Segmentation of Laparoscopic Images: Integrating Graph-Based Segmentation and Multistage Region Merging

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Abstract

This paper presents a method that combines graph-based segmentation and multistage region merging to segment laparoscopic images. Starting with image pre-processing, including Gaussian smoothing, brightness and contrast enhancement, and histogram thresholding, we then apply an efficient graph-based method to produce a coarse segmentation of laparoscopic images. Next, regions are further merged in a multistage process based on features like grey-level similarity, region size and common edge length. At each stage, regions are merged iteratively according to a merging score until convergence. Experimental results show that our approach can achieve good spatial coherence, accurate edge location and appropriately segmented regions in real surgical images.

1. Introduction

Thoracic discectomy is a minimally invasive surgical procedure in which instruments and an endoscope are inserted through small incisions on the patient's body to remove inter-vertebral disc from the spine of patients suffering from scoliosis. This procedure is performed to fuse some vertebral levels in order to stop the progression of spinal deformities. The endoscope acquires images of internal organs and of the instruments; and the surgeon performs the operation by viewing the images displayed on a video monitor. The advantages of this kind of procedure are minimal inconvenience to patients, and improved diagnostic accuracy and therapeutic outcome. Compared to invasive surgeries, this method reduces patient risk and costly in-hospital recovery periods.

Unfortunately, some challenges still need to be overcome to facilitate the adoption of this procedure. By using an endoscope, the surgeon loses the depth perception. Furthermore, context depth cues are scarce. Hence, a lot of training is necessary for surgeons before practicing this procedure on a patient. Laparoscopic images obtained in the context of thoracic discectomy are also very challenging as intensity fall-off rapidly with radial distance from the image center, strong specular reflections caused by the instruments and moist tissues, large changes in apparent size of objects due to motion and focusing of the endoscope, and exposed tissues or cuts which cause variations in textures and colours.

To help the surgeon, first we need to localize the boundary of the removed disc, identified in the image as a cavity. The segmented cavity areas from a series of images shall then be used in 3D reconstruction of the cavity which will help estimate the relative distance between the instrument and the spinal cord. The reconstruction is based on the 3D registration of the cavity with a preoperative 3D model of the spinal cord obtained from MRI images.

In this paper, we focus on the segmentation of the cavity. Our contribution is a multistage region merging process that follows a coarse graph-based segmentation to overcome usual graph-based segmentation drawbacks.

Some researches have been conducted in recent years to process laparoscopic images for the development of 3D navigation system to assist the surgeon. Most researchers focused on segmenting the instruments in the images and tracking their movements. Ueckery et al. [1] used a Bayesian classifier to segment images into two classes, which are organ and instrument. Benny et al. [2] used a similar method in their tissue/instrument segmentation. Recently, Boisvert et al. [3] used a support vector machine for the classification. There are two major hurdles to be faced for statistical learning based methods: data selection and feature selection. Our data which represents cavities operated during a thoracic discectomy procedure changes drastically during the operation and from patient to patient. Here, we do not want only to segment instruments and tissues, we also want to segment cavity tissues from

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other tissues. Instruments are rigid objects and have regular shapes, which is a very good feature for building a model and for learning by a specific learning algorithm. On the contrary, the shape of the cavity is irregular, and it changes from frame to frame depending on the focus of the scope. Hence, specific features are hard to select and therefore features from our data cannot be reliably learned. Without powerful discriminating features, the classifier would not work well or even fail. In addition, the training set must be constructed with images in which the true classifications of objects are known, and this commonly requires user intervention.

The top-down approaches in [1, 2, 3] require a learning step for the classifier, and there are only two classes to distinguish. The purpose of our research is to segment the image into more than two classes. We want to separate homogeneous regions such as blocks of tissues, instruments and cavities, which can be used individually or conjointly for tracking or positioning in 3D an instrument based on the localization of tissues and cavities. We also want the segmentation free of learning and to segment a variety of images on the fly. The planned application is to find a reference feature (a cavity), reconstruct it in 3D, and then, based on the reconstruction, to estimate the relative distance between the instrument and the spinal cord. This should assist the surgeon by providing some depth cues so he can have a better idea of where exactly he is operating relative to the spinal cord.

