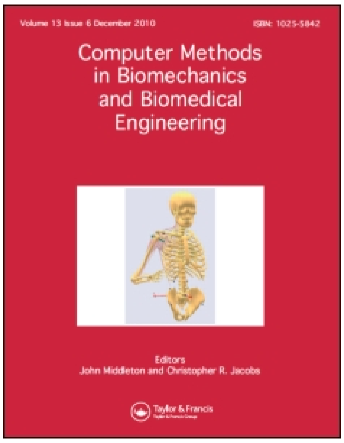


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# A review of algorithms for medical image segmentation and their applications to the female pelvic cavity

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# A review of algorithms for medical image segmentation and their applications to the female pelvic cavity

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This paper aims to make a review on the current segmentation algorithms used for medical images. Algorithms are classified according to their principal methodologies, namely the ones based on thresholds, the ones based on clustering techniques and the ones based on deformable models. The last type is focused on due to the intensive investigations into the deformable models that have been done in the last few decades. Typical algorithms of each type are discussed and the main ideas, application fields, advantages and disadvantages of each type are summarised. Experiments that apply these algorithms to segment the organs and tissues of the female pelvic cavity are presented to further illustrate their distinct characteristics. In the end, the main guidelines that should be considered for designing the segmentation algorithms of the pelvic cavity are proposed.

**Keywords:** bioengineering; biomedical engineering; medical imaging; algorithms review; thresholding techniques; clustering techniques; deformable models; female pelvic cavity



## 1. Introduction

High resolution images produced by modern imaging modalities offer medical doctors multi-orientation views and many more details, considerably assisting clinical diagnosis and the treatment that follows. The first step of processing these images is to segment the desired organs or structures from the image series. Usually, to perform the manual segmentation medical technicians need to sketch the contours slice by slice using pointing devices such as a mouse or a trackball. This procedure is very time-consuming and the results may suffer from intra- or inter-observer variability. In the past few decades, many algorithms have been proposed to perform computer-aided segmentation. The incorporations of modern mathematical and physical techniques have greatly enhanced the accuracy of the segmentation results.

Compared with the algorithms for common images, the ones for medical applications need more concrete background. Information used for medical image processing comes not only from image appearances but also from imaging devices and doctors' professional knowledge. *A priori* knowledge such as the imaging environment or structures' biomechanical behaviour can be crucial information for designing an effective algorithm, especially when the images are influenced by noise or partial volume effects (PVEs; Zaidi 2005). Also, the appearances of the same organs or structures may vary in different slices and imaging modalities and therefore, may need distinctive segmentation algorithms. For example, high-density structures such as bones and calcified plaque have high Hounsfield unit (HU) values in CT images and can be easily segmented, while they have much lower appreciable features in MR images so the segmentation algorithm may not be trivial.

In the following sections, segmentation algorithms are classified into three main types based on their principal techniques, specifically the ones based on threshold, the ones based on clustering techniques and the ones based on deformable models. The main ideas, application fields, advantages and disadvantages of each type are discussed and summarised. Each type is described using their typical algorithms and illustrated by the experimental results after these algorithms have been applied to the pelvic cavity. As it is common that multiple segmentation techniques are used in one algorithm, definite classifications of certain algorithms may not be feasible. The general principle of classification in this paper is the most appreciable characteristics of an algorithm.

The motivation for focusing on the segmentation of the pelvic cavity originates from the recognition of the high prevalence of pelvic floor (PF) disorders. PF disorders include a group of conditions that affect adult women including pelvic organ prolapse, urinary incontinence, faecal incontinence, and other sensory and emptying abnormalities of the lower urinary and gastrointestinal tracts. The fact that women will be living longer and are more often attending to PF disorders makes its study urgent, particularly due to its high complexity and societal

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impact. It is estimated that 30–50% of women in Europe and the USA are affected by urinary incontinence (Buchsbaum et al. 2005). Over 20% of French suffer from obstructed defecation (Siproudhis et al. 2006). About 15% of population of New Zealand and 2.2–6.9% of population of the USA suffer from faecal incontinence (Drossman et al. 1993; Nelson et al. 1995; Macmillan et al. 2004). The importance of developing a method to visualise, measure and model the dynamic responses of the pelvic structures has been more and more recognised. A real understanding of the pathophysiology of PF disorders is still lacking.

CT and MR images are widely used modalities for the study of the pelvic cavity. MR images are preferred in the static study of the pelvic cavity because CT images usually contain a large amount of noise and have low spatial resolution of soft tissues. A successful segmentation of 2D image slices can greatly facilitate the later reconstruction of a 3D pelvic cavity model which can help doctors understand its mechanism and establish a more objective basis for the diagnoses and evaluation of clinical treatments. The complex anatomical structures and the inter-connectivity between organs make the segmentation difficult to perform. Consequently, there is no effective algorithm for this task. The segmentation of pelvic cavity includes sketching bladder, urethra, vagina, rectum, obturator internus and levator ani. In this paper, we do not intend to propose a new algorithm but use this example to illustrate the different characteristics of algorithms and make a discussion on their possible applications to this area. Furthermore, the main guidelines that an effective algorithm should adopt for a successful segmentation of the pelvic cavity are indicated.

The paper is organised as follows: In Section 2, a review on the segmentation algorithms is made and their characteristics are illustrated through experiments on the pelvic cavity; In Section 3, the advantages and disadvantages of each type are summarised. In Section 4, some conclusions are summarised and the guidelines of the segmentation algorithms for the pelvic cavity are presented.

