Segmentation of colorectal cancer MR images

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Introduction

Over two-thirds of a million new men and women are affected by colorectal cancer each year and worldwide nearly 400,000 deaths are caused by this form of cancer. Diagnosis and treatment planning for colorectal cancer is a clearly important issue. Figure 1 shows a typical T2 weighted MR image of the colorectum with anatomical annotations. The key clinical questions for the treatment planning are: (1) how big is the tumour, and how far has it infiltrated the surrounding fat? (2) What is the margin of clearance between the mesorectal fascia (**MF**) and the tumour? This margin is referred to as circumferential resection margin (**CRM**). If the minimum CRM is below a certain threshold, surgery of the colorectum is less likely to be successful. (3) Are there any lymph nodes affected with malignancy? In this work, we address the first two questions, obtaining preliminary results for the third. In terms of image analysis, important challenges are: (1) The anatomy of the region is complex, often showing characteristic texture. (2) images are affected by noise, the partial volume effect, and a variety of artefacts: bias field, chemical shift. (3) The boundary along the MF is discontinuous with a variety of features like step edge, ridge, and texture changes along it.

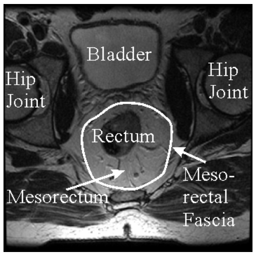

Figure 1: T2 weighted axial MR image of colorectum with anatomical annotations.

Methods

To find the MF and minimum CRM from T2 weighted MR images, we segment a given image into three main classes: the rectum, tumour, and the mesorectum. To take into account the first two image analysis challenges we model the intensity values of T2 weighted MR images with a mixture of non-parametric distributions [1]. The non-parametric distributions enable us to accurately model the complex variation of intensity values within each segmentation class. We then assign each pixel in the image a probability value of belonging to a particular class using the Bayes rule. To account for diverse feature types along the MF, we apply phase congruency [2]. This has the advantage over image gradient-based feature detectors that the latter is only efficient in finding step like edges. The complex anatomy and discontinuous MF boundary are finally segmented using a level set framework for curve evolution [3]. In the level set framework, each segmentation class is associated with a contour, which is then evolved under region based properties of the image obtained from the non-parametric mixture model, and boundary based properties of the image obtained from the phase congruency features. These individual contours eventually fit the actual boundary of the segmentation class. The level set framework imposes curvature based smoothness constraint on the evolving curves. The actual segmentation procedure is divided into two steps. In the first step we generate a mask that covers region inside the MF. The boundary of the mask gives an estimate of the MF. In the second step, the region over which segmentation is performed is restricted by the mask generated in the previous step. The output of this step includes segmentation of the rectum, tumour, and the mesorectum. This step also separates blood vessels and lymph nodes from the mesorectal fat.

Material

Thin section, oblique, small field of view images were taken. TE = 90-120 ms, TR =3500-6500 ms, α = 90 deg., slice thickness = 3 mm. Each slice is either 256 X 256 with pixel size 0.78mm X 0.78mm or 512 X 512 with pixel size 0.39mm X 0.39mm. All the images we show here were acquired on 1.5T GE machine. In this study, we use the datasets acquired from 10 patients.

Results

All the images were preprocessed to remove the bias field. For this we used the Parametric Bias Field Correction (PABIC) method [4]. Despite this some bias field still remains and this can be seen in the result images. Figures 2, 3, and 4 show various results obtained with our non-parametric mixture model based level set method. Results show the maximum of the average differences between an expert's delineation of the MF and that segmented with our algorithm is just over 2 *mm*. This is equivalent to 3 to 5 pixels, depending upon the resolution, in the corresponding MR images. The maximum difference between the minimum CRM found using our algorithm and that found manually, across all the patients, is approximately 2.2 *mm*.

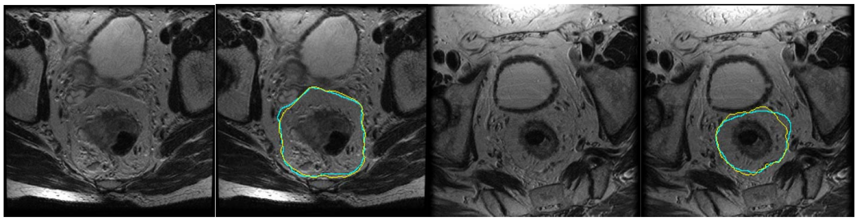

Figure 2: Visual comparison of mesorectal fascia segmentation with our algorithm and that of an expert clinician. Cyan coloured curve is the expert's delineation of the mesorectal fascia, and yellow coloured curve is that by our algorithm.

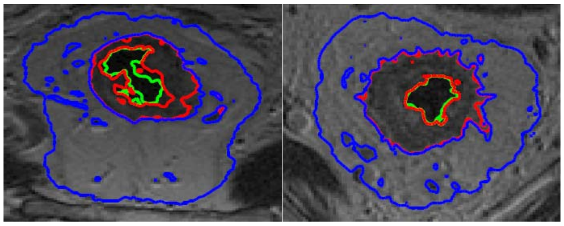

Figure 3: Three class segmentation of colorectal MR images: (*green*) rectum, (*red*) tumour, (*blue*) mesorectum. Non-overlapping areas between two adjoining contours indicate the partial volume effect between the two respective classes.

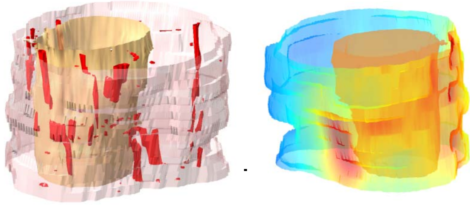

Figure 4: 3D visualisation of segmentation of colorectal MR images. (*Left*) Visualisation of various surfaces: skin coloured cylindrical surface at the center is the outer surface of tumour; transparent pink coloured outer surface is the mesorectal fascia; red coloured small tubular surfaces in the middle are blood vessels/ lymph nodes. (*Right*) Circumferential resection margin (CRM) information is colour coded on the outer mesorectal fascia surface; red denotes smaller CRM, blue denotes larger CRM; also shown is the outer surface of tumour.

Conclusions and future work

We have presented a method to segment 3D colorectal MR images. This can provide useful information about tumour location, size, and configuration. One of the advantages of working with the level set method that we have used is that we can also segment blood vessels and lymph nodes from the mesorectal fat (see Fig. 4). We now plan to identify lymph nodes from blood vessels and characterise them for the presence of tumour. This can help further in staging the tumour.

References

[**1**] Joshi *et al*., Partial volume segmentation of MR images using non-parametric mixture model, Medical Image Understanding and Analysis, 2005, UK. [**2**] Morrone *et al*., Feature detection from local energy, Pattern Recognition Letters, 1987. [**3**] Bond *et al*., Estimating the mesorectal fascia in MRI, Information Processing in Medical Imaging, 2007, Netherlands. [**4**] Styner *et al*., Parametric estimate of intensity inhomogeneities applied to MRI. *IEEE Trans. on Medical Imaging*, 19(3):153–165, 2000.