Since our goal is a precise multi-class segmentation of laparoscopic images, more general bottom-up approaches should suit it better. Roubert used a bottom-up approach in his master's thesis [4], specifically aimed at segmenting instruments. Because he focused on distinguishing instruments from the background, he used thresholding and window filtering to filter out the regions that were considered non-instruments in the first step, and then he used edge detection and line fitting to label the instruments in the remaining image. His method cannot fit our goal since we cannot reject any region to facilitate line fitting. In addition, line fitting does not apply to segmentation of tissues which are unstructured.

Graph-based methods map an image onto a graph where nodes are composed of pixels/regions and edges are composed of links between neighbouring nodes. Each node has a weight based on some feature and each edge has a weight generally defined by the weight difference of the nodes it connects. The algorithm will group nodes [6] or cut the graph into connected regions [19] by edge weight (reflecting similarity of pairs of nodes); it can be used without any supervision, and do not require a learning phase. Graph-based segmentation takes into account global image properties as well as local spatial relationships, and results in a region map that is ready for further processing, e.g. region merging or labelling. Among many variations of graph-based segmentation methods, recursive shortest spanning tree (RSST) based algorithms have been used from 1980s [5]. The algorithm recursively finds the shortest link weight edge and eliminates it (thus the two nodes connected by the edge are grouped in one region). The RSST algorithm groups similar pixels into homogeneous regions in a desired fashion for our application. In the literature, there are many successful applications of this algorithm in various segmentation tasks [6, 7, 8]; most recent ones include object-oriented segmentation for next generation video standard [9, 10].

Although graph-based segmentation is a very good bottom-up approach, it does not generate acceptable results all the time. That is because it has some intrinsic drawbacks. As mentioned above, graph-based segmentation relies solely on weight differences as merging criterion, and it will merge low weight difference regions iteratively. Normally, the algorithm will not stop merging until a certain number of regions are left [10]. A threshold for the edge weight can be used as a stop condition too. In some other graph-based methods such as [12], an initial weight is defined and it will ultimately determine when to stop merging. We call the parameter that defines the stop condition K. We observe that there are three main drawbacks to graph-based segmentation:

- The optimal K is hard to determine, and inappropriate K can cause under-segmentation or over-segmentation. In fact, the value of K depends on the image characteristics of the specific application.
- The average intensity among regions tends to be closer when the regions grow bigger. An average intensity difference criterion may be reasonable at the beginning, but it may not be the most appropriate one when regions grow to some extend.
- Prior knowledge is not used in the merging procedure, so the result is hardly controllable. For example, we expect closed region in many cases, but the region in the acquired image may not be a perfect closed area due to noise, and it is quite possible that the algorithm merges the region with some other regions outside of the area. Another example is small regions remaining inside bigger ones up to the end, because the weight difference among the small regions and their neighbours are too large. Those small regions are possibly spurious areas that we want to get rid of.

The output of any segmentation method can be improved by simply merging similar neighbouring regions together. The idea of region merging is similar to that of graph-based method, but it starts from regions instead of pixels, and can use different merging criteria at different iterations. There are a lot of region merging algorithms proposed in the literature. Brox et al. [14] applied a multistage merging process based on Ward, Mean-Ward and border criteria following a watershed pre-segmentation. Xuan et al. [15] used a merge score based on grey-level similarity, region size and region connectivity in their MR brain image segmentation. Van Droogenbroeck et al. [16] explored texture features for their merging criteria. Asari [21] reported a fast and accurate segmentation technique for the extraction of gastrointestinal lumen from endoscopic images. He used a differential region growing technique on the basis of a similarity criterion, and a dynamic hill-clustering method to ensure the effectiveness of the terminating condition during the growth process.

