Image Segmentation Algorithms and their use on Doppler Images

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ABSTRACT: This paper aims to make a review on current segmentation algorithms used for medical images. Image segmentation algorithms can be classified according to their methodologies, namely the ones based on thresholds, clustering, and deformable models. Each type of algorithms is discussed as well as their main application fields identified; additionally, the advantages and disadvantages of each type are pointed out. Experiments that apply the algorithms to segment Doppler images are presented to further evaluate their behaviour.

1 INTRODUCTION

The main goal of this paper is to present and discuss methods for image segmentation suitable for the construction of geometric models of cardiovascular structures from medical images, appropriate for biomechanical studies.

Detection, localization, diagnostic, staging and monitoring treatment responses are the most important aspects and crucial procedures in diagnostic medicine and clinical oncology (Suri et al. 2005). In the last decades, there were significant advances in medical imaging and computer-aided medical image analysis. Both recent multidimensional medical imaging modalities and computing power have opened new insights in medical research and clinical diagnosis.

In the majority of the developed countries, cardiovascular diseases such as heart attack and cerebral infarction are the most common death causes. Cardiac imaging is an established approach to diagnose cardiovascular disease and plays an important role in its interventional treatment (Bankman 2000; Suri et al. 2005). While cardiac imaging capabilities are developing rapidly, the images are mostly analyzed qualitatively. The ability to quantitatively analyze the acquired image data is still not satisfactorily available in routine clinical care (Himeno 2003; Quarteroni et al. 2000; Taylor et al. 1996). A large part of the acquired data is not totally used because of the tedious and time-consuming characteristics of manual analysis (Mitchell et al. 2002).

Thanks to the new technologies of medical imaging data acquisition, such as computed tomography (CT), angiography, magnetic resonance imaging (MRI) and ultrasound (Doppler), it has become possible the construction of three dimensional models of blood vessels. However, these models still need manual interventions to attain high-quality models (Unal et al. 2008; Guerrero et al. 2007).

Image processing techniques can improve and enhance the information contained in the original images. Additionally, image analysis techniques, such as image segmentation, have a crucial role in extracting high-level information from the processed images. Regarding image segmentation, it plays an essential part in the extraction of useful information and attributes from medical images. Hence, it is a key task for understanding, analyses and interpretation of the image represented structures.

Non-invasive ultrasound imaging of human arteries is a widely used form of medical diagnosis of arterial diseases, like atherosclerosis (a disease of blood vessels caused by the formation of plaques inside the arteries). The diagnosis of atherosclerosis is one of the most important medical examinations for the prevention of cardiovascular events, like myocardial infarction and stroke. Since the carotid is a superficial artery, it is suited for medical ultrasound. B-mode images are user dependent and have poor quality due to some degrading factors such as: speckle, echo shadows, attenuation, low contrast and movement artifacts. However, this technique has lower cost and smaller risks to the patient, when compared to the other alternatives already mentioned. Due to the variability of the carotid shape and the possible existence of extensive occlusions, most of the known model-based segmentation techniques are inadequate (Rocha et al. 2010). This was one motivation for the search of segmentation algorithms.

The main goal of segmentation is to divide the original image into homogeneous regions (or classes) according to one or more characteristics (Ma et al. 2010; Withey et al. 2007). Each of the

regions can be separately processed for information extraction. The most obvious application of this technique in medical imaging is anatomical localization, or in generic terms, region of interest delineation, whose main aim is to outline anatomic structures and regions of interest (Suri et al. 2005).
There are a large number of segmentation techniques that have been proposed, but there is still no gold standard approach that satisfies all of the segmentation criteria. In general, image segmentation techniques can be divided into three main classes: Thresholding-based, Clustering and Deformable Models (Withey & Koles 2007; Ma et al. 2010). These techniques are commonly employed in two-dimensional image segmentation. A review of each of these techniques will be presented in this paper as well as the discussions on their advantages and disadvantages when applied on Doppler images.

