2.

The first analysis was done by the MSE metric, presented in only one case the filter type HGA3D as best. However, taking into account the relevance of this type of meter the best results are those whose values are the smallest, on the other hand it has the contestable confidence level of this metric, making it present the need of comparison with new forms.

In the table 2 is shown an evaluation using a better metric, this metric demonstrates in numerical data an approximation of the human perception of the quality of reconstruction, where not necessarily, but in most cases the larger PSNR values represent a better reconstruction of the image.

When comparing the resulting values demonstrated below it is clear the superiority of the data resulting from the proposed method. With efficiency in 100 % of the cases tested in this approach, it is demonstrated in the table that in only one case, the values were close to the genetic algorithm model. After is realized the difference in values resulting from the methods stay distant, in addition, it is also remarkable the difference between the average of the HGA3D with the means of the other competing methods.

The table 3 demonstrates the analysis using the most accurate evaluative metric currently used, SSIM. This metric improves traditional methods, that show inconsistent with human visual perception.

The results demonstrated here by the tables prove that the combination of several artifact removal techniques show up very favorable in most images, in addition, the few amount of limitations of the HGA3D provides a multitude of options for changing parameters and providing improvements in the final image.

As a visual example of the obtained results, it is shown in figures 3, 4, 5 and 6. In each figure, four images are observed, one referring to the slice added with noise and another three are results of the medium, ellipsoid and HGA3D filtering. In figure 3 it has been the image corrupted with gaussian artifact and a standard deviation of 10%. In the other figures differ in the standard deviation of 20%, 30% and 40% respectively.



Figure 3: Image corrupted with white additive Gaussian artifact and standard deviation = 10%.

In figure 3 was observed that when applying the noise with low deviation, 20 %, it is not visually perceptible the difference of HGA3D in relation to the others. However, in Figures 4, 5 and 6 the difference between the proposed filter and the other two filters that serve as a basis for verifying the quality.



Figure 4: Image corrupted with white additive Gaussian artifact and standard deviation = 20%.



Figure 5: Image corrupted with white additive Gaussian artifact and standard deviation = 30%.

# 6 **DISCUSSION**

With the introduction of the filter it is evident that there is an improvement of resolution in both images, making them more interesting for the observation of the image.

In the table 1, it was observed that in three items the ellipsoid obtained the most efficient filtration condition. The proposed method presented only a signifi-



Figure 6: Image corrupted with white additive Gaussian artifact and standard deviation = 40%.

cant result in the percentage of image degradation of 20 % the best performance. However, the MSE may exhibit similarity failure.

Thus, the efficiency of the HGA3D method is demonstrated when compared to the others exposed in tables 2 and 3, using PSNR and SSIM. Demonstrating the final image after filtering that most closely resembles the original image and provides an increase in quality.

# 7 CONCLUSION

There are several techniques for developing DICOM image filtering, this study applies the hybrid method of genetic algorithm, in which the method obtains optimal filtering and minimizes artifacts.

The efficiency of the model adopted as a filter is the result of the architecture that is found distributed in a selective and evolutionary way in two stages. The first stage consists of the BM4D filtering, the 3d median filter and the ellipsoid filter. The second stage is formed by the application of operators of simple mutations in the previously recovered image, for that was used: intensity change, gaussian filter and average filter.

As comparison the MSE, PSNR and SSIM was used to estimate the filtering efficiency of the restored images. It was observed experimentally that the adopted filter is efficient and robust presenting indexes better than the others in the PSNR and SSIM.

With the study of the HGA3D can generate more

advances and minimize the artifacts, resulting in a better performance in the system. The disadvantage is the limitations of techniques for the random values, that make it difficult the optimal value defined in the filtering

In order to apply more efficient methods of reconstruction of DICOM images, it is intended in future works to approach the methods with the application of new filters to increase efficiency. As an example one has the artificial intelligence in one of the stages.

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# REFERENCES

- Barbosa, R. C. (2014). Metaheuristic algorithm genetic application in optimization of distribution of delivery routes physics products in fortaleza county. In *UFC*.
- Dabov, K., Foi, A., Katkovnik, V., and Egiazarian, K. (2006). Image denoising with block-matching and 3d filtering. In *Electronic Imaging. International Society* for Optics and Photonics, p. 606414-606414-12.
- Danielyan, A., Katkovnik, V., and Egiazarian, K. (2012). Bm3d frames and variational image deblurring. volume 21, pages 1715–1728.
- Fedorov, O. and Rodyhin, M. (2016). A referenceless psnr estimator of compressed jpeg images. In 2016 26th International Conference Radioelektronika (RADIOE-LEKTRONIKA), pages 227–230.
- Gan, Y., Angelini, E., Laine, A., and Hendon, C. (2015). Bm3d-based ultrasound image denoising via brushlet thresholding. In 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI), pages 667–670.
- Gonalves, M., Rodrigue, J., Rodrigues, C., and Rocha, A. (2014). Desenvolvimento de uma solucao de processamento de imagem em ambiente industrial. In ENE-GICOIMBRA2014: inovacao, tecnologia e excelencia: atas do 3 Encontro Nacional de Engenharia e Gestao Industrial, p. 28-29.
- Gonzalez, R. C. and Woods, R. E. (2006). *Digital Image Processing*. Upper Saddle River, NJ, USA: Prentice-Hall, 3rd edition.
- James, A. P. and Dasarathy, B. V. (2014). Medical image fusion: A survey of the state of the art. In *Information Fusion, v. 19, p. 4-19.*
- Jiang, M. and Crookes, D. (2006). High-performance 3d median filter architecture for medical image despeckling. volume 42, pages 1379–1380.

- Maggioni, M., Katkovnik, V., Egiazarian, K., and Foi, A. (2013). Nonlocal transform-domain filter for volumetric data denoising and reconstruction. volume 22, pages 119–133.
- Moore, R. and Lopes, J. (1999). Paper templates. In *TEM-PLATE'06*, 1st International Conference on Template Production. SCITEPRESS.
- Paiva, J. L. (2016). A hybrid genetic algorithm for image denoising. In *Tese de Doutorado*. USP.
- Talbi, M., Ftima, S. B., and Cherif, A. (2015). Image watermarking using data compression. In 2015 World Symposium on Computer Networks and Information Security (WSCNIS), pages 1–9.
- Toledo, C. F. M., Oliveira, L. D., da Silva, R. D., and Pedrini, H. (2013). Image denoising based on genetic algorithm. In 2013 IEEE Congress on Evolutionary Computation, pages 1294–1301.
- Yang, F., Zuo, W. M., Wang, K. Q., and Zhang, H. (2008). 3d cardiac mri data visualization based on volume data preprocessing and transfer function design. In 2008 Computers in Cardiology, pages 717–720.