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Isotropic versus anisotropic techniques in cardiac computed tomography images processing

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Abstract. The objective of the work is to compare the performance of two filters, one isotropic and another one of anisotropic diffusion based on gradient. To do this, experiments are carried out to establish which of the filters exhibits a better behavior against the imperfections that characterize the computed tomography images. The structure of the experiments is as follows: a) The parameters linked to the aforementioned filters are identified. b) The ranges of values of these parameters and the way to use them are established. c) A database of three-dimensional cardiac images is filtered by applying, independently, the aforementioned filters considering a pre-established subset of values associated with the parameters. d) All the filtered images are addressed by a segmentation process, based on the growth of regions, which allows extracting the 3D morphology of the thoracic external aorta. e) As a metric to evaluate the performance of each technique, the Jaccard similarity index (JSI) is used. f) The one that generates the lowest calculated JSI is selected as the best technique when comparing a reference segmentation with all generated segmentations. The results indicate that the anisotropic diffusion filter, based on a gradient, obtained the best performance.

1. Introduction

The digital processing of images can be considered as a set of techniques that operate on the digital representation of an image with the purpose of highlighting some of its elements. The problems or imperfections that generally affect the information of the digital images are generated during the acquisition and / or reconstruction phases and their impact can be minimized using image preprocessing techniques [1].

The importance of this type of technique lies in the fact that its careful and systematic use can substantially raise the quality of the analysis of a scene, modifying the attributes of the images acquired by any of the imaging modalities presented through Figure 1.



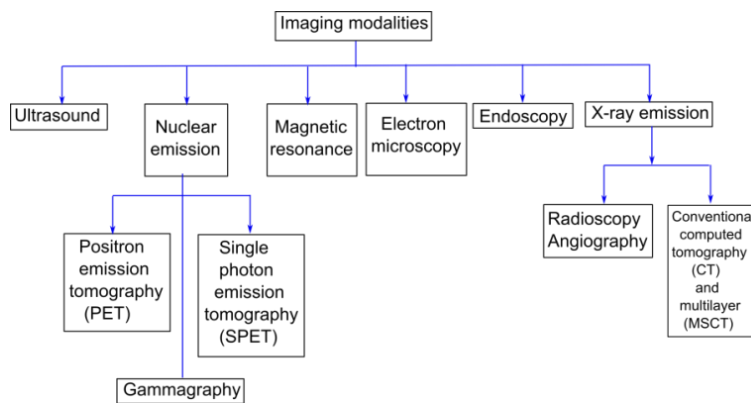


Figure 1. Imaging modalities used in the medical context.

During the image reconstruction process, before the images are generated by medical equipment (scanners, magnetic resonators and ultrasound equipment) a preliminary digital processing phase is applied whose purpose is to raise the quality of the information that those systems of acquisition delivered as final product. However, the imperfections remain latent in the images that the clinical specialist uses to detect, monitor or follow up on any pathology and, eventually, plan their treatment.

Usually, digital image preprocessing techniques are a step prior to the process of segmentation of anatomical structures, organs of the human body or space-occupying injuries that affect the quality of life of people. These techniques are characterized by performing tasks such as: a) Mitigate distortions that affect the quality of the considered image. b) Enhance the contours that define the objects that you want to segment. c) Uniform the information contained inside such contours. d) To exclude unwanted objects or structures by generating clearly delimited regions that contain the object of interest [2].

Additionally, filtering techniques, which represent a subset of digital preprocessing, enable the development of a very important process that facilitates the rest of the phases of digital image processing. In general, the image filtering process consists in the application of algorithms called filters which can be visualized as operators that modify the elements of an image with the purpose of emphasizing certain information or diminishing the effect of the distortions present in it [1]. As a consequence of the above, the filters are characterized by altering, to a certain degree, the characteristics or attributes of an input image with the purpose of attenuating their possible imperfections [2].

An important number of investigations, developed in the international concert, involve the use of filtering techniques with different purposes. Thus, several works have been focused on the reduction of noise present, typically, in medical images [3-12].

This article is focused on the description and systematic evaluation of the performance of two digital preprocessing techniques widely used in the context of image filtering. They are the Gaussian filter and the anisotropic diffusion filter, based on a gradient.

2. Materials and methods

2.1. Dataset description

The database (DB) used contains cardiac images acquired using the multilayer computerized tomography modality. The DB is composed of 326 images of size 512x512 with a pixel space of 0.4882 mm and each image has a thickness of 0.3999 mm. Additionally, there is manual segmentation (reference segmentation) generated by a cardiologist which will serve to evaluate the performance of the filtering techniques considered.

