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MEDICAL IMAGE NOISE REDUCTION AND REGION CONTRAST ENHANCEMENT USING PARTIAL DIFFERENTIAL EQUATIONS

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ABSTRACT

This paper presents a new approach to noise reduction and contrast enhancement for different types of medical images. An anisotropic scheme is used to iteratively reduce noise as well as to define image regions and enhance region contrast. This allows an easier semiautomatic segmentation of the regions of interest. The process is performed in three stages, which consists in reducing noise, enhancing contrast and segmenting regions. The final values of the regions are automatically extracted from the image histogram, thus providing a fast method to obtain the most significant information in the image and a good approximation to region boundaries. This technique can be applied, not only to multiple region image segmentation, but also to certain processes of computer aided diagnosis which include several types of feature extraction and shape analysis.

KEYWORDS

Image processing, noise reduction, contrast enhancement, segmentation, anisotropic diffusion.

1. INTRODUCTION

Medical imaging has enormously increased its importance in the diagnosis and assessment of a wide range of pathologies. At the same time, the advances in different computational techniques related to computer vision and image processing have also increased the relevance of these algorithms for computer aided radiology and surgery. However, the different modalities of medical images still present some disadvantages, such as noise, low contrast or diffuse region boundaries, which may reduce their reliability and make it difficult to apply robust methods for semiautomatic segmentation, computer aided diagnosis, three-dimensional reconstruction and other further applications. We have developed a framework for noise reduction and region segmentation, increasing the visibility and significance of the images.

The applications for which these techniques have been considered include contrast enhancement and boundary extraction in CT (computed tomography) images for three-dimensional organ reconstruction and volume measurement, as well as nodule segmentation and contour analysis in ultrasonography for breast tumor discrimination. In the first case, the accurate measurement of organ and region volume before certain surgery requires a precise delimitation of the boundaries. In the second one, a reliable diagnosis of the malignancy or benignity of a solid breast nodule using ultrasonography depends on the analysis of its shape and the regularity of its contour. Therefore, it is very important to extract an accurate and robust delimitation of the regions of interest. We have used these two applications to illustrate our results.

This paper is structured as follows: Section 2 describes the noise reduction process. Section 3 explains the contrast enhancement technique we have developed. Section 4 presents the region segmentation process. In section 5, we illustrate the proposed techniques with several examples in different medical image modalities. Finally, in section 6, we give an account of our main conclusions.

2. NOISE REDUCTION

The process we propose consists of three stages. The first stage is aimed at reducing noise in the images, but preserving region boundaries. The second stage focuses on trying to concentrate the intensity values in the image into certain reference values, so that the regions of interest can be identified and an initial approximation to their segmentation can be easily applied. Finally, the third stage segments the regions extracting accurate contours for them.

The noise reduction stage consists in the application of Perona-Malik filtering (Perona and Malik, 1987), a partial differential equation in which diffusion is not homogeneously performed, but depending on the magnitude of the gradient, so that the boundaries of the regions are preserved, according to equation (1), where *c(.)* regulates how deep the diffusion is.

$$\frac{\partial I}{\partial t} = div\left(c\left(\left\|\nabla I\right\|\right)\nabla I\right) \qquad (1)$$

$$c(x) = e^{-\lambda|x|}$$

$$I(t=0) = I_0$$

The value of λ determines what contrasts should be preserved and what others should be diffused. This value must be adapted, depending on the modality of medical images and how noisy they are. The discretization of this equation is performed according to the following iterative scheme:

$$u_{i,k}^{n+1} = u_{i,k}^{n} + \frac{dt}{2h^2} M_{i,k}^{n} \qquad (2)$$

$$M_{i,k}^{n} = G_{i,k}^{n} * u$$

where h and dt are the spatial and temporal increments, respectively, and

$$G_{i,k}^{n} = \begin{pmatrix} 0 & W_{i,k+1}^{n} + W_{i,k}^{n} & 0 \\ W_{i-1,k}^{n} + W_{i,k}^{n} & -\begin{pmatrix} W_{i+1,k}^{n} + W_{i-1,k}^{n} + \\ W_{i,k+1}^{n} + W_{i,k-1}^{n} + 4W_{i,k}^{n} \end{pmatrix} & W_{i+1,k}^{n} + W_{i,k}^{n} \\ 0 & W_{i,k-1}^{n} + W_{i,k}^{n} & 0 \end{pmatrix} \qquad (3)$$

$$W_{i,k}^{n} = e^{-\lambda \left\| \left(\nabla u^{n} \right)_{i,k} \right\|}$$

When region difference is based on texture contrast, rather than on intensity contrast, a set of texture detection filters, such as Gabor filters, can be applied to characterize the regions and separate them according to their patterns (Alemán-Flores et al., 2007). In this case, it is the difference in the responses to these filters that regulates how deep the diffusion is. In such case, equation (1) would be transformed into equation (4), in which R represents the outputs of the set of filters which have been applied:

$$\frac{\partial I}{\partial t} = div\left(c\left(\left\| \nabla R \right\| \right) \nabla I \right) \qquad (4)$$

