Noise Attenuation using Genetic Algorithm in CT Image

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Keywords: Medical Images, Genetic Algorithm, Noise Removal.

Abstract: The techniques of image filtering have undergone an explosive growth in the last years to make new advances and challenges. This is due to the fact, among several other reasons, the increase of the volume of images coming from several sources. Digital images have been used for a variety of purposes, from the storage of souvenirs to accurate medical exams. However, Images may be corrupted due to several factors. The challenge of suppression or noise attenuation has led to the search for improved techniques in order to preserve important characteristics of the image, but, on the other hand, there is no solution available to completely solve the problem, boosting the production of the work proposed here. In this paper proposes a method for noise attenuation in computed tomography images using a hybrid genetic algorithm, the proposed method seeks to optimize the results in the space of solutions composed by a series of techniques of noise filtering. At the end the proposed method is compared statistically with two other competing methods and after the resulting filtered images are shown.

1 INTRODUCTION

The techniques of image filtering have undergone an explosive growth in the last years to make new advances and challenges. This is due to the fact, among several other reasons, the increase of the volume of images coming from several sources. Digital images have been used for a variety of purposes, from the storage of souvenirs to accurate medical exams. However, Images may be corrupted due to several factors.

The challenge of suppression or noise attenuation has led to the search for improved techniques, with the objective of preserving important characteristics of the image, improving visual perception in medicine, for example, to increase the clarity of anatomical structures present in DICOM images (Özmen and Özşen, 2018; Kiragu et al., 2017a; Zhang et al., 2017; Baselice et al., 2017a), reconstruction (Barca et al., 2017) and detection of alcohol (Kubicek et al., 2018). However, there is no solution available to completely solve the problem, thus motivating the search for improvements in existing methods, and in particular, boosting the production of the work proposed here.

In the literature there are techniques based on meta heuristics, as is the example of the technique described in (Saraiva et al., 2018), where the authors demonstrate a bioinspired hybrid method formed by a set of filters for noise attenuation in medical images.

The filtering methods by means of wavelets are also widely used (Khmag et al., 2016; Jain and Tyagi, 2016; Broughton and Bryan, 2018), in addition to several other methods proposed for the solution of the noise attenuation problem (Zafari et al., 2017; Fajardo-Delgado et al., 2016; Liu, 2015; Khmag

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Saraiva, A., S. de Oliveira, M., Sousa, J., Ferreira, N., Valente, A. and Soares, S.
Noise Attenuation using Genetic Algorithm in CT Image.
DOI: 10.5220/0007346301400148
In *Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2019)*, pages 140-148
ISBN: 978-989-758-353-7

et al., 2017; Özmen and Özşen, 2017; Dimililer et al., 2017; Kiragu et al., 2017b).

In the technique demonstrated in (Baselice et al., 2017b), the authors explore a method of noise reduction in magnetic resonance imaging based on the random markov field (RMF), next to it is proposed the maximum a posteriori estimator (MAP) to regularize the 3D amplitude MRI acquisition stacks.

The peculiarity of the method is the definition of a local Gaussian random 3D markov field capable of adapting to local image behavior considering a map of hyperparameters that describe the correlation between each pixel and its neighborhood, thus allowing adjustment of filter intensity, preserving smooth areas, edges and small details in an unsupervised manner.

In addition to the previously mentioned method, an innovative technique is demonstrated in (Badretale et al., 2017), the technique, according to the authors, learns directly from an end-to-end mapping of the images in a deep convolutional neural network, in this way, when learning a series of high and low level resources of a data set with images, the proposed algorithm shows itself capable of creating high quality filtered images.

In this paper, a hybrid genetic algorithm is applied for gaussian noise attenuation in computerized tomography medical image and compared with two other methods in the literature through the use of evaluation metrics MSE (Talbi et al., 2015), PSNR (Fedorov and Rodyhin, 2016) and SSIM (Hore and Ziou, 2010).

The GA was chosen because of its ability to perform well in large optimization problems where search space is unknown. In addition, the filter optimization problems have been solved successfully using this technique (Momeni et al., 2017; Mahani et al., 2017; de Paiva et al., 2016; Uzun and Akgün, 2016).

The proposed method combines the genetic metaheuristic algorithm with several filtering techniques available in the literature to solve the attenuation problem with the objective of producing high quality results through the search for possible solutions to improve the results generated.

The hypothesis of the work , is that the proposed model is able to present satisfactory results when compared to other methods present in the literature in several test cases.