2.2. General considerations about filtering techniques

Generally, after the application of a filter, an output image is generated in which the information present in the input image may appear smoothed or enhanced. Accordingly, the filtering techniques

could be classified, preliminarily, into filtering techniques for the enhancement of information of interest and filtering techniques for the removal of unwanted information [1,2].

2.2.1. Enhancement filters. Also known as high pass filters are based on the reinforcement of contours, which, on the one hand, tend to emphasize the edges of the structures present in the input image and, on the other, attenuate the intensity values of the regions almost constants in the image that is being processed.

2.2.2. Filters for removal of unwanted information. Called low pass filters are characterized by applying softening operations oriented, mainly, towards the elimination of the noise present in the considered image. In practice, filters operate on images, in the frequency and spatial domains, in order to: a) Reinforce some type of desired information which may be linked, for example, with a structure or object of interest; b) Minimize or delete unwanted information which may correspond to artifacts, noise, background or other objects other than the object of interest [2].

2.2.3. Space filters. In the context of spatial filtering, the terms neighborhoods, masks, windows, kernels or kernels are frequently used, which can be considered synonymous. The neighborhoods are simply groups of elements belonging to the image that one wishes to process and that fulfill the condition of being neighbors (being in the vicinity) of a particular element called element object of study or current element [13]. The aforementioned neighborhoods are designed considering different topologies, arbitrary sizes and, in certain cases, the allocation (within the mask) of scalars obtained empirically or through the application of pre-established mathematical models.

Spatial filtering techniques can be classified into linear spatial filters and non-linear spatial filters. Linear filters generate an output image (filtered image) by a process, often called convolution, based on the linear combination (LC) of the intensities that the elements of the input image possess [1].

The coefficients that allow such LC to be operationalized are matched to the scalars of a neighborhood centered on the element under study. Usually, the image to be filtered is analyzed element by element, repeating iteratively the aforementioned process.

On the other hand, non-linear spatial filters also consider neighborhoods (without scalars) of the element under study. However, its operation is based directly on the intensity values of the elements that make up such neighborhoods [2]. The following describes two of the spatial filtering techniques most used in image processing.

2.3. Isotropic and anisotropic techniques description

Because Poisson noise is among the main problems affecting cardiac computed tomography images, it was considered to address this problem using an isotropic and anisotropic filter.

In the present work, the isotropic filter is given by the Gaussian filter; while the anisotropic filter is matched to the gradient-based anisotropic diffusion filter. In this sense, Figure 2 and Figure 3 show a scheme of the techniques that will be used during the experiments that will allow to evaluate the performance of the filters addressed in the present work. These techniques are presented below.

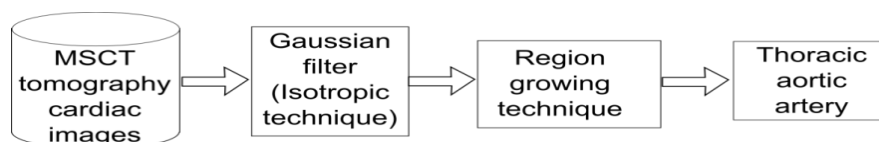


Figure 2. Diagram of the processing strategy based on Gaussian filtering.

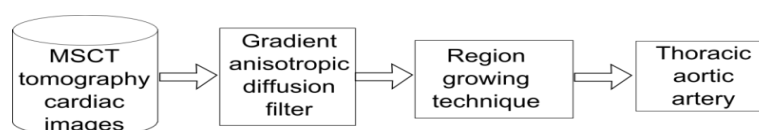


Figure 3. Diagram for anisotropic diffusion filtering.

2.3.1. Gaussian filter (GF). Theoretically, the Gaussian filter verifies certain basic principles such as: causality (derived from its pyramid structure), comparison (maintains the relationship in the gray levels) and invariance (before translations and rotations) [2,14]. In practice, the convolution with a Gaussian is equivalent to the resolution of the heat equation; therefore, the numerical discretization of said equation is approximately equal to the Gaussian filtering.

Gaussian filtering in several dimensions is a one-dimensional superposition in the orthogonal directions. This allows the development of implicit discretization schemes of the heat equation with a stable Gaussian filtering process [15]. In this sense, a discrete Gaussian distribution, represented by a kernel of arbitrary size, can be used. Kernel values are obtained according to Equation (1).

$$G(i, j, k) = \frac{1}{(\sqrt{2\pi})^3 \sigma_i \sigma_j \sigma_k} e^{-\left(\frac{i^2}{2\sigma_i^2} + \frac{j^2}{2\sigma_j^2} + \frac{k^2}{2\sigma_k^2}\right)} \quad (1)$$

where: $0 \leq i, j, k \leq (n - 1)$, n is the size of the Gaussian core, σ_i , σ_j y σ_k are the standard deviations considered.

