A REVIEW ON THE CURRENT SEGMENTATION ALGORITHMS FOR MEDICAL IMAGES

Zhen Ma, João Manuel R. S. Tavares, R. M. Natal Jorge

Faculty of Engineering, University of Porto, Porto, Portugal

zhen.ma@fe.up.pt, tavares@fe.up.pt, rnatal@fe.up.pt

Abstract: This paper makes a review on the current segmentation algorithms used for medical images. Algorithms are divided into three categories according to their main ideas: the ones based on threshold, the ones based on pattern recognition techniques and the ones based on deformable models. The main tendency of each category with their principle ideas, application field, advantages and disadvantages are discussed. For each considered type some typical algorithms are described. Algorithms of the third category are mainly focused because of the intensive investigation on deformable models in the recent years. Possible applications of these algorithms on segmenting organs and tissues contained in the pelvic cavity are also discussed through several preliminary experiments.

1   INTRODUCTION

The developments of imaging techniques such as Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) offer doctors with high resolution images which have greatly assisted the clinical diagnosis. Meanwhile medical technicians have to process a large number of images with much more details; Segmentation is usually a necessary step for the task. However, manual segmentation is very time-consuming and the results may not be reproducible or suffer from intra-observer and inter-observer variability. Compared with the algorithms for common image processing, the ones used for medical images require more concrete application background. A priori knowledge like the imaging procedure or the biomechanical behaviours of organs or structures can be crucial for a successful segmentation. Also, medical images are usually influenced by noises and partial volume effect (Zaidi, 2005), algorithms should be sophisticated enough to handle the segmentation task. In the past few decades, many effective algorithms have been proposed to perform the computer-aided segmentation. The successful implementations of modern mathematical and physical techniques have considerably enhanced the accuracy of the segmentation. In the following sections, these algorithms are classified into three categories: algorithms based on threshold, algorithms based on pattern recognition techniques and algorithms based on deformable models. We focus on the main ideas of each category and summarize their trend and possible applications. In the end, the features of each type are illustrated with an example of their possible applications to segment the pelvic cavity. We also point out that since most of the algorithms incorporate multiple techniques, the classification of an algorithm may not be definite.

The paper is organized as follows: In the next section, we make a review of the algorithms; In Section 3, we summarize the advantages and disadvantages of each category and discuss their possible applications to the pelvic cavity; In Section 4, we give the conclusion.

2   ALGORITHMS REVIEW

2.1 Algorithms Based on Threshold

Most of the algorithms that belong to this category make the premise that the interested structures can be discerned by quantifiable features, like image intensity or gradient magnitude. Segmentation is a procedure of searching for pixels that satisfy the rules defined by the thresholds. Thresholds in these algorithms can be selected manually according to a priori knowledge or automatically through image information. Algorithms can be further divided to edge-based ones, region-based ones and hybrid ones.

Thresholds in the edge-based algorithms are related with the edge information. Structures are depicted by edge points. Common edge detection algorithms such as Canny edge detector (Canny, 1986) and Laplacian edge detector can be classified to this type. Algorithms try to find edge pixels while eliminate the noise influence. For example, Canny edge detector uses the threshold of gradient magnitude to find the potential edge pixels and suppresses them through the procedures of the non-maximal suppression and hysteresis thresholding. As the operations of algorithms are based on pixels, the detected edges are consisted of discrete pixels and therefore may be incomplete or discontinuous. Hence, it is necessary to apply post-processing like morphological operation to connect the breaks or eliminate the holes.

The ideas of region-based algorithms come from the observation that pixels inside a structure tend to have similar intensities. Region growing algorithm (Adams and Bischof, 1994) is a typical algorithm of this type. After selecting initial seeds, algorithms begin to search for the neighboured pixels whose intensities are inside the intervals defined by the thresholds and then merge them to expand the regions. To eliminate the dependence on initial seeds and make the algorithm automatically, statistical information and a priori knowledge can be incorporated to the algorithms. For example, a homogeneity criterion was introduced in (Pohle and Toennies, 2001) which made the region growing algorithms adaptive for the different locations of initial seeds and achieved success in the segmentation of CT and MR images. However, as the algorithms mainly rely on the image intensity information, they are hard to handle the partial volume effects and control the leakage.