2 SEGMENTATION ALGORITHMS

2.1 *Algorithms based on Thresholding*

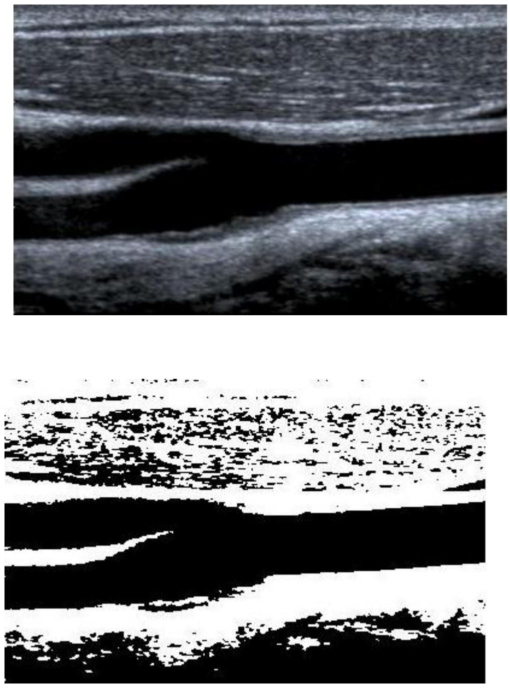
Thresholding is a common segmentation technique because of its simplicity in implementation and intuitive properties. In this technique, predefined values (thresholds) are selected, and an image is divided into groups of pixels having values within the ranges defined by the thresholds and groups of pixels with values beyond such range.

There are several threshold algorithms. The most intuitive approach is the global thresholding, which is best suited for bimodal image. When only one threshold value is selected for the entire image, based on the image histogram, the thresholding is called global. If the threshold depends on local image properties, for example, the local average gray value, the thresholding is called local. If the thresholds are selected independently for each pixel or groups of pixels, then the thresholding is called dynamic or adaptive.

Global thresholding is based on the assumption that the image has a bimodal histogram; therefore, the structure can be extracted from the background by a simple operation that compares image values with a threshold value T. Suppose an image $f(x,y)$ with the histogram with two groups of intensities separated by T. The thresholded image $g(x,y)$ is defined as:

$$g(x,y) = \begin{cases} 1 & if \;\; f(x,y) \geq T \\ 0 & if \;\; f(x,y) \leq T \end{cases}. \qquad (1)$$

As such, the result of thresholding is a binary image, where pixels with intensity value of 1 (one) correspond to structures, while pixels with value 0 (zero) correspond to the scene background. Otsu's method (Otsu 1979) obtains the threshold values automatically by choosing the ones that can minimize the intra-class variance, based on the image histogram, Figure 1.



(a)

(b)

Figure 1. Image of carotid bifurcation obtained by Doppler (a) and the result of Otsu's method on such image (b).

Global thresholding is simple and computationally fast. It performs well if the intensity contrast between the structures and the background is high. However, it may fail when two or more structures have overlapping intensity levels and it may not lead by itself fully automatic. The accuracy of the resulting structures is also not guaranteed as they are separated from the image based on a single threshold value. Threshold selection becomes more difficult with the increasing number of regions or noise, or when the contrast of the image is low.

When the image background is not constant and the contrast of structures varies on the image, global thresholding may not work well in some areas. If the background variations can be described by a known function of position in the image, one could attempt to correct it by using gray level correction techniques, after which a single threshold should work for the entire image. Another solution is to apply local thresholding that can be determined by:

1. Splitting the input image into sub-images and calculating thresholds for each sub-image; or
2. Examining the image intensities in the neighborhood of each pixel.

In the first method, an image is divided into rectangular overlapping sub-images and the histograms are calculated for each of them. The sub-images used should be large enough to include both structures and background pixels. If the sub-image has a bimodal histogram, the local threshold should be the minimum between the histogram peaks. If the histogram is unimodal, then the threshold should be calculated by interpolation from the local thresholds found for nearby sub-images. In the end, a second interpolation is used to find the correct thresholds at each pixel. In the second method, the threshold is selected using the mean value of the local intensity distribution.

Local thresholding is computationally more expensive than global thresholding. It is very useful for segmenting structures from a varying background, and for extraction of regions that are very small and sparse.

According to the information used to define the threshold values, algorithms can be further classified as edge-based, region-based and hybrid ones.