Analyzing Equation (1), it can be established that the parameters of the Gaussian filter are: the standard deviation of each of the spatial dimensions and the radius (r) that defines the size (n) of the nucleus.

2.3.2. Gradient-based anisotropic diffusion filter. In the context of anisotropic diffusion filtering, smoothing is a process that stops at the borders through the proper selection of spatial diffusion values. Depending on the diffusion strength, the filter performs an inter-regional smoothing preserving the edges. Perona and Malik presented the anisotropic diffusion filters [10]. They propose selective diffusion of the image by introducing a coefficient of non-linear conductivity in the heat equation. The formulation depends on Equation (2).

$$u_t = \text{div}[g(|\nabla u|)\nabla u]; \text{ with initial condition } u(x, 0) = u_0(x) \quad (2)$$

where: u_t represents the filtered image at any moment of time, $u_0(x)$ it is the original image, $g(|\nabla u|)$ corresponds to the conductivity coefficient, g is a regular and decreasing function with $g(0)=1$, $g(x) \geq 0$, $g(x)$ tends to zero at infinity.

In Equation (2), if $\nabla u(x)$ is big the diffusion will be penalized and therefore the exact location of the edges is preserved. If $\nabla u(x)$ is small, then x belongs to a homogeneous region of the image and the diffusion is large. As seen, the anisotropic filters use an edge detector (∇u) that guides the diffusion process. The detector is responsible for smoothing noise, whose value tends to infinity when approaching a perfect edge.

Under certain circumstances, the diffusion filters degrade the edges of the images according to the number of iterations and that is why the number of iterations is one of the intonation parameters of this type of filter. According to Equation (2), the other parameters of the anisotropic diffusion filter presented are the conductivity and the time base considered.

2.3.3. Segmentation technique based on region growing (RG). This technique requires initial coordinates of an initial voxel, reported in the literature, as "seed" which was manually matched to the centroid of the thoracic artery.

Once the seed is established, an initial neighborhood of arbitrary size (tam) is constructed, the voxels neighboring the region surrounding the centroid are analyzed, calculating the mean m and the standard deviation σ , adding the position voxels x whose gray intensity values fulfill the condition established in Equation (3).

$$I(x) \in [m - f\sigma, m + f\sigma] \quad (3)$$

being I: imagen, x: position of the neighbor voxel analyzed, m: mean, σ :standard deviation, f: multiplier.

In summary, the parameters that must be intoned for the GR are: a) tam represents the size of the initial neighborhood and f corresponding to the multiplier which can assume any value from the set of natural numbers.

This search process is repeated, iteratively, until we can not add more voxels, because the gray levels of the voxels, which are around the analyzed voxel, do not comply with Equation (3). The segmented thoracic artery is represented by all the elements accepted during the search procedure to which the same level of gray is assigned, thus generating a binary image.

2.4. Parameters tuning

The adequate performance of the techniques considered requires obtaining their optimal parameters. To do this, using the database described, modify the parameters associated with the technique you want to intone considering, systematically, the values that belong to the ranges described below.

The parameters of the gradient-based anisotropic diffusion filter are given by the number of iterations (Iter) [1, 100]; with step size of one unit, conductivity (C) [0 10]; with step size equal to 0.1 and the time base (t) [0, 1]. The literature recommends for t a value of 0.0625 which was assumed in the present work [16].

Gaussian smoothing parameters, in the 3-D domain, are: a) The standard deviations of each direction in which the filtering is intended. b) The size of the Gaussian core. During smoothing, to decrease the number of parameters of the Gaussian filter, the size of its neighborhood is arbitrarily set to $(3 \times 3 \times 3)$; while the values of its standard deviation belong to the interval (1,4), including the extremes, with a step size of 0.1.

During the optimization process of the parameters of the RG, each of the automatic segmentations of the thoracic artery, corresponding to the described database, is compared with the manual segmentations of said artery, generated by a cardiologist, considering the similarity index by Jaccard (JSI) [17].

The JSI can be modeled by Equation (4).

$$JSI = \frac{|MS \cap AS|}{|MS \cup AS|} \quad (4)$$

where: MS is manual segmentation and AS is automatic segmentation.

The optimal values for the parameters of RG (tam and f) are identified from the maximum value for the JSI. For tam values between 0 and 10 are considered, with step size equal to 0.1 and for f integer values between 1 and 20 with step size of one unit.