Thus, in the next section, the methodology is explained. Results and discussion of results are presented in sections 3 and 4, respectively, and section 5 presents the conclusion.

2 GENETIC ALGORITHM

Genetic algorithms are the computational models family inspired by the theory of evolution of the species described by Charles Darwin (Goldberg, 1989). This technique is formed by algorithms inspired by the mechanisms of natural evolution and genetic recombination, in this way it provides an adaptive search method that is based on the principle of reproduction and survival of the fittest.

These algorithms use a population of potential solutions, each one codified, according to a specific problem, into a chromosome-like data structure. These structures envolving using genetic operators where preservation and improvement of critical information are promoted.

According to (Santos, 2015), in Darwin's theory the selection principle privileges the fittest individuals with greater longevity, and therefore, they are more likely to reproduce. Individuals with more offspring are more likely to perpetuate their genetic information in subsequent generations. These genetic information store the identity of each individual and are represented by chromosomes. Thus, these principles are taken into account for the construction of algorithms capable of finding the optimal solution for a given problem through the evolution of populations of solutions encoded through artificial chromosomes.

Represented as a chromosome, each potential solution is subjected to an evolutionary process involving several steps, known as selection, crossover (sexual recombination) and mutation.

At the end, after performing several a evolution cycle (iterations or generations), the fittest individuals are retained and the worst are excluded.The classical GA is exemplified by algorithm 1 and described some steps are below.

Algorithm 1: Genetic Algorithm Classic.

1: $generation \leftarrow 0$;
2: Generate random initial population;
3: Calculate the fitness of individuals in the population;
4: **while** $generation < generationMax$ **do**
5:     Select eligible parents;
6:     Perform crossover between selected parents;
7:     Apply mutation on the children generated;
8:     Calculate children's fitness;
9:     Replace all/some parent individuals in the current population with children;
10:     $generation \leftarrow generation + 1$
11: **end while**

- **Generate Population:** (Line 2) Step where n individuals are generated randomly, in this step each generated individual represent a potential solution of the problem and have their chromosomes encoded as binary string.

- **Evaluation:** (Line 3 and 8) The evaluation of the individual is generally determined by evaluating an objective function that represents the problem and aims to generate a measure of fitness of each individual in the current population that guide the search process.
- **Selection:** The main forms of parent selection are the selection by *ranking, tournament and roulette* (De Jong, 2012) and take into account the fitness of each individual for its execution. These methods are described in sequel.
  - **Roulette:** In the roulette selection method, exemplified in Fig 1, all individuals in the population have a probability of being selected for reproduction. For that each individual is represented in roulette proportionally to its fitness value, then, for each individual to select, the roulette wheel is rotated and the chosen individual is the one whose roulette area is pointed by the roulette needle.

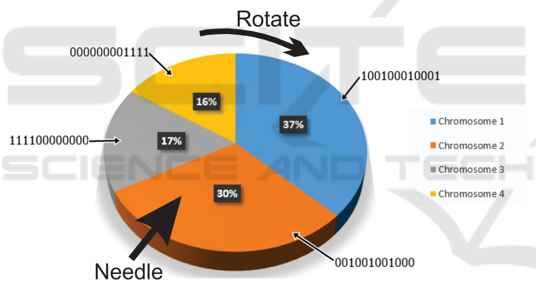

Figure 1: Roulette selection method.

  - **Tournament:** In the tournament method, a number *n* of individuals is chosen in a random fashion, and the one that gets the best fitness among them will be chosen. This process will be repeated until the required amount of parents is reached.
  - **Ranking:** The ranking method behaves differently, all individuals are ranked, the worst will be assigned to rank 1, the second worst will be assigned to rank 2 and the better will be in the maximum rank. The probability selection of an individual is given by its rank over the sum of all ranks.
- **Crossover:** The crossover (mutation) operator (item below) plays a fundamental role in a GA, through which it is possible for the population to diversify and maintain adaptation characteristics through generations.

Considered the predominant operator, the crossover is responsible for the creation of new individuals by the blending of characteristics of the parent individuals by digitally simulating the natural process of gene blending (Eiben et al., 2003). Some popular crossover types are: 1-point crossover, n-point crossover, and uniform crossover (Santos, 2015).

Exemplified by the Fig 2, the 1-point crossing is the method where a point is randomly determined and from this point of division of the characteristics of the parents, then a child is formed by the initial part of the first parent and by the final part of the second parent. The other child is formed by the remaining material of the previous combination.