Information used in the hybrid algorithms combine different image cues to complete the segmentation. Typical examples are the watershed algorithms (Beucher and Lantuéjoul, 1979) which combine the image intensity with the gradient information. In the watershed algorithms, gray scale images are considered as reliefs and the gradient magnitude of each pixel is treated as elevation. Watershed lines are defined to be the pixels with local maximum of gradient magnitude. The segmentation procedure is to construct watersheds during the successive flooding of the gray value relief. Due to the combination of image information, watershed algorithms can achieve better results, but these algorithms tend to over-segmentation especially when the images are noisy or the objects themselves have low signal-to-noise ratio. Hybrid threshold-based algorithms can further combine with other techniques to perform the segmentation (Ng, et al, 2006).

Due to the noise influence and partial volume effect, the edges of organs or structures in medical images are usually not clearly defined and therefore algorithms based on threshold are seldom used alone.

2.2 Algorithms Based on Pattern Recognition Techniques

As structures in medical images can be treated as patterns, techniques from pattern recognition fields can be used to perform the segmentation. Classification algorithms are the most popular ones for the medical image segmentation. In the following, we mainly review the supervised classification algorithms and the unsupervised ones.

Popular techniques used by the supervised algorithms include supervised artificial neural network (Alirezaie, et al, 1997), support vector machine (Wang, et al 2001) and active appearance models (Cootes, et al, 2001). A training set is needed to get the classifiers. Supervised artificial neural networks (ANNs) and support vector machines (SVMs) are non-linear statistical data modeling tools and can be used to model complex relationships between inputs and outputs. Weights in the classifier are selected through optimizing energy functionals defined by the features of structures and are updated through processing each sample in the training set. The extracted information from the training set provides important cues of the structures such as intensity, position and shape, which can be valuable complementary information for the segmentation of test images. Active appearance models (AAM) are statistical models of the shape of structures. Training samples are used to extract the mean shape, mean appearance and define ranges of shape parameters. Restrictions on shape parameters guarantee the similarity between the segmentation result and the training samples. The segmentation procedure is to find the better positions of the shape points according to the appearance information. Algorithms based on classifiers have been widely applied to segment organs in medical images like cardiac and brain images. If properly modelled, supervised

classification algorithms can greatly enhance the segmentation accuracy. However, supervised classification algorithms are sensitive to the initial conditions. To guarantee the correctness of the results, the training set must contain enough samples and the samples should be representative and segmented accurately.

Frequently used unsupervised classification algorithms include Fuzzy C-means algorithm (Mohamed, et al, 1998), Iterative Self-organizing Data Analysis Technique Algorithm (Wong, et al, 2002) and unsupervised neural network (Cheng, et al, 1996). Unsupervised classification algorithms are also called clustering algorithms. No training set is needed. Instead, the structure features are extracted from the classified points. FCM algorithm comes from C-means (CM) or K-means algorithms, where C or K is the pre-defined number of clusters. FCM algorithm is an iterative algorithm with the objective to minimize the intra-cluster variation. The labelled pixels are assigned to the nearest clusters basing on their weighted distances to the cluster centroids, then the cluster centroid is updated and the pixels are re-assigned. The algorithm ends when all the pixels have fixed labels. FCM algorithm is commonly used for nuclear medicine and transmission image segmentation (Mohamed, et al, 1998). Iterative Self-organizing Data Analysis Technique Algorithm (ISODATA) is similar to the FCM algorithm. The main difference is ISODATA algorithm allows for different number of clusters while the FCM assumes that the number of clusters is known as a priori. In medical imaging for example the positron emission tomography (PET) scans, clustering algorithms can be used to segment different types of tissues and blood (Wong, et al, 2002). Unsupervised neural networks are based on unsupervised learning, which means the targets are the same as the inputs. The training of weights used in classifiers is based on the learning rule. For example the Hopfields neural network adopts the learning rule as winner-takes-all to simplify the selection of weights. A successful application of Hopfields neural network to segment the MR brain images can be seen in (Cheng, et al, 1996). Template matching algorithms and atlas-guided algorithms which combine the prior knowledge to assist the segmentation are also frequently used for medical image segmentation (Gindi, et al, 1993; Akselrod-Ballin, et al, 2006).