## 2. Algorithms review

In this section, we present a review based on the principal features of the algorithms, classifying them into three types as referred in Section 1. Due to the fact that backgrounds and requirements for each task are different, a survey on a concrete application is beyond the scope of this paper. Instead, we extract the common features of each type, discuss and summarise their advantages and disadvantages using typical algorithms. Applications of each type to the pelvic cavity are illustrated to further state their characteristics.

### *2.1 Algorithms based on thresholds*

Traditionally algorithms of this type make the promise that the interested structures or organs have distinctive quantifiable features such as image intensity or gradient magnitude. The procedure of segmentation is to search for the pixels whose values are within the ranges defined by the thresholds. Thresholds used in these algorithms can be selected manually or automatically. Manual selection needs *a priori* knowledge and sometimes trial experiments to find the proper threshold values while the latter way combines the image information to get the adaptive threshold values automatically. For example, Otsu's method (Otsu 1979) obtains the threshold values using an image histogram. According to the information used to define the threshold values, algorithms can be further classified as edge-based ones, region-based ones and hybrid ones.

Threshold values in edge-based algorithms are related to the edge information as structures are depicted by edge points. Wavelet transform (Chui 1993) and common edge detection algorithms such as Canny edge detection (Canny 1986), Sobel edge detection and Laplacian edge detection (Davis 1975) belong to this type.

Algorithms try to find edge pixels and eliminate the noise influence. For example, Laplacian edge detection uses the second derivation information of the image intensity; Canny edge detection uses the gradient magnitude to find the potential edge pixels and suppresses them through non-maximal suppression and hysteresis thresholding. Since the operations of the algorithms are based on pixel intensities, the detected boundaries consist of discrete pixels and therefore may be incomplete or discontinuous. It is then necessary to apply post-processing techniques like morphological operations to connect the breaks or eliminate the holes. Due to noise influence and PVE, the edges of organs or structures in medical images are usually not clearly defined. Therefore, algorithms based on edge-detection are seldom used alone but instead as an efficiency pre-processing step for the later segmentation (Andreao and Boudy 2007; Qin et al. 2007).

The idea of region-based algorithms comes from the observation that quantifiable features inside a structure tend to be homogeneous. Algorithms aim to search for the pixels with similar feature values. Region growing algorithms (Adams and Bischof 1994; Pohle and 2001; Yi and Ra 2001; Pan and Lu 2007) are typical examples of this type.

The searching rules are different among Toennies different algorithms. For example, a simple approach can be to choose the initial seeds and merge their neighbour pixels whose intensities are within the threshold values until all the intensities of the surrounded pixels are outside the pre-defined ranges; the rule of seeded region growing method (Adams and Bischof 1994) is to expand a seed region through merging the unallocated neighbour pixels which have the smallest intensity difference between the pixel and the region; the rule of unseeded region growing algorithms is almost the same as seeded region growing except when the within-class variance is too large or too small regions will split or merge. To eliminate the dependence on initial seeds and make the algorithm automatic, statistical information and *a priori* knowledge can be incorporated into the algorithms (Pohle and Toennies 2001; Dehmeshki et al. 2003). For example, a homogeneity criterion was introduced in Pohle and Toennies (2001) which made the region growing algorithms adaptive for different locations of the initial seeds and achieved success in the segmentation of CT and MR images. However, these algorithms have difficulties controlling the leakage or eliminating the influence of PVE due to their reliance on intensity.

Information used in hybrid algorithms combines different image cues to complete the segmentation. Typical examples are watershed algorithms (Beucher and Lantuéjoul 1979; Vincent and Soille 1991; Grau et al. 2004; Ng et al. 2006; Hamarneh and Li 2009) which combine image intensity with gradient information and use mathematical morphology operations to do the segmentation.

In watershed algorithms, grey scale images are considered as reliefs and the gradient magnitude is treated as elevation. Watershed lines are defined to be the pixels with local maximum gradient magnitudes and a region of the image is defined as the pixels enclosed by the same watershed line. The segmentation procedure is to construct watersheds during the successive flooding of the grey value relief. Due to the combination of diverse image information, watershed algorithms can achieve satisfactory results and always produce a complete segmentation of an image. Nevertheless, watershed algorithms tend to present over-segmentation problems, especially when the images are noisy or the desired objects themselves have low signal-to-noise ratio appearances. Hybrid threshold-based algorithms usually incorporate other techniques to perform the segmentation (Haris et al. 1998; Grau et al. 2004; Hamarneh and Li 2009). For example, in Grau et al. (2004) the marker imposition technique was used to combine *a priori* knowledge and successful experiments have been reported on the segmentation of the knee cartilage and white/grey matter in MR images. In Hamarneh and Li (2009), shape and appearance knowledge are used to improve the performance of watershed algorithm and C-means (CM) algorithm is used to handle the over-segmentation problems.