Father 1	0	1	1	0	0	1	0	1	1	0	1	0
Father 2	1	1	0	1	0	1	0	1	0	0	1	1
Child 1	0	1	1	0	0	1	0	1	0	0	1	1
Child 2	1	1	0	1	0	1	0	1	1	0	1	0

Figure 2: 1 point crossing method example.

The n-point crossover works somewhat like the one illustrated above, but in this case instead of just choosing a split point, n points are selected for crossing and parenting. On the other hand in the uniform crossover the individual child has each element with 50% chance of belonging to the first or second parent.

- **Mutation:** The mutation operation simply randomly modifies a characteristic of the chromosome in which it is being applied, this step is important to create new values of features previously non-existent or even that arise in low quantity (Eiben et al., 2003). As in the crossing step, the mutation occurs proportionally at a given probability rate. Fig 3 exemplifies the use of the mutation.

0	1	1	0	0	→	0	0	1	0	0
1	1	0	1	0		1	1	1	1	1

Figure 3: Example of mutations.

In this step it is also possible to use more than one operator, such as the Gaussian mutation operator, the technique that draws a new value for the characteristic from a Gaussian distribution $N(\mu,\sigma)$ with average μ and standard deviation σ and the operator mutation uniform.

3 METRIC METHODS OF EVALUATION

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

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

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.

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

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

The 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) (Tiwari et al., 2015).

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

In the equation (3) μ represents the mean, σ symbolizes the standard deviation and σ_{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.

4 METHODOLOGY

The proposed genetic algorithm (GAP) in this work is based on the technique developed in (de Paiva et al., 2016), where each individual of the population is a two-dimensional image, however, as a contribution, in the algorithm proposed here, the idea was reconstructed and modified so that It is possible to perform filtering on a set of DICOM images automatically.

In choosing the size of the tournament, Paiva found that the worst case of the tournament size 3 tends to be better than the worst of the others. However, testing the different local search rates, although all the results were very close, the value ratio of 0.6 was the one that obtained the best results in comparison to the others. Furthermore, a superiority in the results with the beta 1.5 parameters and the population size is demonstrated.

In this sense, based on the analysis and the results demonstrated by the author, the proposed parameters were used here as proposed values due to the demonstration of the effectiveness of each change.

The proposed method has its beginning when a series of noisy DICOM images are used as input to the method and the other individuals of the population are created from applied mutation operators. In algorithm 2, the pseudocode of the algorithm is shown and its steps are described.

The beginning of the GAP consists of creating the initial population in two steps: first, the noise image is used as input for three noise smoothing methods below, thus, at the end of the first stage, the population has three individuals.

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

- **Ellipsoid** (Yang et al., 2008)

After the first stage, one of the outputs of these techniques is chosen randomly. It is then subjected to a mutation operator also selected at random so that quality changes are made to the previously generated output. As mutation operators, three types were used:

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

At the end of this stage, the resulting image is added to the existing population, then the mutation process is repeated until the population reaches the stipulated size, thus forming a hybrid population, formed by the output of the three methods of suppression of the initial noise plus the images which have gone through the process of mutation.

Algorithm 2: Genetic Algorithm Proposed (GAP).

```
function GAP(DicomPath)
    images ←ReadAllFiles(DicomPath)
    Population ←createPopulation(images)
    best ←Population.best
    while elapsedTime < maxTime do
        cont ← 0
        while cont < maxIter do
            IntermPop ← Population
            for i ← 1 to Population.size do
                ind1, ind2 ←Parents(Population)
                ind3 ←Crossover(ind1,ind2)
                if (Λ ∈ [0,1]) ≤LocalSearchRate
then
                    localSearch(ind3)
                end if
                IntermPop.append(ind3)
            end for
            Sort(IntermPop)
            Population ←IntermPop[1..Popula-
-tion.size]
            if (best =Population.best) then
                cont ← cont + 1
            else
                cont ← 0
            end if
        end while
    end while
end function
```

The GAP runs for a fixed time, in which the population continues to evolve, while there are no changes in the best individual for a maximum number of interactions, step at which the entire population is restarted while only the best individual is preserved.

An intermediate population twice 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 crossover operators, where parent selection is done through the tournament method. Soon after the parent's choice, a new crossover operator is selected randomly for the generation of a new individual (child). For this the following three types are available for selection:

- **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.
- **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.

Once created, the new individual can still be submitted by a local search operator, a process whose purpose is to improve the final quality of the solution by means of transformations in the individual, in this step, if the condition is satisfied that a real value randomly selected within the range of 0 to 1 in the algorithm is less than the local search rate chosen by the user, it will pass through one of the artifact suppression operators already mentioned in the initial step: BM4D, 3D Median Filter or 3D Ellipsoid Filter.