2.3 Algorithms Based on Deformable Models

Compared with the algorithms of the above two categories, the ones based on deformable models are more flexible and can be used for complex segmentations. According to the representation way of the contour, deformable models can be classified to parametric models and geometric models. A moving equation should be defined to drive the initial contours to the structure boundaries. Therefore, the procedure of these algorithms can be viewed as a modelling of curve evolution.

The parametric deformable models have tight relationship with the snake method (Kass, et al, 1987). Contours are sampled as discrete points and are tracked according to their respective moving equations. The explicit tracking has the advantage of high computational efficiency therefore allows for real-time applications. The moving equation for the parametric deformable models can be derived through either energy functional or dynamic forces. The definition of energy functional contains two parts: internal energy and external energy. The internal energy aims to keep the smoothness and regularity of the contour and is usually defined through the geometric properties of the contour such as length, area and curvature; the external energy aims to drive the contour to the right position and the definition is based on image information. Using calculus of variations, we can derive an Euler-Lagrange equation of the energy functional which states that the balancing equilibrium of the moving contour under the external forces and the internal forces is the position of structure boundary. Through adding the time variable to the Euler-Lagrange equation, we then get the dynamic moving equation. A priori knowledge can be easily incorporated to the procedures of parametric models. Snake method is the first deformable model applied to the medical image segmentation. The traditional snake method relies on the gradient information, therefore is sensitive to the initial position of the contour. The contour must be placed to the positions near to the structure boundary so that the external forces are strong enough to attract the contour. Otherwise the contours may shrink or stop at wrong positions. The later proposed algorithms (Cohen, 1991; McInerney and Terzopoulos, 1995; Xu and Prince, 1998) tried to eliminate the dependence on the initial conditions and noise influence. Cohen (Cohen, 1991) added a balloon force to the external forces to make the contour inflation or deflation even if the gradient field is weak. Xu and Prince (Xu and Prince, 1998) replaced the gradient field with the gradient vector field (GVF) which achieves the same capture effect near the structure boundary while changes slowly in other regions.

The geometric deformable models are based on the level set method (Osher and Sethian, 1988) which was initially proposed to handle the 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 contour points, we can track the zero level set of the level set function. The advantage of doing so is that topological changes can be naturally handled and the geometric properties of the contour such as normal vector and curvature can be calculated implicitly. Consequently, the computational complexity is decreased. Like the parametric deformable models, speed functions should be properly defined. Malladi, et al. (Malladi, et al, 1993) and Caselles, et al. (Caselles, et al, 1997) first applied the level set methods to medical images. Malladi's model used the gradient information as a stop criterion. The definition of the speed is intuitive: when the contour moves to the structure boundary, the increase of gradient magnitude decreases the speed value therefore slows down the contour. However, this speed model suffered from leakage due to its mere dependence on the gradient magnitude.

Unlike Malladi's model, geodesic active contour algorithm (Caselles, et. al, 1997) treated the segmentation as an optimization problem of finding the minimal distance curve. The moving equation of GAC is also derived through energy functional. While instead of solving directly the moving equation, the contour is embedded in a level set function and the moving equation then becomes a level set equation. Geodesic active contour algorithm showed a tight relationship between the parametric model and the geometric model. The introduction of level set representation in GAC makes the algorithm flexible to handle the topological changes. GAC and the later improved GAC algorithms are applied to process the MR, CT and ultrasound images like the tumour detection and cardiac segmentation (Paragios, 2002). Another popular geometric model Chan-Vese's model is based on a simplified version of Mumford-Shah energy model (Chan and Vese, 1999). The most appreciable advantage of Chan-Vese's algorithm is that it can obtain a boundary of discrete points, which is quite useful for medical image applications when the interested structures are represented by discrete pixel clusters and have no clear definition of boundaries.