3. CONTRAST ENHANCEMENT

The second stage aims at concentrating the intensity values in the image towards certain reference values which best represent the regions. This requires setting a series of concentration values, i.e. final values in the image, and their corresponding attraction ranges, i.e. intervals which converge towards those values. In order to prevent noisy points to converge to erroneous values, this is combined with the heat equation, so that they will be blurred as the convergence process is gradually applied and noisy points will converge to their region representative.

For the extraction of the reference values and ranges, two alternatives are given. Both of them are based on the image histogram, but the first one directly extracts the maxima and minima of the smoothed histogram, whereas the second one fits the histogram to a polynomial whose grade depends on the number of regions to separate. The first one is simpler and determines the number of reference values according to the image histogram, but sometimes it is more suitable to set the number of desired values a priori.

Although the presence of noise and diffuse edges may alter the shape of the histogram, its global shape can provide the information needed to set the representative values for the regions and the limits of the intensity ranges. The first stage helps reducing the influence of noise but, furthermore, the histogram is also smoothed before adjusting it, in order to prevent noise from generating a wrong shape. For the second alternative, a least-square fitting is carried out to extract the shape of the histogram. From this adjustment, the local maxima and minima are extracted to be used in the next phase. Maxima will determine the values to converge, as they can be considered as the most likely values to agglutinate their neighborhoods, while minima will set the limits of the ranges of intensities that will converge to each region representative. The use of Perona-Malik filtering in the previous stage allows reducing the influence of noise in the result, since certain noise patterns and distributions may cause false maxima to appear, which would make the regions to converge towards wrong intensities. Perona-Malik approach allows preserving the original values of the regions, which would be blurred if isotropic filters were used. In Figure 1, we present the histograms at the different phases of the process.

Once the values have been extracted, a variation of the heat equation using an external term is applied in order to reduce noise while the different pixels converge to their corresponding region representatives, thus increasing the contrast between the regions, as expressed in equation (5),

$$\frac{\partial u}{\partial t} = \Delta u - A \prod_{i=0}^{l} \left(u - T_i \right) \qquad (5)$$

Where l is the number of maxima and minima T_i extracted. The values in the series T are alternatively maxima and minima and they must start and finish with a maximum. The second term in the equation concentrates the values around the representatives extracted in the previous stage, but taking into account that the heat equation will affect this convergence in such a way that those remaining noisy points will be blurred and will converge to the representative of their neighborhoods. Parameter A will determine the relative contribution of this term.

