Magnetic Resonance Signal Processing in Medical Applications

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***Abstract*—Image processing in biomedical applications is an important developing issue. Many methods and approaches for image preprocessing, segmentation and visualization were described. It is necessary to choose a suitable segmentation method to create a correct three-dimensional model. The accuracy of reconstruction depends on precision of regions boundary determining in magnetic resonance slices. A frequent application is detection of soft tissues. To obtain images of the soft tissues mentioned, tomography based on magnetic resonance is usually used. Ideally, several tissue slices in three orthogonal planes (sagittal, coronal, transverse) are acquired. Following reconstruction of shape of examined tissues is the most accurate. In case of acquired slices only in one plane, the high spatial information lost occurs by image acquisition. Then it is necessary to reconstruct the shape of tissue appropriately. At first the images are segmented and with use of particular segments the three dimensional model is composed. This article compares several segmentation approaches of magnetic resonance images and their results. The results of segmentation by active contour, thresholding, edge analysis by Sobel mask, watershed and region-based level set segmentation methods are compared. The results for different values of parameters of segmentation methods are compared. As the test image, slice of human liver tumour was chosen.**

Keywords-magnetic resonance; biomedical image processing; image segmentation; level set; active countour; edge analysis; noise suppression; volumetry

I. INTRODUCTION

Image processing in biomedical applications is an important developing issue. Many methods and approaches for signal/image preprocessing, segmentation and visualizing were described. On the basis of segmented images, it is simple to describe the boundaries of the objects sought; these boundaries serve further processing aimed at calculating the perimeter, area, surface, volumetry or even 3D reconstruction of the object being imaged. To obtain images of the soft tissues mentioned, tomography based on magnetic resonance (MR) is usually used. It is necessary to reconstruct the shape of tissue appropriately. The shape is reconstructed via its segmentation in several slices. The reconstructed model has staggered shape. There are several methods for smoothing the shape. In this article the methodology for shape smoothing is discussed. The results of volumetry with use of several smoothing levels are compared. Impact of shape smoothing to quality of reconstruction is discussed. It is shown that high level of smoothing suppresses the staggered shape but the edge information is lost. With increased smoothing level the staggered shape of the model comes to be suppressed, with the transitions between individual model segments suppressed.

For a comparison of the segmentation properties of the methods, two sets of real medical images were chosen: MR images of the human liver with a tumour visible in several slices, MR images of the human head for the processing of the region of temporomandibular joint (TMJ). The segmentation of the mandibular disc is made difficult not only by the low contrast and the presence of noise but also by the fact that in most of the images obtained the region of the mandibular disc is represented by a very small number of pixels. The liver region exhibits homogeneous distribution of intensity, which is lower than in the surrounding area of the liver. The topicality of the selected topic of liver tumour segmentation is attested by the diverse conferences held and papers published [1] [2] [3] [4] [5] [6].

In the paper, an image segmentation method is described, which reduces the requirements for image pre-processing (elimination of noise) and yields good results also when segmenting a noisy image [7][8][9]. This is of much advantage when processing images exactly by the MR method. State of the art is mentioned in the next chapter. Some publications in the area of liver tumour segmentation are mentioned. It is followed by describing used mathematical models in the next chapter. Implementation problems, results and their comparison with other segmentation methods are shown in rest of the paper.

II. STATE OF THE ART

Extensive research was conducted in the area of processing MR images of tumours in the human liver in the past. The liver region exhibits homogeneous distribution of intensity, which is lower than in the surrounding area of the liver.