3 DISCUSSION

When the interested structures have distinctive quantifiable features, using threshold-based algorithms is effective. Threshold-based algorithms do not need complex operations and are computationally efficient. However, due to their dependence on thresholds, these algorithms are sensitive to noise, hard to combine with spatial information and difficult to be applied to multi-channel images. As medical images are usually noisy and suffer from intensity inhomogeneity, the segmentation results of threshold-based algorithms are usually far from satisfaction. As a result, these algorithms are seldom used alone. Instead they are often used as an efficient pre-segmentation step.

Compared with threshold-based algorithms, the ones based on pattern recognition techniques can better utilize structure information therefore can achieve satisfied results. When the structures in medical images are regular and not much influenced by noises, applying pattern recognition techniques is effective. However, like the threshold-based models, pattern recognition models are also sensitive to noise. The results of these algorithms may depend on their initialization step. For the classifier-based algorithms, the segmentation results depend on the size of the training samples and the correctness of the manual segmentations. For the clustering algorithms, the number of clusters, the position of the initial points and the parameters should be properly selected. The lack of incorporating spatial characteristics is also an obstacle. Due to the large shape variations in medical images, the applications of these algorithms are constrained.

Due to the advantages of being able to handle structures with complex topology, easy to incorporate with other techniques, sub-pixel accuracy, noise insensitive and intuitive interaction mechanisms, the deformable models are intensively investigated in the last few decades. Parametric deformable models have high computational efficiency and are easy to incorporate with other techniques; Geometric deformable models have the advantage of naturally handling the topological changes. For the medical image segmentation, using parametric model or geometric model depends on the applications. In general, when structures have large shape variety or complicated topology, geometric deformable models are preferred; when the interested structures have open boundaries or the structures are thin or the algorithms need real-time operations, parametric models are preferred. However, deformable models usually contain certain number of parameters. To select proper parameters is critical to the final segmentation results while this is usually a time-consuming task.

CT images and MR images are widely used modalities to study the organs in the pelvic cavity. Figure 1 and Figure 3 illustrate these two imaging modalities. The segmentation task includes sketching bladder, urethra, vagina, rectum and pelvic floor. The complex anatomical structures and the inter-connectivity between organs make the

segmentation difficult to perform. We mention that we do not intend to propose new algorithms here but use this example to make a preliminary discussion of possible applications of the three categories of algorithms.

Figure 1 illustrates the segmentation result of region grow algorithm; due to the high resolution and signal-to-noise ratio, bladder and vagina can be segmented successfully. While the boundary of the right obturator internus is leaked due to the influence of partial volume effect. Figure 2 illustrates the segmentation result of geodesic active contour algorithm. The boundaries of the obturator internus are correctly segmented and the boundary of vagina is not leaked in the upward direction. This is due to the restriction of smoothness of the moving contours. The structure boundaries are more regular than the ones in Figure 1. While also due to this restriction, small details of structure boundaries are eliminated so that the boundaries of bladder and levator ani are not complete. For the two segmentations, both boundaries of levator ani are not satisfied. An example of manual segmentation of levator ani is illustrated in Figure 3. In fact, the segmentation of levator ani muscles needs prior shape information therefore a correct segmentation depends on information beyond the presented images. This feature is the advantage of the algorithms based on pattern recognition techniques. For the CT images which contain large amount of noises and low spatial resolution of soft tissues, the priori shape information is more important. The result of applying watershed algorithm to images in Figure 3 is illustrated in Figure 4, from which we can see the noise influence, the discontinuity and the difficulties in this application. A possible way to design a new algorithm can be incorporating the comparative distances of different organs and use prior shape information to constrain the result.

