Image Segmentation Algorithms on Female Pelvic Ultrasound Images

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ABSTRACT: The processing and analysis of structures presented in images has been one of the areas of Computational Vision with greater potential and applicability. The main goal of the researchers of this area has been the development of new computational methodologies to study the behaviour of structures in images. The mentioned image-based analysis is very important in many domains. For example, in Medicine, the information obtained by the proposed automatic analysis is crucial to understand the functioning and the behaviour of organs, and thus to assist medical doctors. A faithful simulation of organs is extremely important to improve the accuracy of medical virtual systems, as of the human body and of computational surgical simulators and robotic surgery. In this work, several algorithms of image segmentation are evaluated on ultrasound images acquired from female pelvic cavity.

1 INTRODUCTION

The pelvic floor constitutes the caudal border of the human's visceral cavity. It is characterized by a very complex morphology, mainly because different functional systems join in this region (Goldman & Vasavada 2007). A clear understanding of the pelvic anatomy is crucial for the diagnosis of female pelvic diseases, for female pelvic surgery as well as for fundamental mechanisms of urogenital dysfunction and treatment. Once knowing the more frequent pathologies, the analysis will be possible if an element does not match the "standard ones".

Pelvic floor disorders are highly prevalent diseases that affect women of different ages. Urinary incontinence is the most well-known of these dysfunctions. Stress urinary incontinence (SUI) affects 6 to 33% of the female population and, although not life-threatening, can severely compromise quality of life as well as impose a financial burden on the health care system (Rahmanian et al. 2008). Modern imaging techniques have been used in the diagnosis of pelvic floor disorders, as well as in determining the extent of pelvic diseases or the staging of pelvic tumors.

Diagnostic imaging is an invaluable tool in medicine. Magnetic resonance imaging (MRI), computed tomography (CT), Ultrasonography, digital mammography, and other imaging modalities provide effective means for noninvasively mapping the anatomy of a subject. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and are a critical component in diagnosis and treatment planning, allowing the medical research and the society to evolve.

In Computational Vision, segmentation refers to the process of partitioning a digital image into multiple sets of pixels, with respect to some characteristics such as intensity or texture. The goal of segmentation is to simplify and/or change the representation of an image into a form that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects or structures (i.e. lines, curves, regions, etc.) in images.

The continuous growing size and number of medical images have triggered an increased need to use computers to ease processing and analysis. In particular, computational algorithms for the delineation of anatomical structures and other regions of interest are becoming increasingly important. In medical imaging, the segmentation process is the separation between anatomical regions or the classification between pathological and non-pathological sets of locations (Suri et al. 2005). These image segmentation algorithms play an essential role in numerous biomedical-imaging applications, such as the quantification of tissue volumes, identification of pathologies, assisting medical diagnosis, treatment planning and computer-integrated surgery.

In this paper, a review on image segmentation algorithms is presented. Hence, the algorithms are classified based on their principal features into three types: 1) threshold-based, 2) clustering-based and 3) deformable models-based (Bankman 2000; Ma et al. 2010). Additionally, the common features of each class are emphasized, discussed and summarized, including their advantages and disadvantages, and their employment on ultrasound images from the female pelvic cavity.

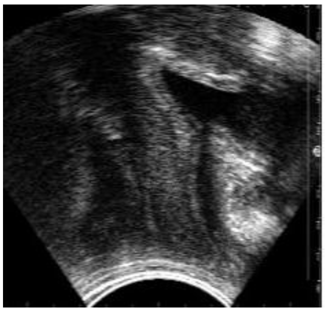
2 SEGMENTATION ALGORITHMS

2.1 *Threshold Algorithms*

Global thresholding is simple and computationally fast. It is based on the assumption that the image has a bimodal histogram and, consequently, the structure of interest can be extracted from the background by a simple operation that compares image values with a threshold value T. Let suppose that there is an image $f\,(x, y)$ with a histogram containing two groups with different intensities, separated by T. The threshold image $\mathrm{g(x, y)}$ is defined as:

$$\mathrm{g(x, y)} = \begin{cases} 1\ if\ (x, y) > \mathrm{T} \\ 0\ if\ (x, y)\ \leq \mathrm{T} \end{cases}. \quad (1)$$

As a result, a binary image is obtained, with white pixels representing the structure and black pixels corresponding to the scene background (Figure 1).



a)

b)

c)

Figure 1. Pelvic ultrasound image a); Result after applying a threshold value of 0.32 b); Result after applying a threshold value of 0.17 c).