With the entire intermediate population completed, individuals are sorted according to fitness, so the first individuals are selected to form the GAP population for the next stage of evolution, where the algorithm checks if there are no changes in the best individual of the population during defined number of evolutionary executions. If the best individual does not change after a maximum number of iterations, that population is restarted. A flowchart of the algorithm execution is shown in Fig 4.

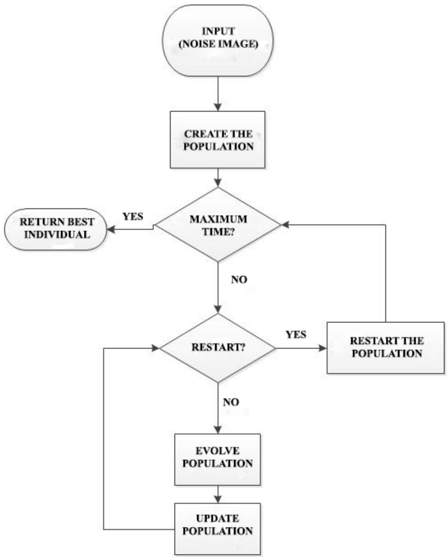

Figure 4: Flowchart of the algorithm execution.

5 EXPERIMENTAL RESULTS

In this chapter, the results of the statistical analysis will be presented through the evaluation metrics. The established comparison is related to two other methods of filtering medical images previously mentioned.

These methods are applied to a computerized tomography DICOM image available in the Repository The Cancer Imaging Archive (TCIA) (Clark et al., 2013). One of the images in the chosen DICOM is shown in the figure 5.

Figure 5: DICOM image initial.

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 GAP.

The first analysis was made by the MSE metric, presented in all cases the filter type GAP as better, taking into account that the best results are those whose values are the smallest. On the other hand, the MSE has the level of confidence that is contested, making it necessary to compare with new forms.

Table 1: Evaluation of the result through MSE.

Gaussian additive noise				
	Noise (MSE)	Median	Ellipsoid	GAP
1%	(161.44)	46.03	118.16	28.73
2%	(517.49)	107.39	159.96	52.73
3%	(887.77)	184.06	218.41	77.65
4%	(1193.96)	275.49	292.24	101.79
5%	(1448.74)	382.22	374.82	126.63
	Average	199.03	232.71	77.50

Table 2: Evaluation of the result through PSNR.

Gaussian additive noise				
	Noise (PSNR)	Median	Ellipsoid	GAP
1%	(26.06)	31.53	27.42	33.56
2%	(21.05)	27.84	26.10	30.88
3%	(18.64)	25.45	24.69	29.25
4%	(17.41)	23.73	23.54	28.10
5%	(16.53)	22.33	22.36	27.00
	Average	26.17	24.82	29.75

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 shown in the table that in only one case the value was similar to the GA model. Then we notice the difference in the values resulting from the methods being distant, in addition, it is also remarkable that the difference between the average of the GAP and the means of the other methods were somewhat close.

Table 3: Evaluation of the result through SSIM.

Gaussian additive noise				
	Noise (SSIM)	Median	Ellipsoid	GAP
1%	(0.94)	0.96	0.95	0.96
2%	(0.90)	0.94	0.93	0.95
3%	(0.89)	0.92	0.92	0.94
4%	(0.88)	0.91	0.91	0.93
5%	(0.87)	0.91	0.90	0.93
	Average	0.92	0.92	0.94

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

The results presented in the tables prove that the combined method of various artifact removal techniques is very favorable in most images, in addition, the few limitations of the GAP provide a multitude of options to change parameters and provide improvements in results.

As a visual example of the obtained results, it is shown in figures 6, 7, 8, 9 and 10. In each figure, four images are observed, one referring to the slice added with noise and another three are results of the ellipsoid, median and GAP filtering.

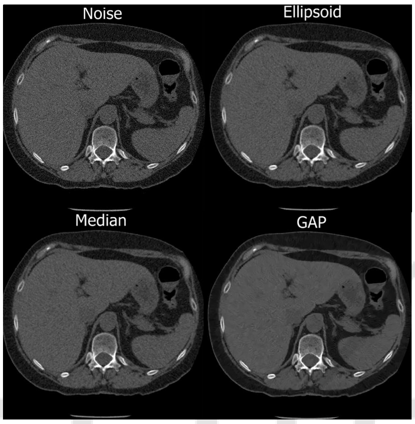

Figure 6: Image corrupted with standard deviation = 1% and filtering results.