4 CONCLUSION

As pointed out in Section 1, most of the algorithms combine multiple segmentation techniques and use diverse image cues to improve the segmentation results. Therefore, a definite classification of an algorithm may be infeasible. In this paper, we classify the current algorithms into three categories and summarize their features. From the discussions we can see that each category has its suitable application fields. For a concrete medical image segmentation task, researchers should combine the application background and practical requirements to design proper algorithms. Accuracy, complexity, efficiency and interactivity of a

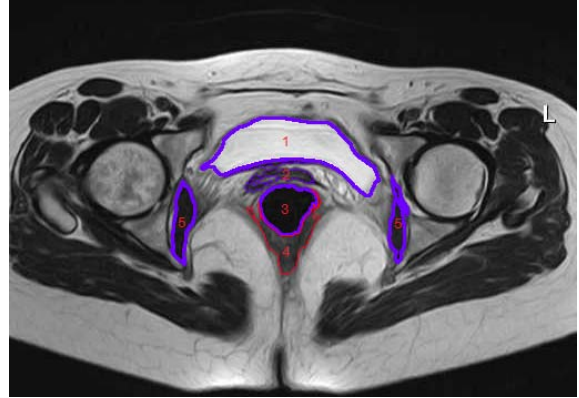segmentation algorithm should all be the considered factors.

Figure 1: Segmentation results of MR image using region growing algorithm: 1-bladder, 2-vagina, 3-rectum, 4-levator ani, 5-obturator internus.
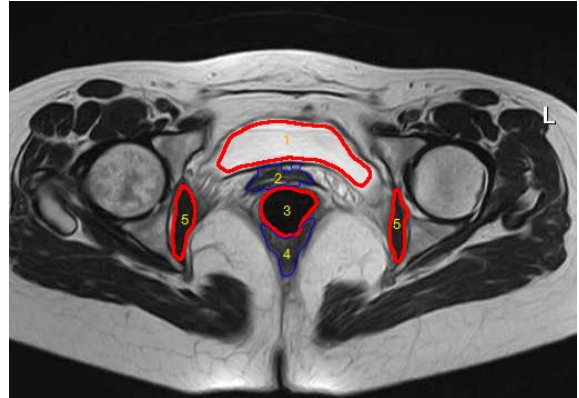

Figure 2: Segmentation results of MR image using geodesic active contour algorithm: 1-bladder, 2-vagina, 3-rectum, 4-levator ani, 5-obturator internus.
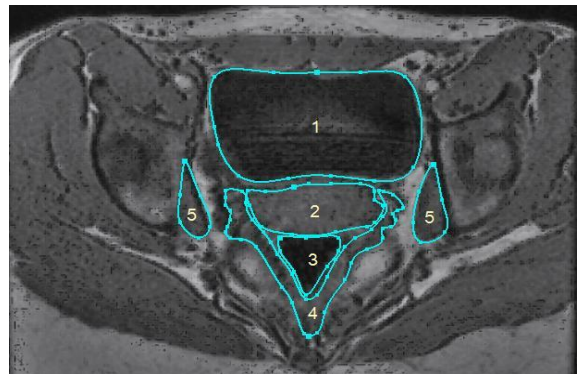

Figure 3: Manual segmentation results of CT image: 1-bladder, 2-vagina, 3-rectum, 4-levator ani, 5-obturator internus.
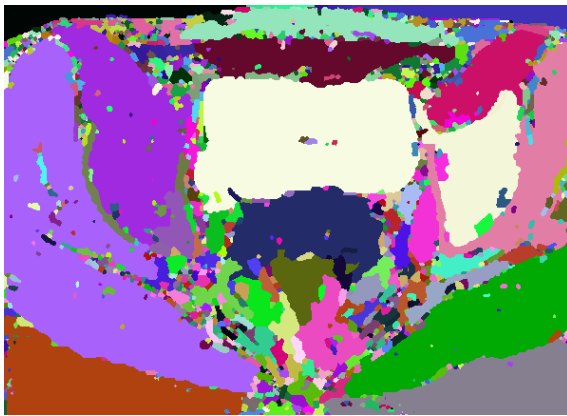
Figure 4: Segmentation results of CT image using watershed algorithm.

ACKNOWLEDGEMENTS

REFERENCES

Adams, R., Bischof L., 1994. Seeded Region Growing. *IEEE Trans. on Pattern Anal Mach. Intelligence*, 16:641-47.

Akselrod-Ballin, A, Galun, M, et al, 2006. Atlas Guided Identification of Brain Structures by Combining 3D Segmentation and SVM Classification. *Int. Conf Med Image Comput Comput Assist Interv.*, 209-16.