Figure 1(a) presents an MR axial pelvic cavity image, from which the appreciable influences of PVEs can be easily seen. The segmentation results of Canny edge detection, a region growing algorithm and a watershed algorithm are illustrated in Figure 1(b)–(d). The boundaries obtained by the Canny edge detection algorithm are discontinuous due to the noises and PVE. Besides, the spatial relationships of edge points are not reflected hence most of the detected boundaries are incomplete or connected wrongly. For the region growing algorithm, the boundary of the bladder and the vagina are well segmented, but the boundary of the right obturator internus leaks; the outer boundary of the vagina is discontinuous and leaks in the upward direction. The watershed algorithm gives a complete segmentation of the image. However, the over segmentation can be seen in the area between the bladder and the vagina because there are a lot of pixels with local maximums of gradient magnitude. Moreover, the levator ani and obturator internus are merged because of the influence of PVE at the joint.

### 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. Clustering techniques are the most popular ones for medical image segmentation. In the following part, two main types of these algorithms are reviewed: supervised classification algorithms and unsupervised classification algorithms.

Frequently used supervised classification techniques include k-nearest neighbour (kNN) classifiers, maximum likelihood (ML) algorithms, supervised artificial neural networks (ANN), support vector machines (SVM), active shape models (ASM) and active appearance models (AAM). A training set is needed to extract structure information but its function is different among different algorithms.

The training phase of a kNN classifier is to store feature vectors and class labels of the training samples. K nearest stored points are selected for each unlabelled point according to the point distance. The classification of an unlabelled point is then 'voted on' by the selected points, for example the most frequent class label appearing in the selected points. The training step of ML algorithms is to identify the parameters used in the statistical models. ML algorithms assume that the pixel intensities are independent random variables with parameterised probability distributions, so the probability distribution of this mixture model is given by the multiplication of these parameterised probability functions. Parameters are then evaluated by maximising the likelihood function of the mixture model. As the calculations are based on probability, ML algorithms provide a soft segmentation. Application of kNN and ML algorithms can be found in Sarti et al. (2005) and Vrooman et al. (2006).

Supervised ANNs are non-linear statistical data modelling tools and can be used to model complex relationships between input and output. Weights or parameters in different layers are updated after processing each sample to minimise the cost function defined by the

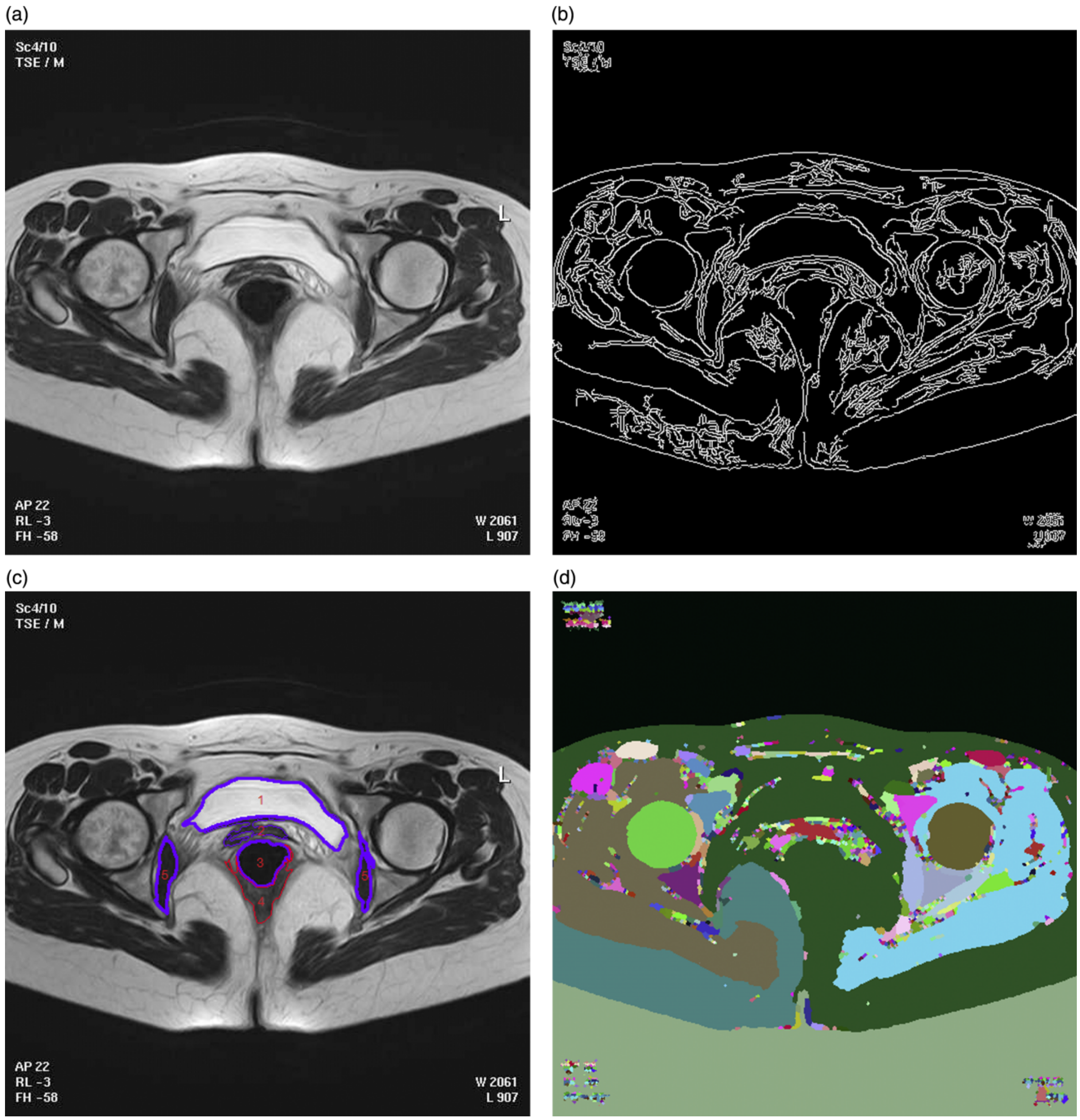


Figure 1. (a) MR image of the pelvic cavity; (b) Canny edge detection; (c) region growing algorithm: 1-bladder; 2-vagina; 3-rectum; 4-levator ani; 5-obturator internus; (d) watershed algorithm.