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The topicality of the selected topic of liver tumour segmentation is attested by the diverse conferences held and papers published. Evidently, the greatest impulse to investigate methods for processing liver images was the workshop “3D Segmentation in the Clinic: A Grand Challenge II” [1], which was part of the conference “Medical Image Computing and Computer Assisted Intervention 2008”. The aim of holding the Conference was a) to define the input data (64 or 40 slices in each set of images obtained by computer tomography were available, slice thickness 1 – 1.5 mm), and b) to define the criteria for the evaluation of the methods In [4], a chain of processing CT images of the human liver is described which, in brief, consists of image pre-processing – histogram-based segmentation of the region, multimodal thresholding, maximum a posteriori decision-making, and of the segmentation of the liver region, which is given by the basic local properties. The image processing chain gives very good results. A disadvantage can certainly be seen in the many degrees of freedom of this chain. A simpler approach is described in [3]. In the proposed methodology, the pre-processing of images is eliminated. Prior to the segmentation using the level set method the images are pre-segmented by fuzzy cluster algorithms. The author demonstrates the segmentation function on several selected CT images. But, the results are not discussed and there is no mention of important parameters such as segmentation speed or differences in comparison with the actual/real division of tissues, for example by tracing manually the tumour edges. A similar approach, segmentation of liver tumour area by the level set method, is described in [4]. The level set segmentation is preceded by the initialization method, which pre-processes the image prior to its segmentation proper. This initialization method is the so-called spiral-scanning method with supervised fuzzy pixel classification. The paper describes the segmentation of the liver tumour area in images produced by computer tomography. We can also come across methods that are based on segmentation approaches that are today considered traditional, e.g. the watershed method [5], thresholding method [6] and region growing method [7]. The development of the method for the segmentation of liver tumours follows from the previously published work [8], in which region-based level set segmentation was used.

The greatest disadvantage of the methods described above can be seen in that either a greater interaction of the physician in the segmentation of the liver tumour in tomographic images is required or it is necessary to choose a large number of segmentation parameters or to pre-process the images.

III. MATHEMATICAL MODELS

The selected segmentation methods are based on the solution of partial differential equations. These are iterative algorithms with initial conditions whose solution is used to shape the curve placed in the image. The steady-state solution is a curve delineating the image regions, which satisfies the sought minimum of the energy function of the mathematical model of a given method. The problem is to delineate by a smooth closed curve only the tumour region such that the curve does not delineate any other tissues. This can happen in the comparatively frequent case when the tumour is at the liver periphery; it is then important not to exceed the liver boundary. Better results were obtained using the edge-based analysis, which satisfied the above condition of delineating the tumour region alone.

The edge-based segmentation is described by this energy functional [9]:

$$F(\phi)=\lambda\int_{\Omega} g\delta(\phi)\left|\nabla\phi\right|\mathrm{d}x\mathrm{d}y+\nu\int_{\Omega} gH(-\phi)\mathrm{d}x\mathrm{d}y\,, \qquad (1)$$

where the first term means the length of the zero level curve of Φ (level set distance function) and the second term is called weighted area of Ω_{Φ}^{-}. λ and ν are the weighted coefficients of the mentioned terms, $\delta(\phi)$ is the Dirac function and H is the Heaviside function. The g function is the edge indicator defined by [10]

$$g=\frac{1}{1+\left|\nabla G_{\sigma}*I\right|^{2}}\,, \qquad (2)$$

where I is the original image and G_{σ} is the Gaussian kernel with standard deviation σ. By calculus of variation, the first variation of the functional in (2) can be written as [9]

$$\begin{aligned}\frac{\mathrm{d}\phi}{\mathrm{d}t}&=\mu\left[\Delta\phi-\mathrm{div}\left(\frac{\nabla\phi}{\left|\nabla\phi\right|}\right)\right]+\\&+\lambda\delta(\phi)\,\mathrm{div}\left(g\frac{\nabla\phi}{\left|\nabla\phi\right|}\right)+\upsilon g\delta(\phi).\end{aligned} \qquad (3)$$

This gradient flow is the evolution equation of the level set function Φ. The second and third term in the equation (3) correspond to the length and area energy functional. The first term penalizes the deviation of the level set function from a signed distance function during its evolution.