Alirezaie, J., Jernigan, M. E., Nahmias, C., 1997. Neural Network-Based Segmentation of Magnetic Resonance Images of the Brain, *IEEE Trans. on Nuclear Science*, 44:194-8.

Bezdek, J. C., Hall, L. O., Clarke, L. P., 1993. Review of MR Image Segmentation Techniques Using Pattern Recognition, *Med. Phys.*, 20:1033-48.

Canny, J., 1986. A Computational Approach to Edge Detection. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 8:679-714.

Caselles, V., Kimmel, R., Sapiro, G., 1997. Geodesic Active Contours. *Int. J. of Comp. Vision*, 22:61-79.

Chan, T., Vese, L. A., 1999. An Active Contour Without Edge. *Int. Conf. Scale-Space Theories in Computer Vision*, 141-151.

Cheng, K. S., Lin, J. S., Mao, C. W., 1996. The Application of Competitive Hopfield Neural Network to Medical Image Segmentation. *IEEE Trans. on Med. Img.*, 15:560-7.

Cohen, L. D., 1991. On Active Contour Models and Balloons. *CVGIP: Image Understanding*, 53:211-8.

Cootes, T. F., Edwards, G. J., Taylor, C. J., 2001. Active Appearance Models. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 23: 681-85.

Davis, L. S., 1975. A Survey of Edge Detection Techniques. *Comp. Graphics and Image Processing*, 4:248-70.

Flitti, F., Collet, C., Joannic-Chardin, A., 2005. Unsupervised Multiband Image Segmentation Using Hidden Markov Quadtree and Copulas. *IEEE Int. Conf. on Image Processing*, 2:634-37.

Gindi, G., Rangarajan, A., Zubal, G., 1993. Atlas-Guided Segmentation of Brain Images via Optimizing Neural Networks. *Proc. SPIE Biomedical Image Processing IV*, 1905-58.

Kass, M., Witkin, A., Terzopoulos, D., 1987. Snakes: Active contour models. *Int. J. of Comp. Vision*, 1:321-31.

Malladi, R., Sethian, J. A., Vemuri, B., 1993. A Topology Independent Shape Modeling Scheme. *SPIE Conf. on Geometric Methods in Computer Vision II*, 2031:246-58.

McInerney, T., Terzopoulos, D., 1995. A Dynamic Finite Element Surface Model for Segmentation and Tracking in Multidimensional Medical Images with Application to Cardiac 4D Image Analysis. *Computerized Medical Imaging and Graphics*, 19:69-83.

Mohamed, N. A., Ahmed, M. N., Farag A., 1998. Modified Fuzzy C-mean in Medical Image Segmentation. *Proceedings of the 20th Annual International Conference of the IEEE*, 3:1377-80.

Ng, H. P., Ong, S. H., et al, 2006. Medical Image Segmentation Using K-Means Clustering and Improved Watershed Algorithm. *IEEE Southeast Symposium on Image Analysis and Interpretation*, 61-5.

Osher, S., Sethian, J., 1988. Fronts Propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations. *J. Comp. Phys.*, 79: 12-49.

Paragios, N., 2002. A Variational Approach for the Segmentation of the Left Ventricle in Cardiac Image Analysis, *International Journal of Computer Vision*, 50:345-62.

Pohle, R., Toennies, K. D., 2001. Segmentation of Medical Images Using Adaptive Region Growing, *SPIE*, 1337-46.

Wang, S., Zhu, W. Y., Liang, Z. P., 2001. Shape Deformation: SVM Regression and Application to Medical Image Segmentation, *Eighth International Conference on Computer Vision*, 2:209-16.

Wong, K. P., Feng, D., et al, 2002. Segmentation of Dynamic PET Images Using Cluster Analysis. *IEEE Trans. on Nuclear Science*, 40:200-07.

Xu, C. Y., Prince, J. L., 1998. Snakes, Shapes, and Gradient Vector Flow. *IEEE Trans. on Image Processing*, 7:359-69.

Zaidi, H., 2005. *Quantitative Analysis in Nuclear Medicine Imaging*, Springer.