In our earlier experiment on laparoscopic image segmentation, we observed that the graph-based segmentation method could not generate satisfying results, no matter how we set the parameter. Then we explored region merging, and formed a multistage region merging strategy to improve the segmentation results significantly at the end. Compared to the former mentioned region merging approaches, our algorithm is composed of three merging stages and it uses different merging criteria. The contribution of this paper is the multistage region merging process that can overcome the previously enumerated drawbacks of graph-based segmentation. Our method is presented along with some promising preliminary results on laparoscopic images. The remainder of this paper is organized as follows: Section 2 describes the proposed method, Section 3 provides some experimental results, and Section 4 concludes.

2. Proposed method

Laparoscopic surgical images differ from natural scenes in that they are acquired in a compact viewing area with limited illumination, and are mainly composed of tissues in similar red-like colours. Another difficulty of this kind of images is the specular reflection from moist tissues and metallic instruments that changes unpredictably from frame to frame. The nature of this kind of images (noisy, low contrast and fuzzy boundary), requires image pre-processing, such as smoothing, contrast enhancement, etc. Pre-processing can enhance discriminating features, but it is still hard to obtain a perfect segmentation from graph-based method, especially with laparoscopic images.

We propose a method that integrates graph-based segmentation and region merging as follows:

1) Pre-process input images. Processing includes Gaussian smoothing, brightness and contrast enhancement, colour space conversion and specular reflections removal.
2) Do a relatively coarse graph-based segmentation. Parameter K can be roughly selected because it will not affect much the final segmentation result.
3) Do a simple post-processing to remove very small regions. These regions are considered to be spurious areas.
4) Do a multistage region merging with different criteria at different stages. The criteria are selected by making use of prior knowledge or reasonable hypotheses that will be described later. We use a formula to combine different criteria for computing a merging score, then decide whether to merge or not by a threshold.

These steps are shown in a flow chart (Figure 1), and are described in detail in the subsequent sections following a brief discussion on criteria selection.

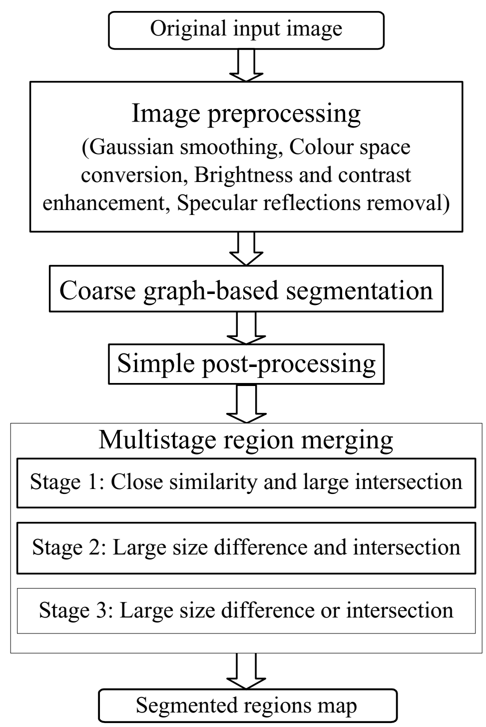


Figure 1. Flow chart of the proposed method

2.1. Criteria selection

Many image features can be used as criteria of homogeneity for image segmentation, such as colour, intensity (grey level), texture, motion vector, elemental model, etc.

For laparoscopic surgical images, due to noise, poor illumination and similarity in colours, boundaries between different structures are not clear. There are also some unwanted specular reflections in the images.

Among these image features, intensity is considered to be the most suitable one as our segmentation criterion. Because there is not much texture and no dominant background or foreground in laparoscopic images, texture and motion vector are not reliable in this situation. On the other hand, the colour differences among regions are small, and the shapes of the regions are variable, so colour and shape model are not reliable criteria either. In fact intensity is the most commonly used criterion, because it is a fundamental characteristic of images, and it is simple and efficient in many situations. It is worth mentioning that whole image pixels are variations of red, so colour information are not relevant in our case.