2.1.1 *Edge-Base Segmentation*

An edge can be briefly described as a collection of connected pixels that lie on the boundary between two homogeneous regions having different intensities; i.e., edges can be defined as abrupt changes in pixel intensity that can be reflected by the gradient information. A gradient is an approximation of the first-order derivative of the image function. For a given image $f(x, y)$, it is possible to calculate the magnitude of the gradient as:

$$|G| = \sqrt{{G_x}^2 + {G_y}^2} = \sqrt{[\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2]}, \qquad (2)$$

and the direction of the gradient as:

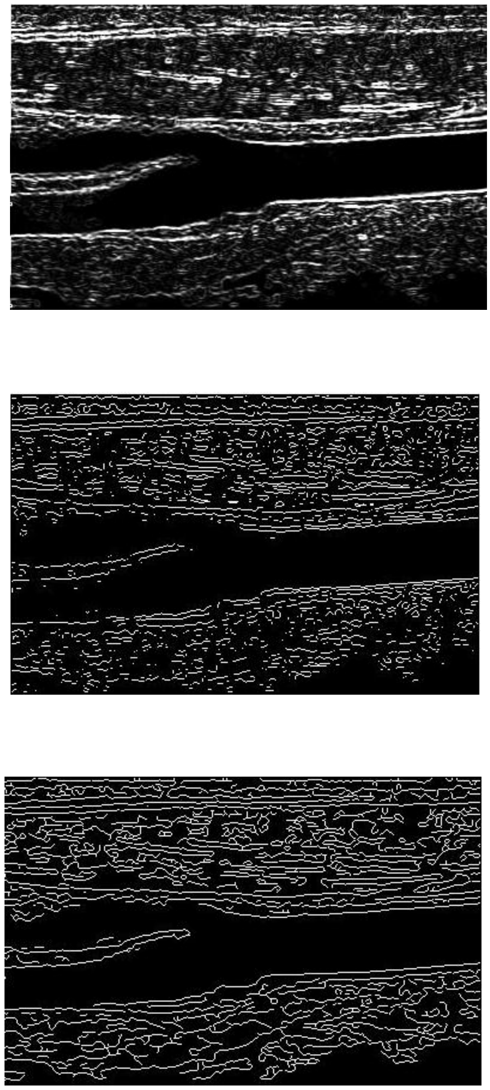
$$D = \tan^{-1}\left(\frac{G_y}{G_x}\right), \qquad (3)$$

where G_x and G_y are gradients in directions x and y, respectively.

Some know algorithms of this class are gradient operators, like Sobel, Laplacian and Canny operators (Ma et al. 2010). Laplacian edge detector uses the second derivation information of the image intensity, and both Canny and Sobel edge detectors use the gradient magnitude to find the potential edge pixels and suppresses them through non-maximal suppression and hysteresis thresholding.

Edge-based techniques are computationally fast and do not require a *priori* information about the image contents. A usual problem of these techniques is that often the edges do not enclose the structures completely. To avoid this problem, a post-processing step of linking or grouping the detected edges that correspond to the structures' boundaries is needed. However, in general, edge linking is computationally expensive and not very reliable.

Results of Sobel, Canny and Laplacian edges detectors can be seen in Figure 2.



(a)

(b)

(c)

Figure 2. Results of Sobel (a), Canny (b) and Laplacian (c) edges detectors applied on the image of Figure 1a.

2.2 *Region based Segmentation*

Region-based segmentation approaches examine pixels in an image and build disjoint regions by merging neighborhood pixels with homogeneous properties based on a predefined similarity criterion.

The simplest region-based segmentation technique is called *region growing*, and it is used to extract a connected region of similar pixels from an image. This technique starts with a pixel or group of pixels called *seed(s),* which belongs to the structure of interest. Seeds can be chosen by the operator or determined by an automatic seed finding algorithm. Then, the neighboring pixels of each seed are inspected and the ones with properties similar enough to the seed are added to the region that the seed belongs to, and thus, the region is growing and its shape is also changing. The procedure continues until no more pixels can be added. It is possible that some image pixels may remain unlabeled when the growing process stops.