features of structures. Typical examples of neural networks include feedforward networks and radial basis function networks (Bishop 2006). SVMs are also known as maximum margin classifiers because the algorithms try to find a hyperplane to maximise the margin between two classes. SVMs can simultaneously minimise the empirical classification error and maximise the geometric margin between classes. For ANNs and SVMs, information extracted from the training set provides the features of structure in the form of weights or parameters that can be used for the later segmentation. Common applications of ANNs and SVMs are on the segmentation of cardiac images and brain images inside which the organs and tissues have comparably stable shapes and anatomical structures (Bezdek et al. 1993; Alirezaie et al. 1997; Wang et al. 2001; Benamrane et al. 2006). Further classification and detailed procedures of ANNs and SVMs can be found in James (1985) and Mitchell (1997).

Unsupervised classification techniques include CM algorithms fuzzy C-means (FCM) algorithms iterative self-organising data analysis technique algorithms (ISODATA) and unsupervised neural networks. These algorithms are also called clustering algorithms. Structure features are extracted from the classified points.

CM algorithms are also called K-means algorithms, where C and K are the pre-defined number of clusters. The algorithm tries to minimise the intra-cluster variation through iterations. The unlabelled pixels are assigned to the nearest clusters based on their distances to the cluster centroids, then the cluster centroid is updated and the pixels are re-assigned. The algorithm runs until all the pixels have fixed labels. ISODATA algorithm is similar to the CM algorithm while the number of clusters is determined by the threshold defined in the merging and splitting procedure. Applications of these algorithms are commonly used for nuclear medicine and transmission image segmentation (Jacobs et al. 2000; Biswal et al. 2006; Tai and Song 2007). For medical applications, FCM algorithms that combine CM algorithm with fuzzy theory have more applications. The procedures of FCM algorithm are the same as the ones of CM algorithm except FCM adds weights to the calculation of cluster centroids and point distance. FCM algorithms are fuzzy clustering techniques that can provide soft segmentations in the way that instead of classifying a pixel into a fixed cluster, the algorithm calculates the membership or possibility that it belongs to each cluster. A soft segmentation is preferred as the complex imaging conditions such as shading artefacts or PVEs intrinsically determine the vagueness of the pixels. The performance of FCM algorithms can be improved through adding spatial influence to the objective function (Pham and Prince 1999; Ahmed et al. 2002; Cai et al. 2007; Wang et al. 2008; Zhou et al. 2008) or using kernel techniques that can better transfer non-linear problems to linear problems (Zhang and Chen 2003; Liao et al. 2008). For example, in Ahmed et al. (2002) the objective function is modified by adding an influence term defined by the labels to the neighbourhood pixels. In Liao et al. (2008), the proposed algorithm used a kernel filter to map the data into a higher-dimensional feature space and then apply the FCM algorithm with strategies introduced in Cai et al. (2007) to gain high computational efficiency. FCM algorithms are widely applied to the segmentation of MR images especially for the MR brain images (Clark et al. 1994; Mohamed et al. 1999; Wang et al. 2008).

Unsupervised neural networks are based on unsupervised learning which means the targets are the same as the inputs (Sarle 1994). The weights in the classifiers are trained according to the learning rule. For example, the Hopfields neural network adopts the learning rule as winner-takes-all to decide the weights either to be 0 (zero) or 1 (one). A successful application of Hopfields neural network to CT and MR images can be seen in Cheng et al. (1996) and Lin et al. (1996). Other popular learning rules include Hebbian learning and competitive learning (Bishop 2006). A review of unsupervised neural network learning procedures and their applications can be found in Becker and Plumbley (1996).

There are also algorithms that use other pattern recognition techniques. For example, image registration techniques such as template matching algorithms and atlas-guided algorithms are also frequently seen to be applied for medical image segmentation (Gindi et al. 1993; Ginneken et al. 2002; Akselrod-Ballin et al. 2006). *A priori* knowledge is used in these algorithms to assist the segmentation. For example, in Akselrod-Ballin et al. (2006) prior probability knowledge of anatomic structures is incorporated into an MRI probabilistic atlas to extract the structure features, then an SVM is trained using the extracted information to finally segment the brain structures.

Figure 2 presents the segmentation result of the CM algorithm and its refinement using Markov Random Field techniques (Kindermann and Snell 1980). Four clusters are defined with the initial mean intensities: 25, 80, 150 and 213. With these parameters, CM algorithm can correctly segment the boundary of bladder. Most of the pixels that represent the same organ are clustered into one group. However, the noise influences are also appreciable. The boundaries of vagina and right obturator ani are incomplete and the boundaries of rectum and left obturator ani leaked. The refined result in Figure 2(b) gives a smoother segmentation with less noise influence because spatial constraint is incorporated using MRF techniques. Both segmentation results are very sensitive to the selection of the initial number of groups and their mean intensity values.