There are many ways to select the value used in the global threshold process. However, frequently, a suitable value cannot be found from the histogram, or a single threshold value cannot give good segmentation results over an entire image. For example, when the intensity distribution of the background is not homogeneous and its contrast with the structures varies across the image, a case that often happens on medical images. In those cases, threshold may work well in some parts of the image, but not in other areas. A solution is to apply local thresholding, which can be determined by splitting an image into sub-images and calculating global thresholds for each one of those sub-images. Another approach to determine the local threshold values is by examining the image intensities of the neighboring pixels and selecting a threshold as the mean value of the local intensity distribution (or other statistics, such as mean plus standard deviation, mean of the maximum and minimum values or others based on local intensity gradient magnitude) (Bankman 2000).

Based on the information used to define the local threshold values, the segmentation algorithms can be classified as: region-based, edge-based or hybrid.

2.1.1 *Region-based Algorithms*

The idea of region-based algorithms comes from the observation that quantifiable features inside a structure tend to be homogeneous. For example, a simple approach can be to choose a pixel, or group of pixels (called seeds) and merge their neighbor pixels whose intensities are within the threshold values until all the intensities of the surrounded pixels are outside the pre-defined ranges (Bankman 2000). If two adjacent pixels are similar, merge them into a single region. If two neighboring regions are collectively alike enough, merge them, likewise. This collective similarity is usually based on the comparisons between the statistics of the regions.

The selection of similarity criteria depends not only on the problem under consideration, but also on the type of image data available, for example, if the image is in grayscale or color (Gonzalez et al. 2003). Eventually, this method will converge when no further merging are possible (Suri et al. 2005).

The advantage of region growing-based approaches is the ability to correctly segmenting regions that have the equivalent properties and are spatially separated, generating connected regions (Bankman 2000). On the other hand, the primary disadvantage is that manual interaction to obtain the seed point is usually required. Thus, for each region that needs to be extracted, a seed must be defined, and different initial seeds can generate dissimilar segmentations on the same image (Suri et al. 2005).

An application of this type of approach to segment magnetic resonance images from the pelvic cavity can be seen in (Pasquier et al. 2007).

2.1.2 *Edge-based Algorithms*

An edge (or contour) is the border between two regions with distinct properties in an image. Its detection is made by determining the points where the pixel intensity abruptly varies, since sudden changes in images usually reflect important events on the scene (like the transition between object/background or changes on material properties). As such, an edge is defined by the local pixel intensity gradient, which is an approximation of the first-order derivative of the image function. For a given image $f\,(x, y)$, the magnitude of the gradient can be obtained as:

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

and the direction of the gradient as:

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

where Gx and Gy denote the gradient in the directions x and y, respectively. Some of the most well-known algorithms of this type include the Sobel, Laplacian (Davis 1975) and Canny's edge detectors (Canny 1986), Figure 2.

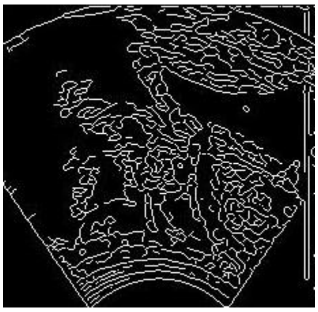
An advantage of these methods is the fact that they are computationally fast and do not require priori information about the image. On the other hand, edge detection methods are very sensitive to noise and usually cannot correctly segment the entire image, causing discontinuous lines (Bankman 2000). For this reason, other image processing techniques are needed after the edges detection (Ma et al. 2010).

2.1.3 *Hybrid Algorithms*

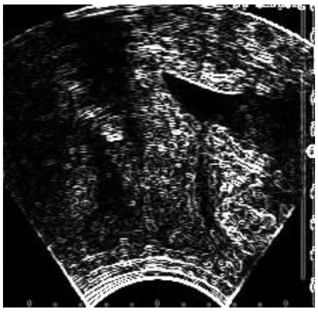
Hybrid segmentation algorithms combine different image clues to perform the segmentation. Typical examples are the watershed algorithms (Beucher & Lantuéjoul 1979),(Vincent & Soille 2001; Hamarneh & Li 2009), which combine edge-based with region-based approaches. There are several watershed algorithms, but they all use the same basic concept: A grey-level image is "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.

In image processing, different watershed lines may be computed. In graphs, some may be defined on the nodes, on the edges, or hybrid lines on both nodes and edges (Körbes & Lotufo 2010).

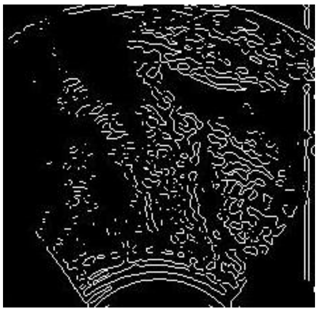
These algorithms can present very good results, since they combine different information of the original image. However, the result of the watershed transform is degraded by the background noise and often produces over-segmentations. (Ma et al. 2010).



a)



b)



c)

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

2.2 *Algorithms based on Clustering techniques*

As structures in medical images can be treated as patterns, techniques from pattern recognition fields can be used to perform the segmentation. Two main types of these techniques are: supervised classification algorithms and unsupervised classification algorithms. These can be supervised if samples of each area to be classified are provided, so that the system "knows" *a priori* what the regions are, or unsupervised, if we allow the system to try to find which are the different kind of areas by itself (Suri et al. 2005).