We will use intensity as basic criterion during segmentation and do some pre-processing to make the region boundary clearer before applying the segmentation algorithm.

2.2. Image pre-processing

Images are basically a set of pixels that are often less than a perfect representation of reality. By pre-processing some unwanted variations, noise can be reduced and desired features enhanced [18]. We apply the following procedures to pre-process our data.

- Gaussian smoothing
- Brightness and contrast enhancement
- Colour to intensity image conversion
- Specular reflections removal

Gaussian smoothing allows us to remove variations and noise. We use a 2-D convolution operator with a standard 5 x 5 kernel. Enhancing brightness and contrast allows us to improve information visibility. We use the classic brightness/contrast adjustment algorithm. The colour image is then converted to intensity image, which we will segment. There are many ways to do the colour space conversion [11]. The following three standards are most often used for RGB to grey level conversion:

- Rec 601-1: Intensity = 0.299 * Red + 0.587 * Green + 0.114 * Blue
- Rec 709: Intensity = 0.213 * Red + 0.715 * Green + 0.072 * Blue
- ITU standard: Intensity = 0.222 * Red + 0.707 * Green + 0.071 * Blue

We have chosen to use the Rec 709 standard because it gives less weight to the red component, and hence increases the differences between the reddish regions. Finally, pre-processing ends by removing spurious pixels that are actually very high intensity pixels caused by specular reflections from polished instruments and liquids in the scene. Using simple histogram thresholding, the intensity of these pixels is truncated. This is very important, because those pixels have large weights and they may affect region-growing result unexpectedly. The graph-based segmentation algorithm follows.

2.3. Graph-based segmentation

Our method is based on an efficient variant of the RSST algorithm [12]. In RSST, an image can be naturally mapped onto a graph. A 2D image is described as an undirected graph G = (V, E), in which pixels $v_i \in V$ are mapped to nodes in the graph, and neighbouring pixels form the edges $(v_{i,} v_j) \in E$. The graph can be 4-connected or 8-connected. It means that a pixel can be only linked to its 4-neighbors or 8-neighbors to form edges. In our case, we have chosen a 4-neighbour because it forms fewer edges so that the process is faster. On the other hand, it will result in a coarser segmentation that is just what we need for the multistage region merging. Each node and each edge has a corresponding weight. The weight of a node is the intensity (grey level) in our case, and the weight of an edge is the weight difference of the two ends. During the segmentation process, similar neighbouring pixels are grouped into regions, and then the weight of a region is simply the average intensity of composing pixels.

A segmentation S is a partition of V into regions such that each region R corresponds to a connected subset of the edges in E. It is conducted by recursively finding the least weight edge and merging the two regions (which are originally pixels) connected by the edge. After each merge, the weights of affected regions are recomputed. The traditional RSST based segmentation algorithm [5] will recompute weights of related edges as well and then find the least weight edge to merge. Since sorting of edges is slow as there are a lot of edges (e.g. 153 040 edges in a 320 x 240 image), putting it in the computation cycle is really time-consuming. More efficient algorithm [12] will neither recompute weight of edges, nor re-sort edges, but use an internal difference criterion to judge if two regions can be merged. Although the efficient algorithm makes the segmentation criterion and stop condition not as clear as the traditional one, it is much faster (nearly real-time running on a Pentium IV 2.4GHz PC). We found the efficient algorithm was hundreds of times faster than the traditional one on segmenting a typical 320 x 240 image, and the quality of segmentation result is not much different. Actually, the exact level of similarity depends on the parameters used. In our case, it does not matter since we just need a coarse result from graph-based segmentation. We use this efficient algorithm to generate an initial segmentation map as the input to the multistage region merging process.