Algorithms based on clustering techniques can be applied to segment the levator ani muscles. A successful segmentation of levator ani muscles is critical for the later 3D reconstruction of the pelvic cavity. The muscles should have a presumed anatomy if they are not severely damaged. This characteristic can be easily guaranteed using algorithms based on clustering techniques. A manual segmentation of these muscles is shown in Figure 2(c). However, one should notice that the appearances of levator ani in static images are usually highly textured and have considerable variances in different slices. To identify the correct boundaries professional knowledge such as anatomical structures or information from multi-view images are needed. Modifications should focus on incorporating the spatial relationship between these muscles and other structures.

### 2.3 Algorithms based on deformable models

Compared with the above two types, the ones based on deformable models are more flexible and can be used for complex segmentations. Algorithms treat the structure boundary as the final status of the initial contours. The procedure of these algorithms can be viewed as a modelling of curve evolution. According to the way that is used for tracking the moving contour, deformable models

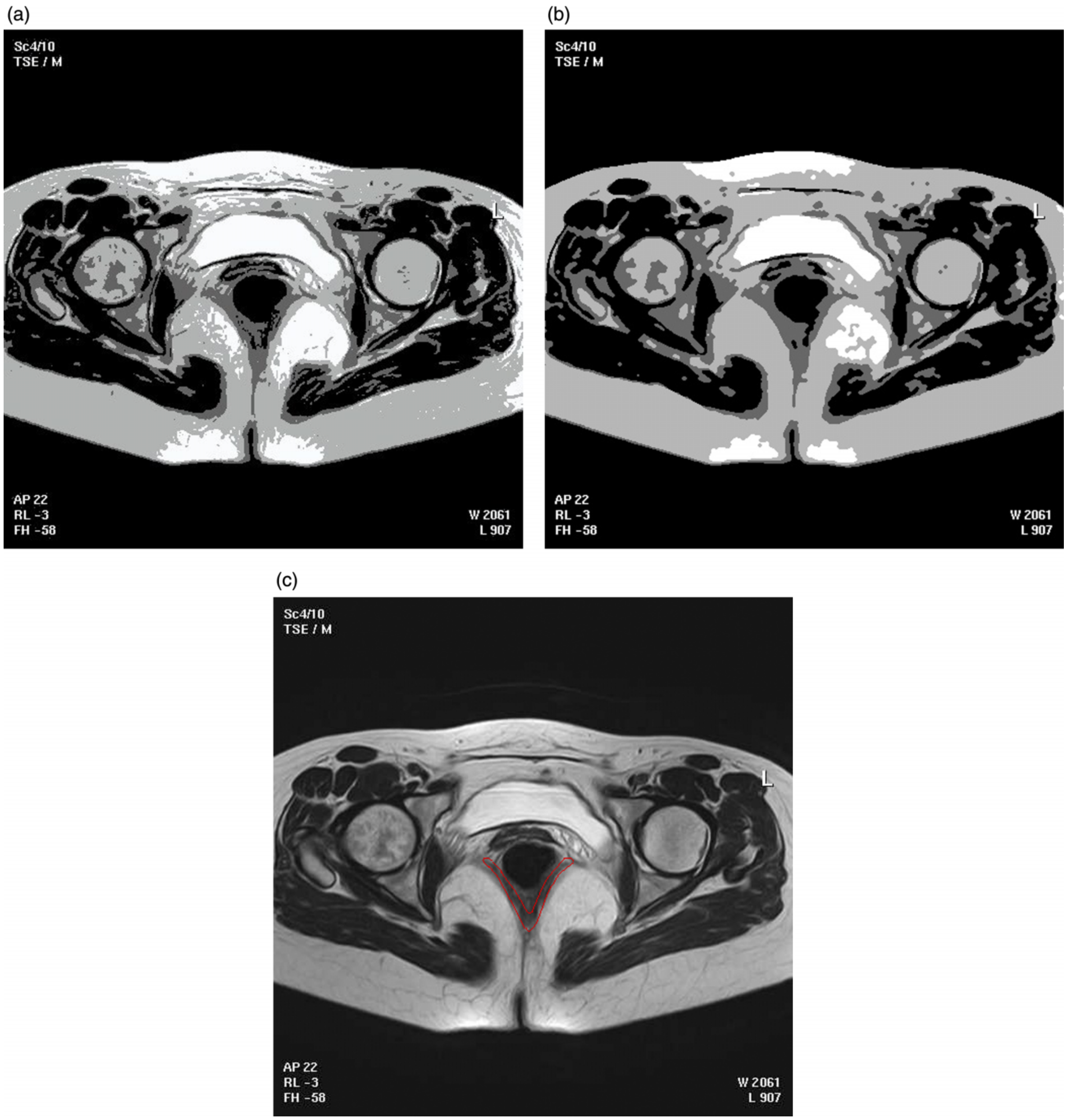


Figure 2. (a) C-means algorithm (number of groups: 4; initial mean values of intensity: 25, 80, 150, 213); (b) Refined by MRF; (c) manual segmentation of levator ani muscles.



can be further classified into parametric models and geometric models.