Examples of supervised classification techniques include k-nearest neighbour (kNN) classifiers (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). A training set is needed to extract structure information and its definition is different among distinct algorithms.

Unsupervised clustering techniques include the *fuzzy K-means* (FKM) (Jacobs et al. 2000), the ISODATA (Ball et al. 1967) and the *unsupervised neural networks* (Bankman 2000).

Algorithms based on clustering techniques can be applied to segment the *levator ani* muscles (Ma et al. 2010).

2.3 *Algorithms based on deformable Models*

Image segmentation (2D, 3D or 4D) based on deformable models has been considered one of the main successes in Computational Vision, over the last decades, mainly on the medical imaging field (Silva et al. 2004).

Compared with the two classes previously described, the ones based on deformable models are more flexible and can be used for more complex segmentations (Ma et al. 2010). These algorithms treat the structure boundary as the final status of the initial chosen contours.

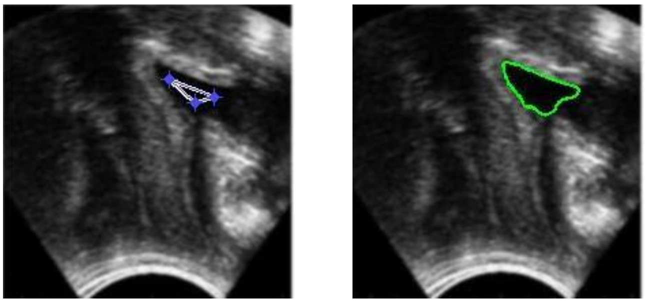
Deformable models are geometrically or parametrically defined curves or surfaces that move under the influence of forces, which have two components: internal and external forces (Suri et al. 2005). Hence, these algorithms can be viewed as the deformation of an initial contour as a curve evolution that moves towards the boundaries of the structures (Silva et al. 2004).

The mathematical fundaments of this type of models can be found, for example, in (Bankman 2000) and (Xu et al. 1999).

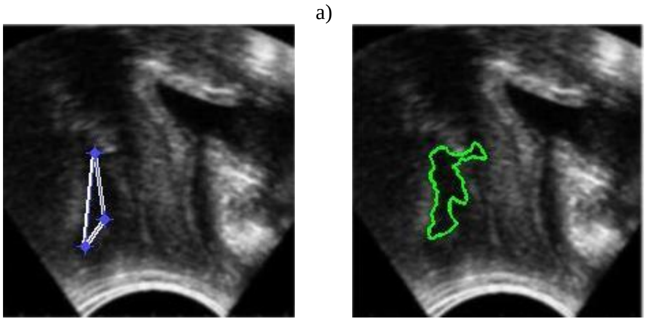
2.3.1 *Parametrical Deformable Models*

Parametric deformable models, or active contours (being the most well-known the snake model), are a special case of a more general formulation that tries to adjust a deformable model to a contour in an image by using an energy minimizing formulation. Typically, the user initializes the snake near the wanted contour, and then it is driven towards an appropriate result (Silva et al. 2004).

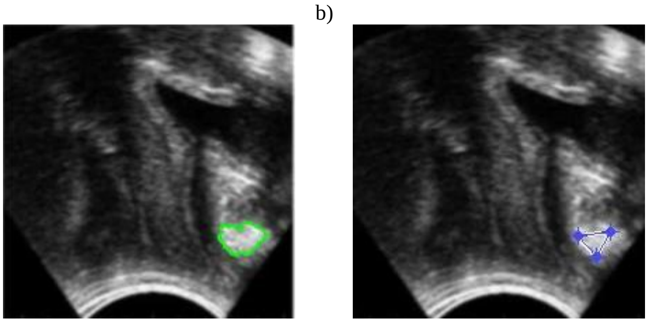
The original mathematical formulation of the snakes can be found in (Kass et al. 1988). The segmentation process is defined as the evolution of the modeled curves that flow under the influence of internal forces, which keeps the model smooth during the deformation, and external forces that force the moving contours towards the borders.



a)



b)



c)

Figure 3. Snakes results: initial contour and the segmented bladder a); Initial contour and the segmented anal-rectal junction b); Initial contour and the segmented symphysis pubis c).