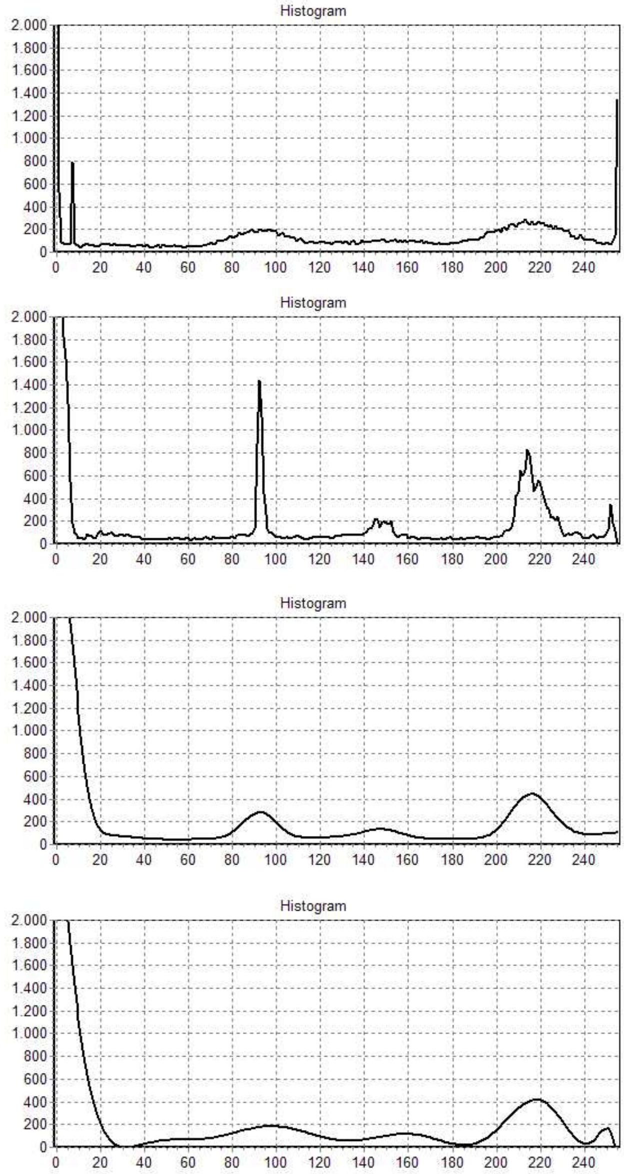

Figure 1. From top to bottom: Original histogram, histogram after image anisotropic diffusion, smoothed histogram and polynomial fitting.

4. REGION SEGMENTATION

The final purpose of the previous stages in the particular application of our project is the extraction of a more suitable image for region segmentation in order to accurately extract organ, tissue or region boundaries. The first stage reduces noise while the second one enhances image contrast congruently with image values. This allows a semiautomatic segmentation of different regions. Initially, by determining certain ranges of intensities, an initial approximation to the contours can be extracted, but they may not be accurate enough. In the case of a region *R* and its background, they are determined by a binary function *u(0,x,y)* (it is 1 if its final value in the previous phase is the desired intensity and 0 otherwise, as explained in equation (6)), which is considered as an initial approximation of a certain region. Afterwards, we apply active contours (Caselles at al., 1997) to improve these initial approximations. Active contours are based on equation (6):

$$\frac{\partial u}{\partial t} = g_\sigma(I) div\left(\frac{\nabla u}{\|\nabla u\|}\right)\|\nabla u\| + \lambda \nabla u \nabla g_\sigma(I) \qquad (6)$$

$$g_\sigma(I) = \frac{1}{\sqrt{1+\alpha\|\nabla I_\sigma\|^2}}$$

$$u(o,x,y) = \begin{cases} 1 & if\ (x,y) \in R \\ 0 & if\ (x,y) \notin R \end{cases}$$

This equation consists of two terms. The first one tries to regularize and smooth the contour, while the second one attracts the contour to the highest contrasts in the neighborhood. Function g_σ acts as a stopping function, so that the contours will converge to its minima. The values of the parameters α, λ, σ respectively determine the weight of the gradient in the stopping function g_σ, the weight of the attracting force in the active contour equation, and the diffusion performed to the initial image in order to smooth it.

5. RESULTS

We have tested our method with different modalities of medical images. In some of them, such as CT, noise is moderate, but region contrast may be low (see Figure 2). When three-dimensional organ reconstruction is aimed or tissue boundaries are to be located, this low contrast produces certain ambiguities. In other types, such as ultrasonography, the acquisition process introduces a high level of noise which makes it very difficult to extract the boundaries of nodules and regions, and avoids a robust and accurate assessment (Revell at al., 2002) (see Figures 3 and 4).