2.4. Multistage region merging

Region merging methods are often utilized along with other segmentation methods such as region growing and watershed methods, which generate an over-segmented result as an initial segmentation. Many region merging approaches were proposed to process the initial segmentation map for meeting some specific goals. We have mentioned some of them in the introduction part. Compared to these methods [14, 15, 16, 21], our algorithm is composed of three merging stages and it uses different merging criteria. At each stage, regions are merged iteratively from small to large until convergence, i.e. no more merging. Merging scores are computed and thresholded at each stage. Stop conditions are used to prevent over-merging. The merging scores are computed from the following region features: grey-level similarity, region size and common edge length. The formulation of the scores is based on what we believe are reasonable hypotheses in the context of our work, and it is distinct in different stage as we will see in the next sections. The stop conditions are based on prior knowledge; in our case, we use minimum number of regions and minimum and maximum size of regions (percentage of the whole image). The stop conditions are kept unchanged at each stage.

2.4.1. Merge Stage One

Discrimination between adjacent areas with different means and standard deviations can be made according to Fisher's criterion (the ratio of the between-class variance to the within-class variance) [20]:

$$F = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}, \qquad \text{(EQ.1)}$$

where μ and σ^2 are the mean and the variance operators respectively. In other words, if two regions have good separation in their means, and low variance, then they can be discriminated. However, if the variance becomes high and the mean difference is low it is not possible to separate them.

Although Fisher's criterion is a good representation of similarity, we also want the two neighbouring regions that are going to be merged to be intersecting each other as much as possible. By intersecting, we mean that they have some boundary pixels side by side and these pixels form what we call a common edge. In practice, we also found that a variation of Fisher's criterion has better performance in our algorithm. We write it as F':

$$F' = \frac{|\mu_1 - \mu_2|}{\sqrt{\sigma_1^4 + \sigma_2^4}}. \qquad \text{(EQ.2)}$$

So we have the merging score formula:

$$\text{Score 1} = \frac{|\mu_1 - \mu_2|}{\sqrt{\sigma_1^4 + \sigma_2^4}} \times \frac{P}{L} \qquad \text{(EQ.3)}$$

Where P is the perimeter of the smaller region and L is the common edge length, P and L are counted in number of pixels.

Given a region, we will find the smallest score among its neighbours, and then merge the two regions if the score is less than a threshold (determined through experiments) and the common edge is not too small ((P/L)<5, means 20% of the perimeter of the smaller region). Hence at this stage, we favour merging regions of close similarity as well as with large intersection.

2.4.2. Merge Stage Two

Now that we have merged similar regions, suppose some ribbons of regions remain unmerged. Generally speaking, these ribbons are not likely to be independent objects. In our case, we want them to be merged into big neighbours as long as they intersect each other adequately. The merging score should include a size term and a common edge term:

$$\text{Score 2} = \frac{S_1}{S_2} \times \frac{P}{L} \qquad \text{(EQ.4)}$$

Where S_1 is the size of the smaller region, S_2 is the size of the larger region, P is the perimeter of the smaller region and L is the common edge length. S_1, S_2, P and L are counted in number of pixels.

Given a region, we will find the smallest score among its neighbours, and then merge the two regions if the score is less than a threshold (determined through experiments) and the intensity difference is moderate (<25). So at this stage we favour merging regions of large size difference as well as large intersection.

2.4.3. Merge Stage Three

This stage is a relaxation of stage two for further forming larger regions. First we disregard the size factor (S_1/S_2) and focus on the common edge term (P/L) to remove regions that are almost contained in other regions. Then, we disregard the common edge factor and focus on the size term to remove small regions adjacent to very large regions. At this stage intensity difference is still used as a condition to avoid merging too different regions, but it is relaxed too (<50).