The results of region growing depend strongly on the selection of the homogeneity criterion. If it is not properly chosen, the regions leak out into adjoining areas and merge with regions that do not belong to the structure of interest. Another problem of region growing is that different starting points, i.e. seeds, may not grow into identical regions.

The advantage of region growing is that it enables the correct segmentation of regions that have the similar properties and are spatially separated, and also the building of connected regions.

The resultant segmentation of an image of carotid bifurcation by using a region growing algorithm can be seen in Figure 3.

Figure 3. Result of a region growing algorithm on the image of carotid bifurcation shown in Figure 1a.

2.2.1 *Hybrid Algorithms*

Hybrid segmentation algorithms combine different image properties to achieve the segmentation. Watershed is a region based technique that uses image morphology (Bankman 2000), and it has been a powerful tool for image segmentation. The basic concept of watershed is that a grey-level image may be seen as a topographic relief, where the grey level of a pixel is interpreted as its altitude in the relief. A drop of water falling on a topographic relief flows along a path to finally reach a local minimum. Intuitively, the watershed of a relief corresponds to the limits of the adjacent catchment basins of the drops of water.

The common watershed algorithm needs at least one marker ("seed" point) interior to each structure of the image, including the background as a separate structure. The operator is responsible by the manual selection of the markers or it can also be selected by an automatic seed finding algorithm. The neighboring pixels of each seed are inspected and the ones with properties similar enough to the seed are added to the corresponding region where the seed is, and therefore, the region is growing and its shape is also changing. The growing process is repeated until no pixel can be added to any region.

Due to the combination of diverse image clues, watershed algorithms can achieve satisfied results and always produce a complete segmentation of an image. However, watershed algorithms tend to present over-segmentation problems, especially when the images are noisy or the desired structures have low signal-to-noise ratio appearances.

2.3 *Clustering Algorithms*

Clustering is the process of grouping similar image structures into a single cluster, while structures with dissimilar features are grouped into different clusters based on some similarity criteria. The similarity is quantified in terms of an appropriate distance measure.

Clustering techniques can be divided into two main classes: supervised and unsupervised.

Supervised clustering techniques need a training set to be efficient. They need predefined images with the structures of interest already segmented. With this training, there is an adaptation and these predefined images will be a prototype image. Afterwards, the prototype is overlapped to the image to be segmented. These techniques include k-nearest neighbor (kNN) (Vrooman et al. 2006), maximum likelihood (ML) algorithms (Sarti et al. 2005), supervised artificial neural networks (ANN) (James 1985), support vector machines (SVM) (Cortes et al. 1995), active shape models (ASM) (Cootes et al. 1992) and active appearance models (AAM) (Cootes et al. 1992).

Unsupervised classification techniques are also called clustering algorithms and, with these techniques, the structure features are extracted from the classified points. The system finds by himself the different structures to be segmented. Unsupervised classification includes fuzzy C-means algorithms (FCM) (Jacobs et al. 2000), iterative self-organizing data analysis technique algorithms (ISODATA) (Ball et al. 1967) and unsupervised neural networks (Bankman 2000).

2.4 *Algorithms based on Deformable models*

Deformable models are segmentation techniques that are able to represent the complex shape and broad shape variability of anatomical structures. Deformable models overcome many of the limitations of traditional low-level image techniques, by providing compact and analytical representations of structures, by incorporating anatomical knowledge and by providing interactive capabilities.

Deformable models can be parametrically or geometrically defined, according to the way used to track the moving contours.

2.4.1 *Parametrical Deformable Models*

Parametric deformable models, or active contours, try to adjust a deformable model to an image by using an energy minimizing formulation. The snakes are the most well-known method in this category. The user starts the snake near the border of the structure of interest and it is driven to an appropriate result. However, the snake can get stuck in a place of local minimal solutions caused, for example, by noise or a wrong starting solution (Bankman 2000). After incorporating the deformable curve to an energy function, the optimization of the energy functional segmentation process is needed, led by an energy minimization of the contour, which makes the deformable curve evolve gradually from the initial contour to the desired limit of the structure. The energy function contains two parts: internal energy E_{int} and external energy E_{ext}.