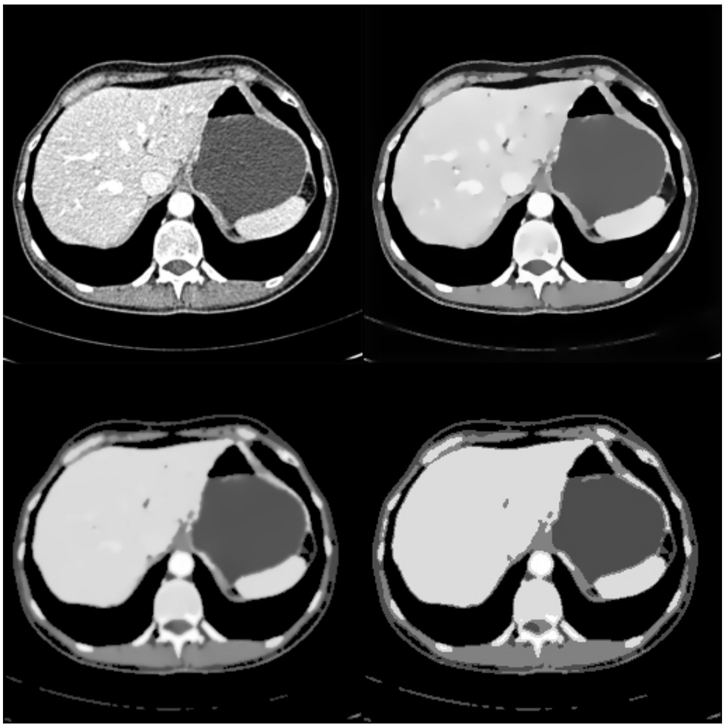

Figure 2. From top to bottom and from left to right: Original CT image, filtered image with Perona-Malik filtering, resulting image after heat equation with external term and final segmented image.

The CT image in Figure 2 corresponds to the abdomen and the limits of the different organs must be precisely determined to combine several images in a tomography, generate a three-dimensional visualization of the regions and measure their volumes and dimensions.

The ultrasonographies in Figures 3 and 4 correspond to two breast nodules, whose evaluation, in order to determine its malignancy or benignity, is mainly based on contour analysis (Stavros et al., 1995). This makes it very important to be able to segment the nodules from the surrounding tissues in an accurate way.

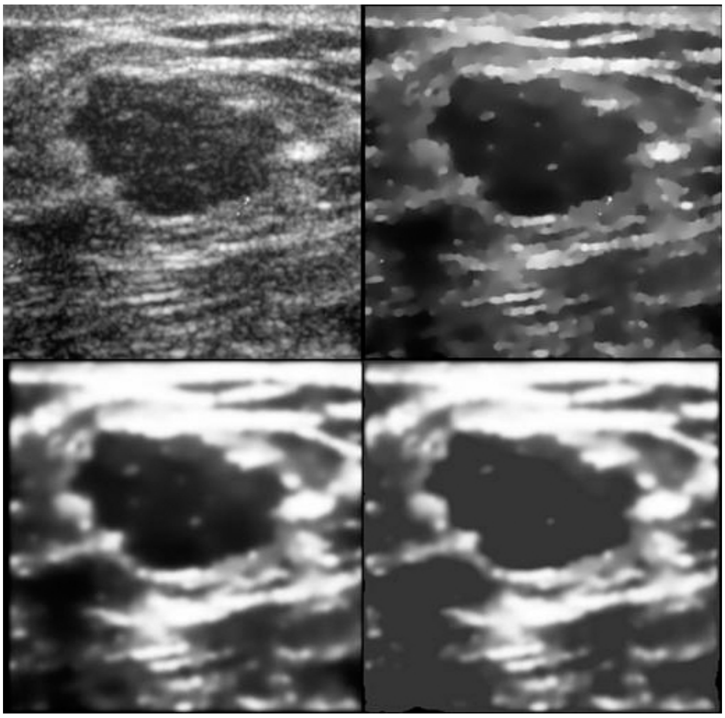

Figure 3. From top to bottom and from left to right: Original ultrasound image, filtered image, contrasted image and region extraction.

In spite of noise and blurred edges in the original images, our results are quite satisfactory and allow determining precise boundaries, as well as a better visualization of the tissues and organs.

As observed in Figures 2, 3 and 4, region growing algorithms, front propagation schemes and more robust methods such as active contours (Caselles at al., 1997) will work much better in the processed images than in the original ones, thus providing an efficient method for region segmentation. An increase in the number of significant values, i.e. in the degree of the polynomial, results in a higher number of regions extracted. This allows detecting lower contrast areas, but may cause a single organ or tissue to be split into more than one region (see Figure 5).