The region-based segmentation method is of greater advantage when segmenting an image in which there are no sharp transitions or in the case when the extraction of an object in the image is required when the statistical properties of intensities at the site of the object sought are known. With this approach the principle is that no edges are sought in the image – regions in the image are viewed according to the local intensity statistics and, according to the given properties, the image is subdivided into two or more regions. The model of which is given by the energy functional [10]:

$$\begin{aligned}F_{n}(\mathbf{c},\mathbf{\Phi})=&\sum_{1\le I\le n=2^{m}}\int_{\Omega}\left(u_{0}(x,y)-c_{I}\right)^{2}\chi_{I}\mathrm{d}x\mathrm{d}y\\&+\sum_{1\le i\le m}\nu\int_{\Omega}\left|\nabla H(\Phi_{i})\right|\end{aligned} \qquad (4)$$

and for the two-phases result the general energy functional (4) is in shape [10]:

$$F(c_1, c_2, \phi) = \int_\Omega (u_0(x,y) - c_1)^2 H(\phi)\,\mathrm{d}x\mathrm{d}y + \int_\Omega (u_0(x,y) - c_2)^2 (1 - H(\phi))\,\mathrm{d}x\mathrm{d}y + \nu \int_\Omega |\nabla H(\phi)|, \quad (5)$$

where the first two terms divide the area Ω of the original image u_0 to two subareas with the mean values of intensity c_1 and c_2. The third term minimizes the length of the resultant contour. It can be used for suppression of noise in the image and the final contour is smoother. This term is weighted by the coefficient ν. H is the Heaviside function. This function recognizes where the level set function ϕ is positive, respectively negative.

$$\frac{\partial \Phi}{\partial t} = \delta_\varepsilon(\Phi)\left[\nu\,\mathrm{div}\left(\frac{\nabla\Phi}{|\nabla\Phi|}\right) - (u_0 - c_1)^2 + (u_0 - c_2)^2\right]. \quad (6)$$

This gradient flow [10] is the evolution equation of the level set function Φ. The first term in the brackets (6) corresponds to the length functional.

Thresholding - the simplest segmentation method is defined as:

$$g(i,j) = \begin{cases} 1 & \text{pro } f(i,j) \ge \mathrm{T} \\ 0 & \text{pro } f(i,j) < \mathrm{T} \end{cases}. \quad (7)$$

The biggest disadvantage of this method is that it is very sensitive to noise, but it is very often used in medical practice in manual processing. It is very simple and fast.

Image segmentation based on Sobel mask convolution is defined by convolution kernel:

$$S_x = \begin{pmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{pmatrix}, S_y = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}. \quad (8)$$

IV. IMPLEMENTATION

The algorithm was implemented in Matlab 7.0. The equation (3) was approximated by central and forward difference schemes and solved by iterative process. The Dirac function was approximated by [10]:

$$\delta_\varepsilon(x) = \begin{cases} 0, & |x| > \varepsilon \\ \frac{1}{2\varepsilon}\left[1 + \cos\left(\frac{\pi x}{\varepsilon}\right)\right], & |x| \le \varepsilon \end{cases}. \quad (9)$$

V. RESULTS, LIVER TUMOUR SEGMENTATION

The aim of processing is to segment the tumour in all slices, reconstruct the obtained segments back to a 3D image and calculate the tumour volume so that the tumour evolution in time can be monitored (Fig. 1) In the case of liver tumour, a correct diagnosis is very important as it is decisive in determining the treatment procedure. The main drawbacks of traditional segmentation methods include, in the first place, the necessary individual pre-processing of images in order to suppress their unfavourable properties (presence of noise in images, blurred edges, low contrast), the necessity of individually adapting the segmentation method according to the number of image subregions sought (segmentation into two (background/object) or more subregions), etc. The aim was to simplify as much as possible the image processing chain, i.e., to find a method by means of which it would be possible in ideal case to segment the regions sought, without the necessity of image pre- and post-processing. For the segmentation of liver tumours the edge-based segmentation method was selected [9][10]. Good results were obtained using the edge-based analysis, which satisfied the above condition of delineating the tumour region alone.

Figure 1. Example of MR slice through human liver; the tumour sought is in the delineated region.

Fig. 2 shows the results of segmenting a liver tumour by the active contour method based on the edge-based analysis of image. The contour smoothness is given by the filtering properties of the method itself, which thus does not require any pre-processing of the image (smoothing, filtering, focussing) and which delineates only the region of the tumour proper and, in spite of the very similar mean value of brightness does not evolve in time towards delineating some narrow regions connected with the tumour.