A snake can be defined parametrically as $v(i) = [x(i), y(i)]$, where $x(i)$ and $y(i)$ are the coordinates x, y along the contour. The energy function to minimize can be described as (Suri et al. 2005):

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

where E_{int} and E_{ext} represent the internal and the external energies, and N is the total number of points of the snake.

The internal energy can be defined as:

$$E_{int}(i) = \propto_i \|v_i - v_{i-1}\|^2 + \beta_i \|v_{i-1} - 2v_i + v_{i+1}\|^2, \tag{5}$$

where α_i and β_i specify the stiffness and the flexibility of the snake. These models are called “active” due to its dynamic (Kass et al. 1988), allowing not only the detection of boundaries but also the tracking of its movement, which can be extremely helpful to study the pelvic cavity (Rahmanian et al. 2008). A disadvantage of this method is its weak application to structures with great bends. There are several snake algorithms, like the one proposed in (Jr. et al. 1999). An example of its application to pelvic cavity ultrasound images can be seen in Figure 3.

2.3.2 *Geometrical Deformable Models*

Geometric deformable models provide a solution to address the primary limitations of parametric deformable models. These models are based on the level set method (Osher & Sethian 1988) that was initially 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. Then, instead of tracking the discrete contour points, one can track the zero level set of the level set function (Ma et al. 2010). Examples can be found, for example, in (Malladi et al. 1993; Chan & Vese 2001).

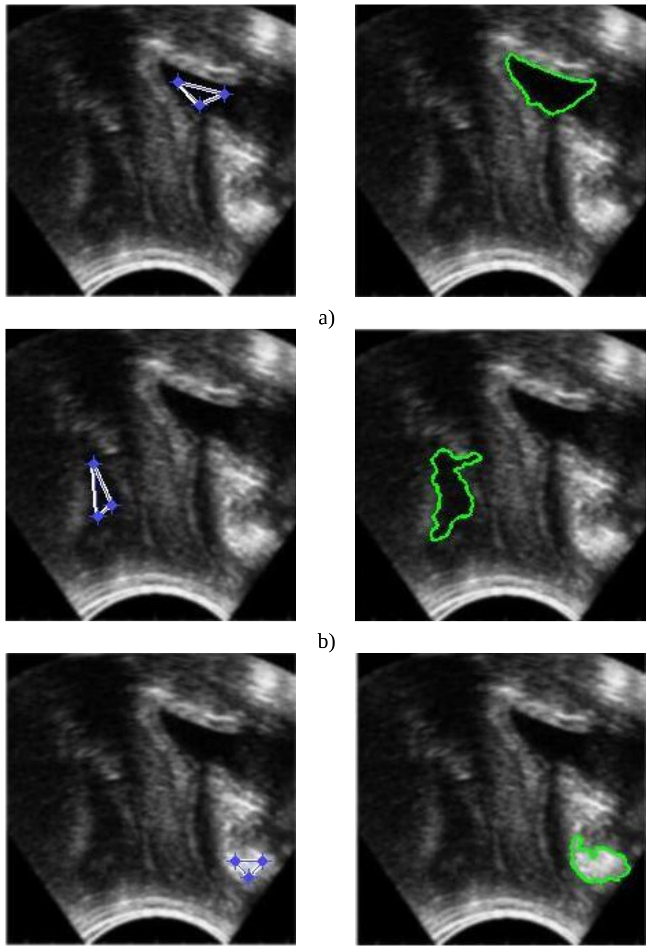
The proficiency of adaptation to changes in the topology can be useful in many applications. However, sometimes it can lead to undesirable results, producing segmentations not consistent with the structure to be segmented. The level set methods have been commonly applied on medical images (Jayadevappa et al. 2009), (Schmid & Magnenat-Thalmann 2008),(Ma et al. 2011). An example can be seen in Figure 4, where the Chan-Vese's model was used to segment several organs in ultrasound images from the pelvic cavity.

3 CONCLUSIONS

The growing significance of medical imaging to diagnose and treat health problems or diseases has brought along a set of challenges to accurately segment anatomical structures from medical images. Segmentation on medical images is affected by many factors, like the size of the data involved, the complexity and variability of the structures to segment, and others, inherent to limitations from the information used.

There are a great number of image segmentation algorithms, and many of them have some kind of application to the medical field. However, the deformable models, namely the snakes and the level set methods, are the more complete ones, and the ones that usually provide best segmentation results.

The study in this area continues, looking for algorithms that are more robust to the influence of noise and initialization conditions, and can offer an entirely automatic segmentation, without manual intervention, particularly designed for the structures of the pelvic cavity in ultrasound images.



a)

b)

c)

Figure 4. Results of the Chan-Vese's model: Initial contour and the segmented bladder a); Initial contour and the segmented anal-rectal junction b); Initial contour and the segmented *symphysis* pubis c).

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