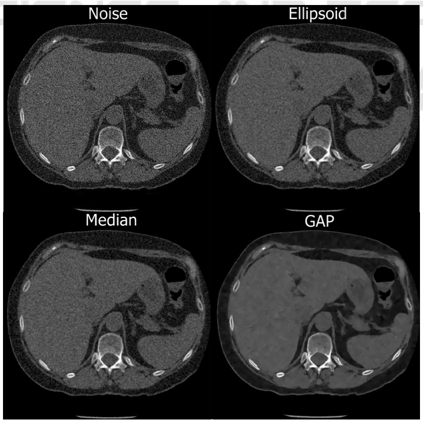

Figure 7: Image corrupted with standard deviation = 2% and filtering results.

In Fig 6 , the image was corrupted with gaussian artifact and a standard deviation of 1%. In the other figures (3-6) differ in the standard deviation of 2%, 3% , 4% and 5% respectively.

In Fig 6 it was observed that when applying the noise with low deviation, 1%, the difference of the GAP in relation to the others was already visually perceptible. In addition, in the figures 7, 8, 9 and 10 the

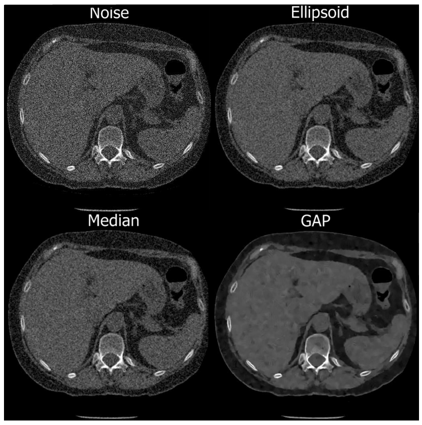

Figure 8: Image corrupted with standard deviation = 3% and filtering results.

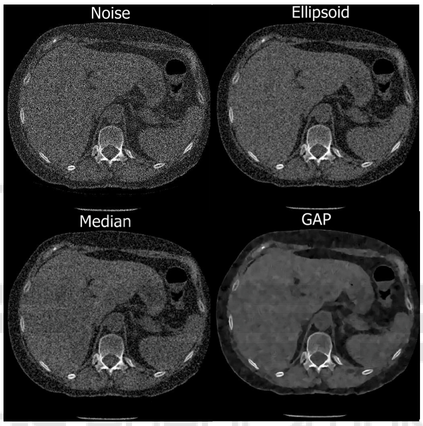

Figure 9: Image corrupted with standard deviation = 4% and filtering results.

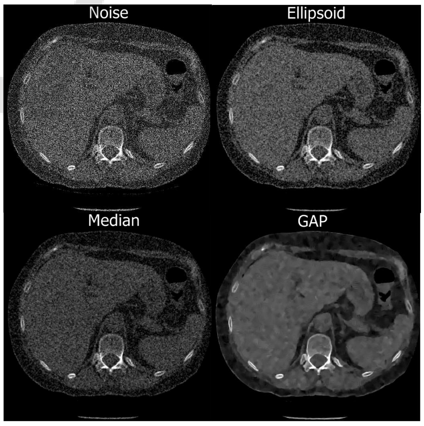

Figure 10: Image corrupted with standard deviation = 5% and filtering results.

difference between the proposed filter and the other two filters that serve as the basis for the quality check.

In the figures 9, 10 it was observed that when applying high noise it was visually perceptible that the GAP was able to recover good information from the badly corrupted images if it excelled in relation to the other competitors.

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 Table 1, it was observed that in all items the method demonstrated the most efficient filtration condition and presented significant results in the percentage of degradation of DICOM images. However, MSE may exhibit similarity failures.

Thus, the efficiency of the GAP 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 a hybrid method using a 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 distributed in a selective and evolutionary way in two stages. The first stage consists of the BM4D filtering, the 3d medium 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: change of intensity, gaussian filter and average filter.

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

With the study of the GAP can generate more advances and minimize the artifacts, resulting in a better performance in the system. The disadvantage is the limitations of techniques for random values, which hamper the ideal value set in the filtering.

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

ACKNOWLEDGMENT

This work is financed by the National Funds through the FCT - Fundação para a Ciência e a Tecnologia (Portuguese Foundation for Science and Technology) as part of project UID/EEA/00760/2019.

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