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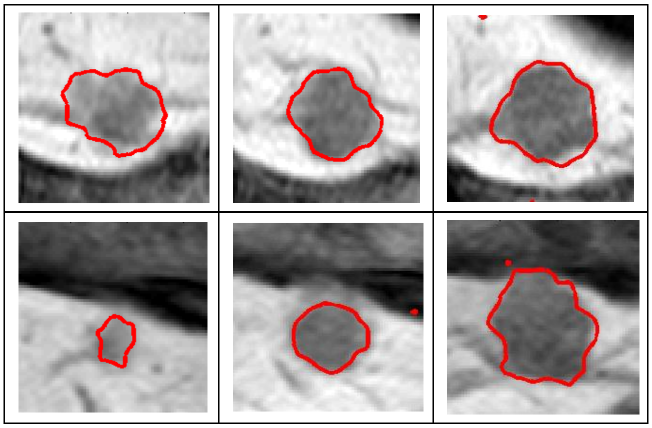

Figure 2. Results of segmenting a liver tumour by the active contour method based on edge-based analysis; 6 chosen slices.

VI. RESULTS, MANDIBULAR DISC SEGMENTATION

The aim of processing is to segment the mandibular disc in all slices and reconstruct the obtained segments back to a 3D image (Fig. 3). In the case of TMJ disorder in the disc area (rupture, dislocation) a correct diagnosis is very important as it is decisive in determining the treatment procedure. . The main drawbacks of traditional segmentation methods are similar to the previous one. The aim was to simplify as much as possible the image processing chain, i.e. to find a method by means of which it would be possible in ideal case to segment the regions sought, without the necessity of image pre- and post-processing. The MR slices with visible mandibular discs were segmented by edge-based level set segmentation method. This level set approach gives very good results in segmentation of noised MR images with low contrast and smooth edges so that it is not necessary to preprocess the image before the segmentation of image.

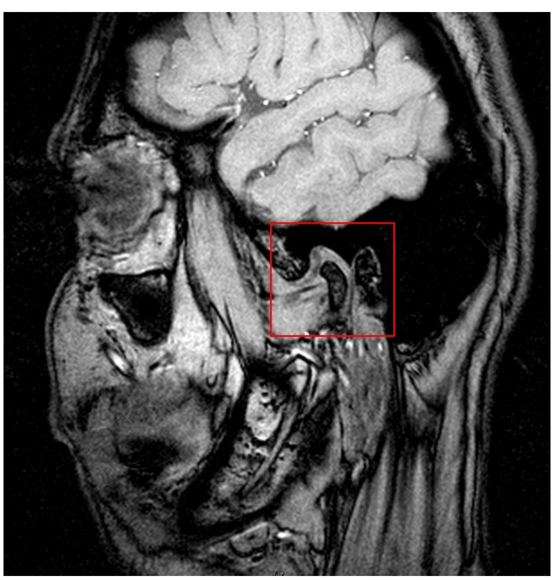

Figure 3. Example of MR image of human head for diagnosing TMJ, with delineated region of temporomandibular disc.

The results of segmentation without any kind of preprocessing are given in Fig. 4.

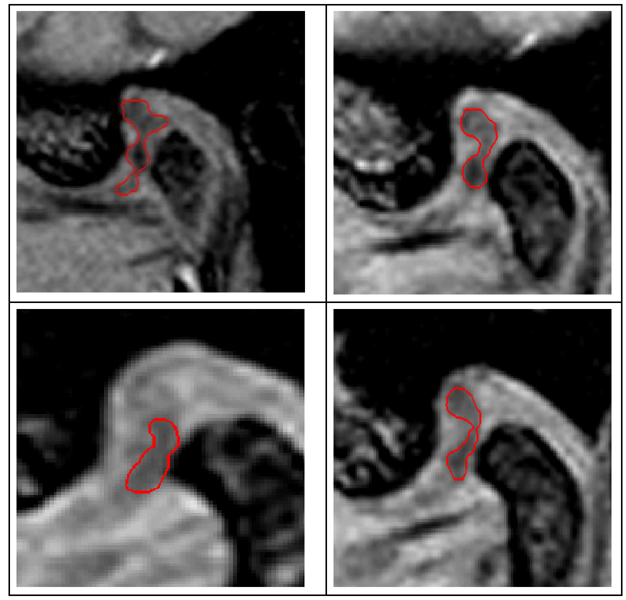

Figure 4. Result of segmentation of TMJ in four selected slices by edge-based segmentation active contur method.