### 2.3.1 Parametric deformable models

Parametric deformable models track the evolution through sampled contour points. Explicit tracking has the advantage of high computational efficiency and allows for real-time applications. The moving equation for the contour can be derived through energy functions or defined directly through dynamic forces. *A priori* knowledge can be incorporated in the procedure of defining the energy function, the initial conditions or the parameters. A typical energy function includes the internal energy and the external energy. The internal energy aims to keep the regularity of the contour and is usually defined through the geometric properties of the contour such as length, area or curvature; the external energy attracts the contour to the boundary position and is defined by the image information. The definitions of external forces are the main differences between algorithms. Using calculus of variations, the Euler–Lagrange (E–L) equation of the energy functional with the internal forces and external forces can then be derived simultaneously. Since the definition of energy function guarantees that its minimum is achieved when the contours are at the position of structure boundaries, the E–L equation states that the balancing equilibrium of the contour under external forces and internal forces is the right position of the structure boundary. Then the moving equation can be derived through adding a time variable to the E–L equation.

The development of parametric deformable models has a tight relationship with the snake method (Kass et al. 1987) which is the first deformable model applied to the medical image segmentation. The original snake method used the tension and rigidity of the contour as the internal energy and the gradient magnitude as the external energy. However, the snake method is sensitive to the initial conditions. The moving contour may stop at places with local functional minimum or places where the gradient magnitude is too small so that the external force tends to be zero. Also, the explicit tracking has the difficulty of handling topological changes. Consequently, in order to get a correct segmentation the initial contour must have the same topology as the desired object and must be placed near the object boundary so that the external forces are strong enough.

The later proposed algorithms, such as the ones proposed in Cohen (1991), McInerney and Terzopoulos (1995), Xu and Prince (1998), and Gonçalves et al. (2008), aimed to eliminate the dependence on the initial position and the noise influence. For example, in order to prevent the curves from shrinking or stopping on local minima, Cohen (1991) added a balloon force to the external forces to make the contour inflate or deflate when the gradient field is weak. Xu and Prince (1998) analysed the reason why snake methods have poor convergence to boundaries with large curvatures and replaced the gradient field with the gradient vector field (GVF), which has a larger capture region and slowly changes away from the boundaries. Consequently, the dependence on initial positions is decreased but the field can attract the moving contour to the right position. In McInerney and Terzopoulos (1995) except for adding the balloon force, an interactive mechanism was developed that allows user to select control points in order to form a constraining force to influence the curve movement. Numerical comparisons (He et al. 2008) have shown that these improved algorithms considerably decrease the influence of initial conditions and improve the segmentation results.

Parametric deformable models which incorporate statistical techniques are also popular. Typical examples include ASM (Cootes et al. 1994, 1995) and AAM (Cootes et al. 2001). Training samples are used to extract the mean shape and define proper ranges of the parameters. After finding an approximate position of the new examples, ASM uses the edge information to move the shape points to better positions while AAM uses the mean texture of each shape point to find a better position. The searching procedure is like the snake methods but the movements of shape points are constrained by the ranges of shape parameters which guarantee the similarity between the segmentation result and the training samples. This characteristic is very useful when the shape or topology of structures can hardly be identified from their appearances in the images. ASM and AAM have been applied widely in medical image segmentation and registration (Cootes et al. 1994; Ginneken et al. 2002; Beichel et al. 2005; Vasconcelos and Tavares 2008).

Parametric deformable models are widely used in structure segmentation and 3D reconstructions. A system review can be found in McInerney and Terzopoulos (1996). However, the computational complexity such as parameterisation of the contours, handling of topological changes, and re-distribution of the contour points considerably restricts their applications.

### *2.3.2 Geometric deformable models*

Geometric deformable models are based on the level set method (Osher and Sethian 1988) which 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. The advantage of doing so is that the topological changes can be easily handled and the geometric properties of the contour can be implicitly calculated. Therefore, the computational complexity of geometric deformable models is decreased. Like in the parametric deformable models, speed functions should be defined properly to drive the contour to the right position. Malladi et al. (1993), Malladi and Sethian (1996) and Caselles et al. (1997) applied level set methods to medical image segmentation. Malladi's algorithms used the gradient information to define the speed function and add the curvature influence to keep the contour smooth. The function of Malladi's speed model is intuitive: when the contour moves to the structure boundary, the increase of the gradient magnitude decreases the speed value so that the evolution of the contour slows down. Then, the evolution can be stopped after a time to gain the position of the structure boundary. However, Malladi's speed models suffered from the drawback of leakage due to their bare dependence on the gradient information. The stopping criterion should be selected carefully to make sure the contour stops at the right position. If the images are noisy or blurred, the contour may leak or shrink to disappearance after a long evolution (Kichenassamy et al. 1996; Siddiqi et al. 1998; Suri et al. 2002). To handle the leakage, the edge strength item (Kichenassamy et al. 1996) and area forces item (Siddiqi et al. 1998) were incorporated to improve the model.

Unlike Malladi's model, the geodesic active contour (GAC) algorithm modelled the segmentation as an optimisation problem of finding the minimal distance curve in the image. Like in the parametric deformable models, the moving equation of GAC is derived from an energy function; the procedure of finding the optimal solution corresponds to the searching of the structure boundary. The moving equation is then obtained through the E-L equation. Instead of tracking the contour points, the contour is embedded in a level set function and therefore the moving equation becomes a level set equation. The speed function in GAC does not have an intuitive meaning; instead the derivation of the moving equation comes from the energy function. Unlike in Malladi's models, the equilibrium state of the moving contour guarantees that a long computation time will not lead to leakage.