3. Experimental results

The algorithm is implemented in C++, and it uses some image processing functions from an open source library (OpenCV, [17]). Images are dynamically extracted from video files. The laparoscopic videos were supplied by Sainte-Justine Hospital in Montreal. Sample results of laparoscopic image segmentations are shown in Figure 2, where results of graph-based segmentation are shown from coarse to fine (a-c), and the result with our algorithm by region merging (d) following the coarser segmentation in (a).

Analysing results from Figure 2 shows that a finer graph-based segmentation could not improve the quality of the results as the tissues are over-segmented. However, our multistage region merging algorithm helped to partition the image into more meaningful structures or objects (block of tissues, cavity, and instrument). In fact, because of the single criterion used during the whole segmentation, graph-based segmentation could not remove spurious areas inside an object; or it would segment the whole image into few very large regions that are not corresponding to meaningful objects (see Figure 2c). On the contrary, our algorithm tries to merge every small region into its neighbours and finally segments the image into several subjectively meaningful large regions. Our experiences show that it is not influenced by small variances in the regions (see Figure 2d).

Figure 3 shows another set of images including intermediate results of multistage region merging. Note that merging stage one did most of the work of forming homogeneous regions (Figure 3b), but there are still some small regions left because the compound score of similarity and intersection is within the threshold. Then at merging stage two (Figure 3c), small regions are merged into large neighbours as long as their intensity differences are not too big. At the last stage (Figure 3d), further merging happens when a region is almost contained in a neighbour region or it is adjacent to a relatively very large neighbour. As it can be observed from this result, our algorithm does handle the drawbacks of graph-based segmentation.

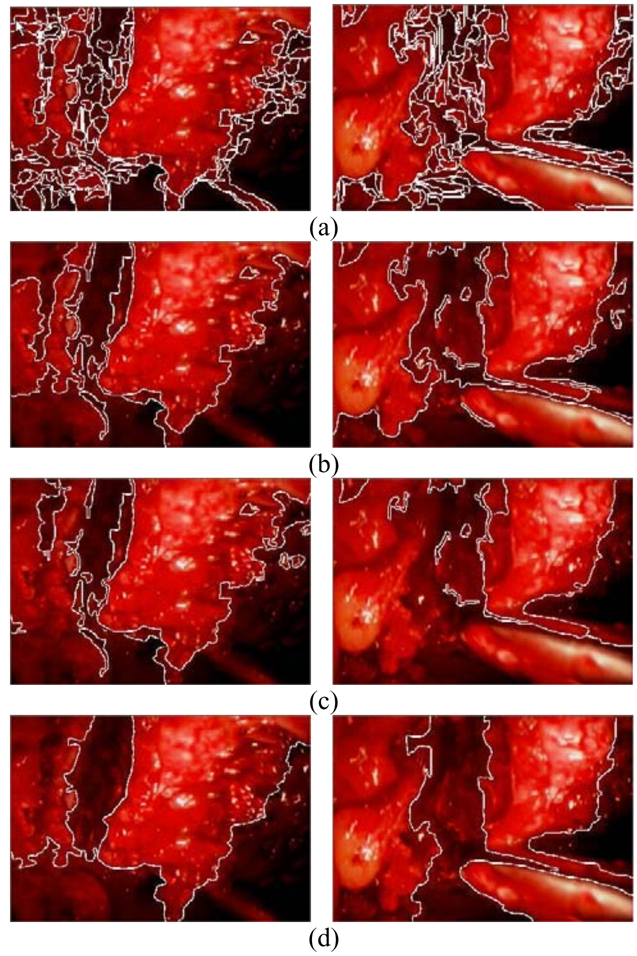
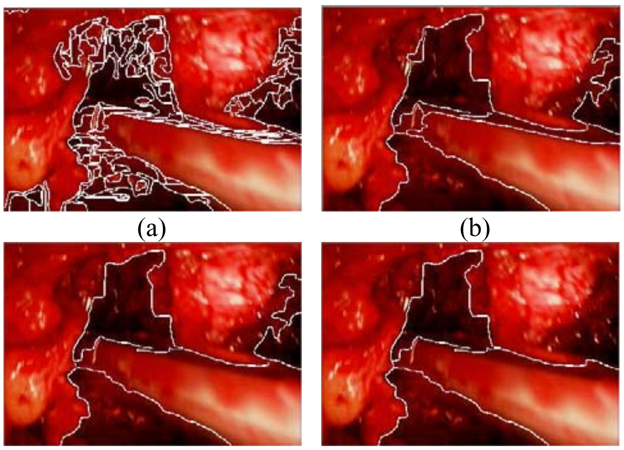