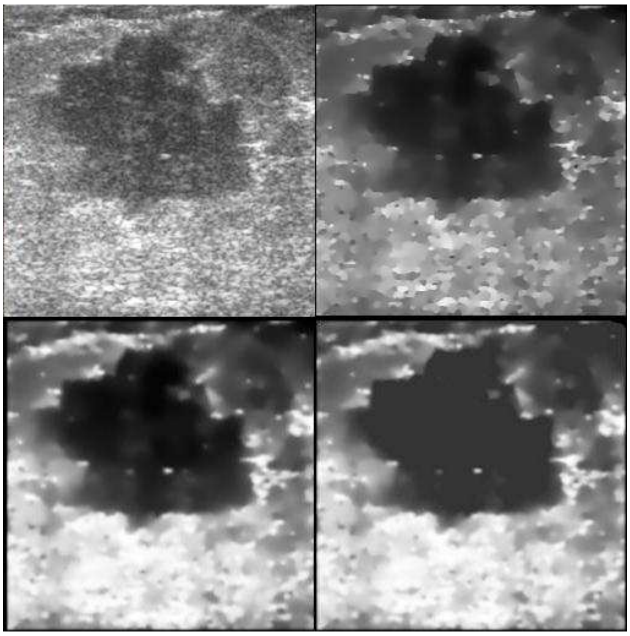

Figure 4. From top to bottom and from left to right: Original ultrasound image, filtered image, contrasted image and region extraction.

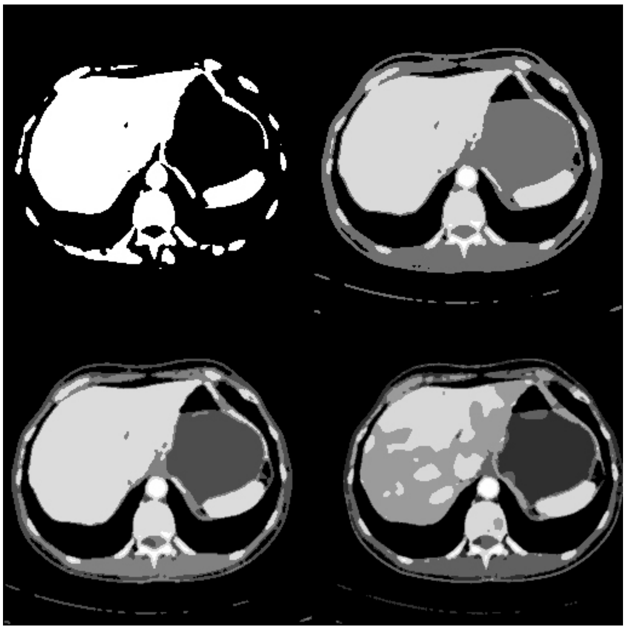

Figure 5. From top to bottom and from left to right: Resulting regions for 3, 9, 13 and 21 discriminating coefficients.

When dealing with a whole series of images corresponding to the same section of the body, the process can be simplified. Once the values and ranges have been extracted for a significant image, they can be directly applied to the rest of the series, since the intensities of the regions of interest will not drastically change. This is illustrated in Figure 6.