The GAC algorithm shows a tight relationship between the parametric model and the geometric model. The introduction of the level set expression makes the algorithm flexible to handle the topological changes. GAC and the later, improved, GAC algorithms are widely applied to process MR, CT and ultrasound images in order to accomplish tumour detection and cardiac segmentation. For example, in Leventon et al. (2000) *a priori* statistical techniques and shape information were incorporated. The contours are post-processed with the priori shape knowledge by using statistical techniques such as maximising a posterior (MAP) and principle component analysis (PCA). In Paragios (2002), the proposed algorithm combined the gradient vector flow field with the GAC algorithm to eliminate dependence on the initial conditions; intensity distributions in the left ventricle and the distance between the interfaces of endocardium and epicardium are also incorporated. The results are better than the original GAC algorithm.

Another popular geometric model is proposed by Chan and Vese (1999) and Chan and Vese (2002). Chan–Vese's model is a simplified version of the Mumford–Shah energy model. The algorithm extracts the desired object through simultaneously minimising the intensity variations inside and outside the contour. The most appreciable advantage of Chan–Vese's model is that it can obtain a boundary of discrete points, which is quite useful when the objects of interest are represented by discrete pixel clusters and have no clearly defined boundaries.

Most of the moving equations of the later proposed geometric deformable models are derived through the energy function because *a priori* knowledge and other techniques can be easily incorporated to the energy function. Algorithms based on geometric deformable models aim to eliminate noise influence, prevent leakage, enhance accuracy and efficiency, and make the algorithms more automatic and less dependent on the initial conditions. In order to achieve these goals, algorithms incorporate various cues such as image intensity and prior knowledge of structures. More details of geometric deformable models can be found in Niessen et al. (1998) and Suri et al. (2002). A survey of algorithms that combine statistical techniques with level set methods can be found in Cremers et al. (2007).

Figures 3 and 4 illustrate the segmentation results of Malladi's algorithm and the GAC algorithm. Compared with the former segmentation results, the structure boundaries are more regular and less influenced by noise

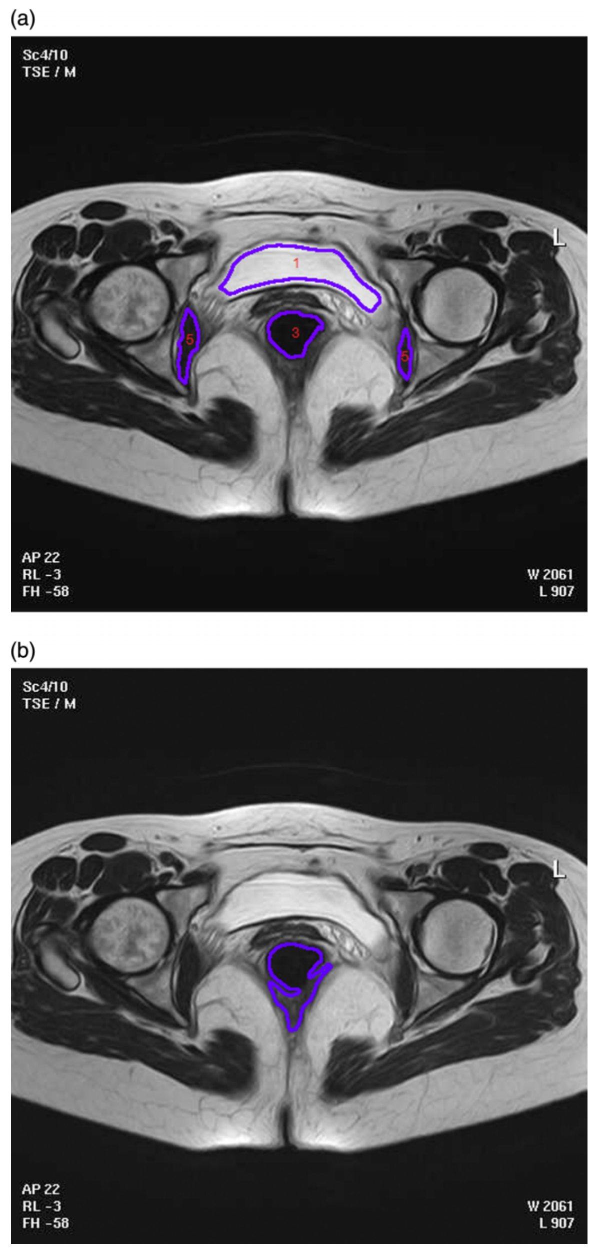


Figure 3. (a) Malladi's algorithm (annotations are the same as in Figure 1(c)); (b) leakage due to over evolution using Malladi's algorithm.