Figure 2. A laparoscopic image without instruments (left) and another one with instruments (right). Region contours are superimposed on original image. (a) Result of coarse graph-based segmentation, K=100. (b) Result of fine graph-based segmentation, K=8000. (c) Result of finer graph-based segmentation, K=12000. (d) Result of our region merging algorithm following the coarse segmentation in (a).

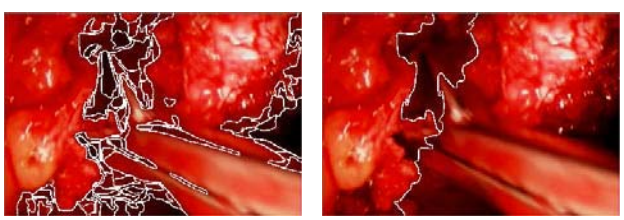
Recall we used image pre-processing, graph-based segmentation and region merging in the whole process. It is a complex process and some parameters need to be specified at each phase. The pre-processing methods are general except for histogram thresholding, which is application specific. Actually it is not necessary to use the thresholding for most natural scenes. In the graph-based segmentation only a parameter K leading to a coarse segmentation needs to be specified. Our merging algorithm is not sensitive to the initial segmentation as long as it is not too fine (under-segmented). In the multistage region merging phase, we need to decide the thresholds and other parameters coming from prior knowledge and experiment. In fact, parameters need to be fine-tuned according to the image characteristics, but once they are set, they can be applied to similar images (In our case, complete sequence of laparoscopic images).

Although multistage region merging can significantly improve the segmentation results, it does not guarantee success all the time. Note that the merging is based on the output of initial segmentation, so the final result may not be perfect if the initial segmentation has under-segmented some regions. This happens especially on the laparoscopic surgical images with instruments in the field of view (Figure 4), because the reflection on the instrument makes its colour or intensity very close to the surrounding tissues. In this case we consider using some other ways to refine the boundary, such as the contour modification method used in [15]; or using a special filter to make the difference between the instruments and surrounding tissues large enough for a correct segmentation.



(a) (b) (c) (d)

Figure 3. Results of multistage region merging. (a) Result of coarse graph-based segmentation, K=100. (b) Result of merging stage one. (c) Result of merging stage two. (d) Result of merging stage three – final result.



(a) (b)

Figure 4. False segmentation of a laparoscopic image with instruments. (a) Result of coarse graph-based segmentation, K=100. (b) Result of multistage region merging following the coarse segmentation.

4. Conclusion

In this paper we have introduced a segmentation method combining graph-based segmentation and multistage region merging. The method first uses an efficient variant of the RSST algorithm to do an initial coarse segmentation, and then uses an original three-step method to further merge regions into more meaningful structures or objects. Experimental results on laparoscopic images of a thoracic discectomy procedure show that our method can segment the cavity adequately for a variety of challenging images. In contrast to graph-based merging method using a single criterion, our multi-criteria merging method shows significant improvements on final results. We have also shown how at each stage the segmentation is improved by removing unwanted regions.

Our future work is to further develop the algorithm to track a specific object in the video sequence. We will also investigate the way to improve the segmentation results when they are not satisfactory, particularly when operating instruments are in the field of view of the endoscope. The results of these works will then be applied to the 3D reconstruction of the cavity to estimate the relative distance between the instrument and the spinal cord in real time during the surgery.