3. Results

The tuning process, for a particular filter, stops when the optimal value for its parameters is obtained, that is, when the values for which the best segmentation is generated are analyzed, considering JSI. In this sense, the Gaussian filter parameter, called the standard deviation (σ), produced its best performance for a value of σ equal to 1.6, which generated a maximum JSI of 0.9477. For the gradient-based anisotropic diffusion filter, the maximum JSI was 0.9807 and the optimal values for its parameters were conductance 0.5 and number of iterations equal to 58. Regarding the RG, the optimal values for the tam and f were: (tam = 1, f = 6.8) for Gaussian filter; while for the anisotropic filter was obtained (Iter = 2, C= 7.7).

Figure 4 shows a 2D view of both the original image and the processed versions after applying the proposed techniques to the database considered.

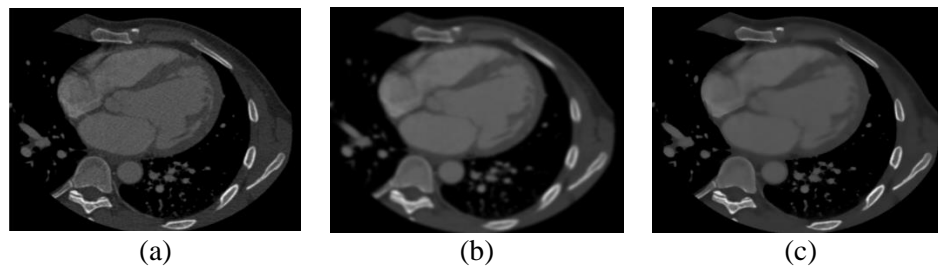


Figure 4. Filtering process using a Gaussian and anisotropic technique. (a) Original, (b) gaussian, and (c) anisotropic.

In Figure 4, the effect of both filters is observed, noticing a better definition of the objects, present in the considered image, when the filtered versions are compared with the original image. Additionally, through Figure 5, the segmentations generated from the filtered images are presented after applying growth of regions. Figure 5 (c) shows an overlap of both segmentations, showing a high correspondence in the internal part of the considered artery but there are differences in the edges.

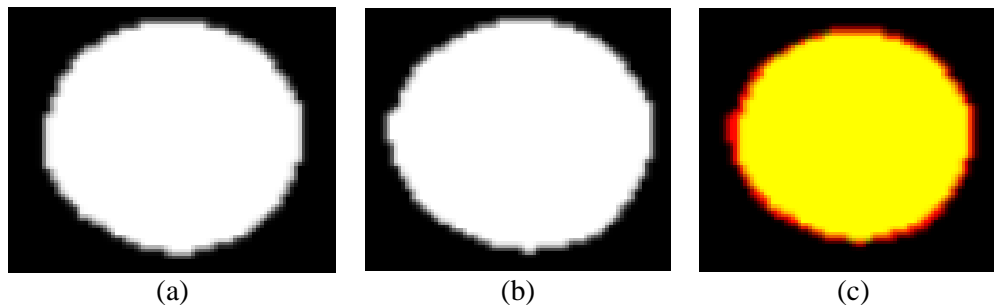


Figure 5. 2D view of the segmented thoracic artery. (a) Gaussian, (b) anisotropic, and (c) gaussian + anisotropic.

Finally, Figure 6 shows the three-dimensional representations of the segmented thoracic artery.



Figure 6. Three-dimensional view of segmented thoracic artery. (a) Gaussian segmentation, and (b) anisotropic segmentation.

The Gaussian filter, with σ equal to 1.6, requires a computational time of 30 seg; while the diffusion filter requires approximately 19 minutes, for the combination of parameters (Iter=2, C=7.7). These times are reported for aPC Intel Core I7-6500 of 3.3 Ghz and 8 Gigas RAM.

According to these results, from the point of view of precision, the anisotropic filtering generated the best performance. However, the Gaussian filter generated a good JSI and, undoubtedly, this type of filter will be an alternative when a fast-acting filter is required.

4. Conclusions

Through this work, a semiautomatic technique was developed which allowed a precise segmentation of the thoracic aorta artery, present in computed tomography images. On the other hand, the two strategies considered minimized the Poisson noise problems present in the MSCT images.

Both strategies achieve a value for the high JSI, which is a clear indication of the high quality that they exhibit. However, it is undeniable that at the expense of a high computation time the anisotropic filtering, based on a gradient, generates the most precise segmentations. In any case, isotropic filtering,

using Gauss, is still used because it is a very fast technique. In the future, it is planned to compare anisotropic filtering techniques based on gradient-based anisotropic curvature. Also, we will incorporate parallel programming techniques to reduce the computation time of anisotropic filter.

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