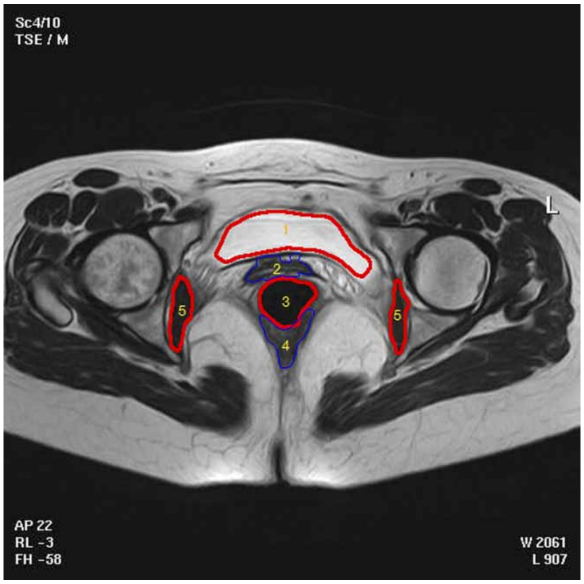


Figure 4. Geodesic active contour algorithm (annotations are the same as in Figure 1(c)).

due to the smoothing items defined in the speed function. Nevertheless, small shape details such as the left bottom part of bladder are also erased. Proper stopping criterion should be defined for Malladi's algorithm, otherwise the moving contours may leak, like the one illustrated in Figure 3(b). In this case, the PVEs decrease the stopping strength at the right bottom boundary of rectum; hence the contour leaked due to long evolution time. In Figure 4, the GAC algorithm provides a good segmentation of the obturator internus, rectum and vagina. The regulating effects of internal forces make the boundary shape more reasonable and less influenced by noise. Also, leakage will not happen after a long evolution time.

Deformable models are promising for the segmentation of the pelvic cavity because these models can easily incorporate statistical information, *a priori* knowledge and other techniques, while using curve evolution to find the optimal boundaries can provide a contour with regular geometric properties. One possible way is to incorporate the comparative distances between organs and use prior shape information to constrain the deformation of the moving contour.

## 3. Discussion

When the interested structures have distinctive quantifiable features, using threshold-based algorithms is effective. Procedures of these algorithms do not include complex operations and therefore, are computationally efficient. However, due to their dependence on threshold values, algorithms are sensitive to noise, and most of them are difficult to apply to multi-channel images. As medical images usually suffer from noise and intensity inhomogeneity, the segmentation results of threshold-based algorithms are far from satisfactory. Consequently, these algorithms are seldom used alone. Instead they are often used through incorporating *a priori* knowledge (Dehmeshki et al. 2003; Pan and Lu 2007) or as an efficient pre-segmentation step (Andreao and Boudy 2007; Qin et al. 2007).

Except for the training step of the supervised classification algorithms, algorithms based on clustering techniques are also computationally efficient. Structure information can be easily used in these algorithms. When the interested structures in medical images are regular and not much influenced by noises, using pattern recognition techniques can sometimes achieve better results (Bezdek et al. 1993; Becker and Plumbley 1996). If properly modelled, supervised classification algorithms can greatly enhance segmentation accuracy, especially when the appearance of structures is blurred or influenced by noise. The lack of incorporating spatial characteristics can be solved through using the MRF model (Held et al. 1997; Flitti et al. 2005). Unsupervised classification algorithms can be applied to cases where there are few available segmentation samples or when the interested structures have large shape variations and have shown promise for medical image segmentation in fields like tumour detection in positron emission tomography (PET) imaging (Zaidi 2005). However, pattern recognition models are also sensitive to noise. Results of these algorithms depend on the initial conditions. For the supervised algorithms, the segmentation results depend on the size of the training sets and the correctness of the segmentations in samples. For the unsupervised algorithms, the number of clusters, the position of initial points and the parameters used in the model should be properly defined. The applications of both supervised algorithms and unsupervised algorithms are constrained because of the large shape variations of organs and structures in medical images.

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, deformable models have been intensively investigated in the last few decades. Parametric deformable models have high computational efficiency and can easily incorporate *a priori* knowledge (McInerney and Terzopoulos 1996). However, these models cannot naturally handle topological changes and are sensitive to initial conditions. Geometric deformable models have the advantage of naturally handling the topological changes and are widely studied for medical segmentation (Niessen et al. 1998). Using a parametric model or geometric model depends on the concrete segmentation task. Topological flexibility is not always a desirable feature under some applications (Han et al. 2003;

Guyader and Vese 2008). 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.

Deformable models in medical image segmentation have shown promising results and may continue to be focused an in the next few years. Nevertheless, the deformable models also have disadvantages. Algorithms usually contain a certain number of parameters. Parameters must be selected properly to get a satisfactory result while this is usually a time-consuming task.

## 4. Conclusions

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, current algorithms are classified into three types and their respective characteristics are summarised. Applications of the current algorithms to segment the organs contained in the pelvic cavity were illustrated. These examples were also used to further state the distinct characteristics of different types of algorithms. From the discussions, one can see that each segmentation algorithm category has its suitable application fields.

For the segmentation of the pelvic cavity, as some organs like the bladder can be successfully segmented using the current algorithms, its information should be combined with the relative position of organs or a 3D atlas and other image cues to segment the objects that are influenced by PVE or intensity inhomogeneity. To perform this, applying the algorithms based on deformable models can be a good choice. For structures such as the PF muscles whose boundaries cannot be defined through the image appearance, *a priori* shape models and a restriction on shape variations are needed. These tasks can be better fulfilled using the algorithms based on clustering techniques. Pixels with special features such as the edge points can be used to identify the boundary position or define the energy functional. The searching of these pixels can then be done by the efficient algorithms based on thresholds. In conclusion, for a concrete segmentation task in medical images, the application background and practical requirements such as accuracy of segmentation, computational complexity and interactive ability should all be considered in the design of algorithms.

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