References

[1] D. R. Uecker, C. Lee, Y. F. Wang and Y. Wang, “Automated Instrument Tracking in Robotically-Assisted Laparoscopic Surgery”, Journal of Image Guided Surgery, Vol. 1, No. 6, 1996.

[2] B. P. L. Lo, A. Darzi and G. Yang, “Episode Classification for the Analysis of Tissue/Instrument Interaction with Multiple Visual Cues”, MICCAI (1) 2003, pp. 230-237.

[3] J. Boisvert, F. Cheriet and G. Grimard, “Segmentation of Laparoscopic Images for Computer Assisted Surgery”, SCIA03, pp. 587-594.

[4] J. Roubert, “Automatic Guidance of a Laparoscope Using Computer Vision”, master thesis, Lund University, November 2002.

[5] O. J. Morris, M. J. Lee and A. G. Constantinides, “Graph theory for image analysis: An approach based on the shortest spanning tree”, in Proc. Inst. Elect. Eng., vol. 133, April 1986, pp. 146–152.

[6] T. Vlachos and A.G. Constantinides, “A graph-theoretic approach to colour image segmentation and contour classification”, Proc. Int. Conf. Image Processing and its Applications, 1992, pp. 298-302.

[7] J. Mulroy, “Video content extraction: Review of current automatic segmentation algorithms”, Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS97), June 1997.

[8] S. Cooray, N. O'Connor, S. Marlow, N. Murphy and T. Curran, “Semi-Automatic Video Object Segmentation using Recursive Shortest Spanning Tree and Binary

Partition Tree", Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS 2001), May 2001.
[9] R. Piroddi and T. Vlachos, "Object-based Segmentation of Moving Sequences using Multiple Features", IEEE Proc. Digital Signal Processing, July 2002.
[10] E. Tuncel and L. Onural, "Utilization of the Recursive Shortest Spanning Tree Algorithm for Video-Object Segmentation by 2-D Affine Motion Modeling", IEEE transactions on circuits and systems for video technology, vol. 10, No. 5, August 2000.
[11] Color space FAQ, http://www.neuro.sfc.keio.ac.jp/~aly/polygon/info/color-space-faq.html
[12] P. F. Felzenszwalb and D. P. Huttenlocher, "Efficient Graph-Based Image Segmentation", *IJCV(59)*, No. 2, pp. 167-181, September 2004.
[13] S. Chandran and K. K. Madheshiya, "A Fast Segmentation Algorithm Revisited", Proceedings of Indian Conference on Computer Vision, Graphics, and Image Processing, December 2002.
[14] T. Brox, D. Farin and P.H.N. de With, "Multi-stage region merging for image segmentation", in Proceedings of the 22nd Symposium on Information Theory in the Benelux. May 2001.
[15] J. Xuan, T. Adali and Y. Wang, "Segmentation of Magnetic Resonance Brain Image: Integrating Region Growing and Edge Detection", ICIP-C 95, pp. 544-547.
[16] M. Van Droogenbroeck and H. Talbot, "Segmentation by adaptive prediction and region merging", In Digital Image Computing Techniques and Applications, Volume II, DICTA 2003, pp. 561-570, December 2003.
[17] Intel Open Source Computer Vision Library Reference Manual, http://sourceforge.net/projects/opencvlibrary/
[18] M. Sonka, V. Hlavac and R. Boyle, Image Processing, Analysis and Machine Vision, 2nd edition, PWS Boston, 1998.
[19] J. Shi and J. Malik, "Normalized Cuts and Image Segmentation", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, No. 8, pp. 888-905, 2000.
[20] T.Y. Young and K.-S. Fu. Handbook of Pattern Recognition and Image Processing, Academic Press, 1986.
[21] K. V. Asari, "A fast and accurate segmentation technique for the extraction of gastrointestinal lumen from endoscopic images", Medical Engineering & Physics, Volume 22, Issue 2, Pages 89-96, March 2000.