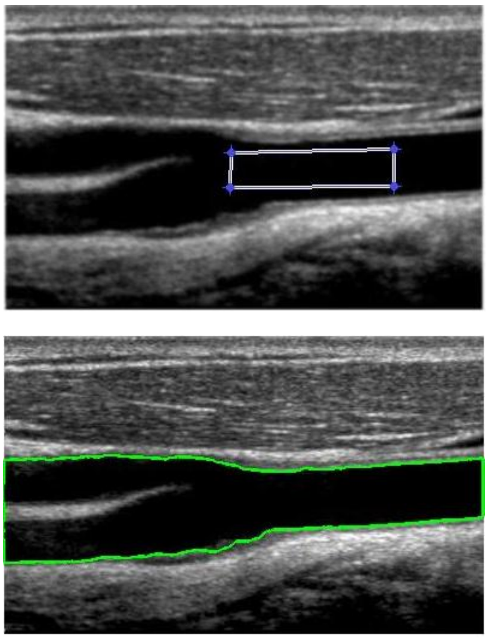
Generally, the internal energy E_{int} only imposes restrictions on the smoothness of the curve, such as the behaviour of the elasticity and curvature, while the external energy E_{ext} is responsible for "pulling" the curve of the Snake in the direction of the boundaries of the structure to be segmented (Xu et al. 1999). These two energies are usually added to form an energy functional, which can be minimized by deforming the contour in an optimization process:

$$E_{Snake}=\sum_{i=1}^{N}[E_{int}(i)+E_{ext}(i)], \qquad (4)$$

$$E_{int}(i)=\alpha i\|v_i - v_{i-1}\|^2+\beta i\|v_{i-1} - 2v_i + v_{i+1}\|^2, \qquad (5)$$

where α_i and β_i specify the stiffness and the flexibility of the snake, and N is the number of points.

A segmentation example obtained using a snake algorithm can be seen in Figure 4.



(a)

(b)

Figure 4. Initial contour used (a) with Yessi's algorithm (Snake) applied on an image of a carotid bifurcation (b).

2.4.2 *Geometrical Deformable Models*

Geometric deformable models are based on the level set method, which was proposed to handle topological changes during the curve evolution. The main idea of the level set method is to implicitly embed the moving contour into a higher-dimensional level set function and view the contour as its zero level set (Osher et al. 1988). Then, instead of tracking the discrete contour points, one can track the zero level set of the level set function. The proficiency of adaptation to changes in the topology can be useful in many applications. A segmentation example can be seen in Figure 5, where the Chan-Vese's model was used to segment the carotid bifurcation in a Doppler image.

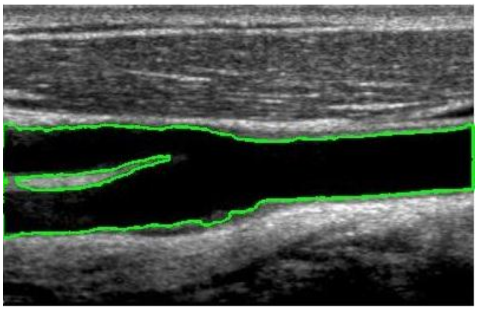


Figure 5. Result of the Chan-Vese's model on the image of a carotid bifurcation, with an initial contour similar to the one shown in Figure 4(a).

CONCLUSIONS

Most segmentation algorithms combine several techniques of image processing to improve their performances. For this reason, there is no universal classification on segmentation algorithm. In this paper, segmentation algorithms were classified into three categories, and their main characteristics were reviewed. Deformable models, namely the snakes and the level set methods, are the more complete ones, and the ones that provided better segmentation results in the Doppler images used.

Computerized segmentation methods have demonstrated their useful applications in medical image analysis and used for better understanding, diagnosis and treatment of disorders.

Research in this area remains active, while pursuing segmentation algorithms that are more robust to noise and initialization problems, as well as other factors that may prevent a successful segmentation.

Future research on the segmentation of medical images will be targeted to improve the accuracy, precision and computational speed of segmentation methods, as well as reduce the amount of the manual interaction required.

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