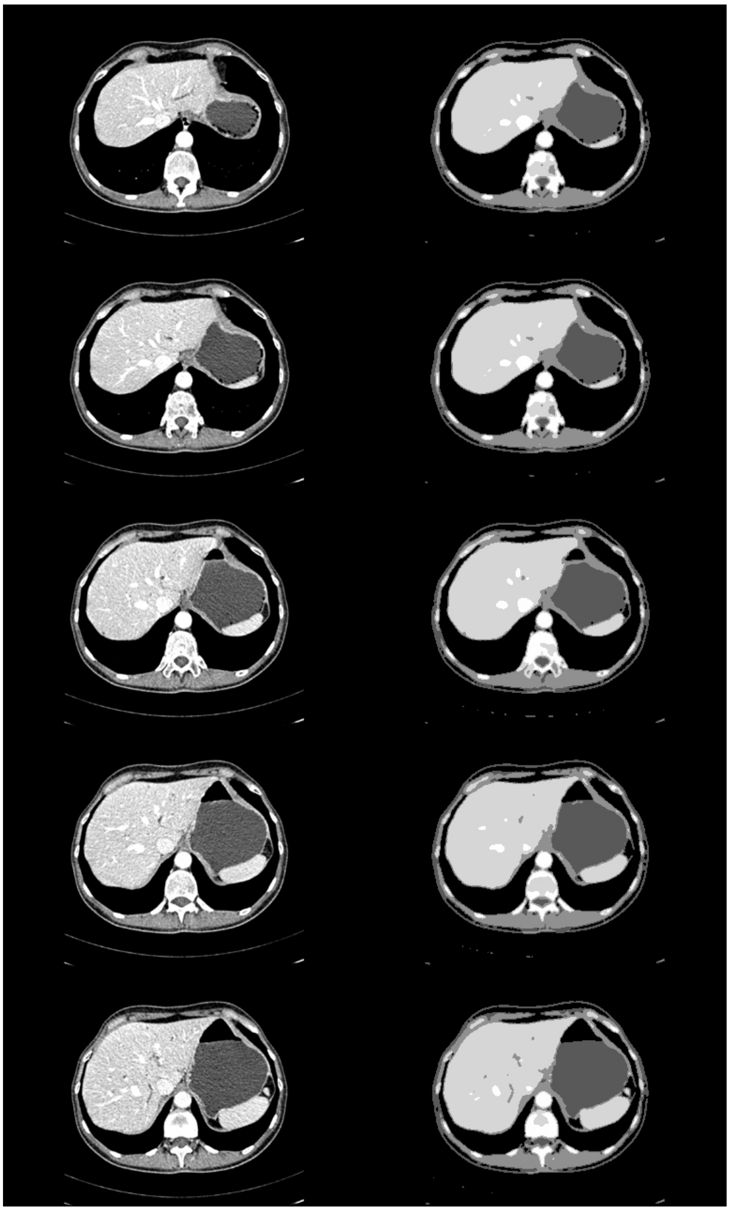

Figure 6. Series of original images corresponding to a CT analysis (left) and their corresponding extracted regions (right).

The initial approximations which can be obtained from the first two stages are refined using active contours. Figures 7 and 8 show how the active contours improve the initial segmentations by adapting them to the real values of the images. They correspond to a CT image (Figure 7) and an ultrasound image (Figure 8).

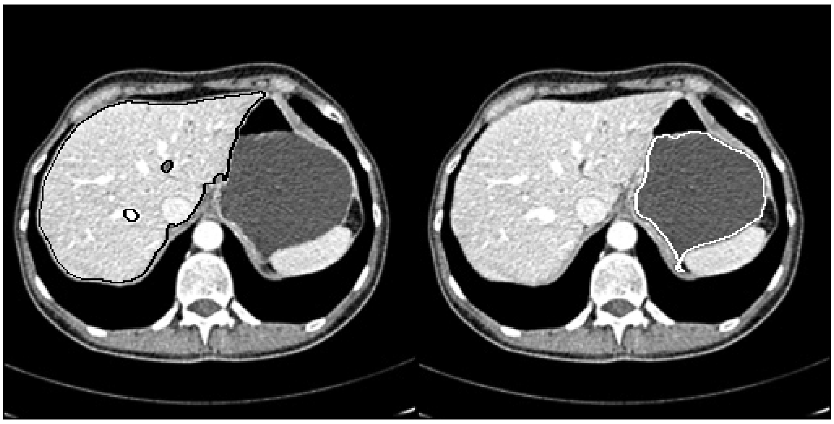

Figure 7. Examples of two segmented regions using active contours approach. The black line on the left and the white line on the right correspond to the final segmentations.

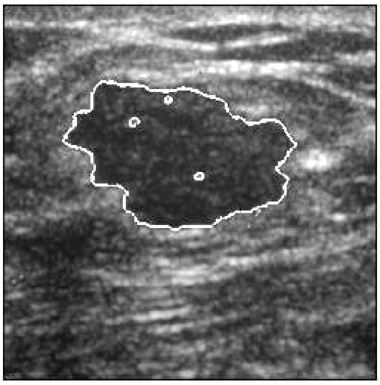

Figure 8. Example of a segmented nodule in a breast ultrasound image.

6. CONCLUSION

Region segmentation processes usually require either a good initial approximation, or some a priori knowledge about the shape and dimensions of the regions. In the case of medical images, this is not always possible, and the presence of noise and low contrast areas makes it very difficult to extract satisfactory results.

We have proposed a new approach which allows improving the visualization of different modalities of medical images including computed tomography and ultrasonography. This process consists of noise reduction, contrast enhancement and automatic region segmentation. The results are quite satisfactory and can be applied in computer aided radiology and surgery.

The initial noise reduction allows extracting a more representative histogram of the image, and region boundaries are preserved while noise is reduced. From this histogram, the representative values and intensity limits of the regions are extracted, so that regions themselves define their ranges and final values and the interaction with the user is reduced, since the processes are automated as much as possible. The introduction of external terms in the heat equation allows attracting the values of the pixels to the extracted final values while more homogeneous regions are defined. Finally, the initial approximations extracted are improved using active contours, which provide satisfactory results with these initializations.

With these results, a three-dimensional reconstruction from boundary extraction can be performed in a more accurate way. The combination of the information obtained from adjacent layers in the tomography allows a faster and more robust contour extraction since they are assumed to preserve the ranges of intensities from one layer to the next one.

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