VII. COMPARISON OF RESULTS WITH OTHER METHODS

In this section, a comparison is shown of the segmentation of a selected image (MR, human liver) and other traditional segmentation approaches. The first to be chosen was the simplest segmentation method, which is used very often in medical practice and is supported by the majority of professional software applications designed for MR images that are processed by physicians. This method is thresholding. Fig. 5 gives the result of segmenting the image of a slice through liver tumour by the thresholding segmentation method with two different thresholds, which were established empirically (100, 150). A mere subjective assessment is enough to conclude that in spite of its simplicity and speed, this method cannot be used to process such an image. With a low threshold level the darker regions inside the tumour were segmented while with a higher threshold level a contour was found that delineates the tumour region and goes through the tumour "edge" but this curve is not closed and penetrates farther into the liver region, out of the tumour. It is obvious that in the case of processing a large set of images the search for a suitable threshold would be demanding and the segmented images would have to be further processed in order to obtain a complete segmentation result.

Fig. 6 gives the result of the Sobel mask edge-based analysis [1, 2] with two different levels of thresholding the edge-based analysis image (0.05, 0.15).The edge-based analysis yields results similar to those of the segmentation thresholding method. Choosing a low threshold value gives an oversegmented image while a higher threshold will yield information only on very pronounced edges in the image.

The other edge analyzers give similar results; the result of edge-based analysis must be additionally processed and can be used, for example, as additional information for another segmentation method. Practically, never does this method give a closed curve representing the edges of the region of interest sought.

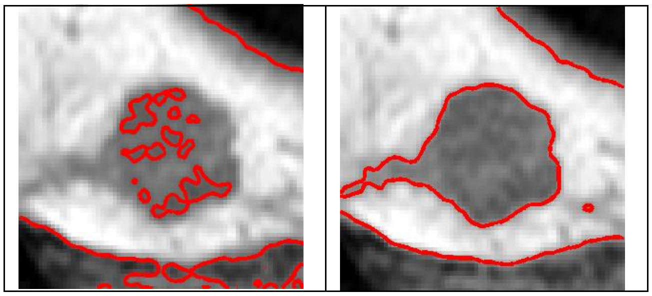

Figure 5. Result of segmenting the image of a slice through liver tumour via thresholding with thresholding levels a) 100, c) 150, within a brightness intensity range of 0 – 255.

Fig. 7 shows the result of image segmentation of a slice through liver tumour using the water shed segmentation method [1]. This segmentation method gives good results and is frequently used in practice. It has, however, one great disadvantage – the result of segmentation without prior image processing is oversegmented and the image must practically always be adapted in an appropriate way. Fig. 7 b) gives the result of watershed image segmentation after prior processing of the grey-tone image by thresholding (with automatic threshold search) and by transforming the binary image into a grey-tone image representing the Euclidean distance of every single pixel of the binary image from the background. The watershed image segmentation with prior image processing gives very good results. However, the method is dependent on an appropriate determination of the threshold of primary segmentation and the segmented region of the tumour reaches into the liver region since the method responds to any tiny interruption of the edge by merging the regions.

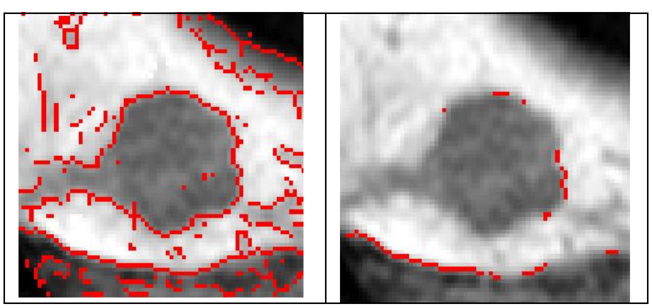

Figure 6. Result of edge-based analysis of a slice through liver tumour using the Sobel mask, with threshold values a) 0.05, c) 0.15.

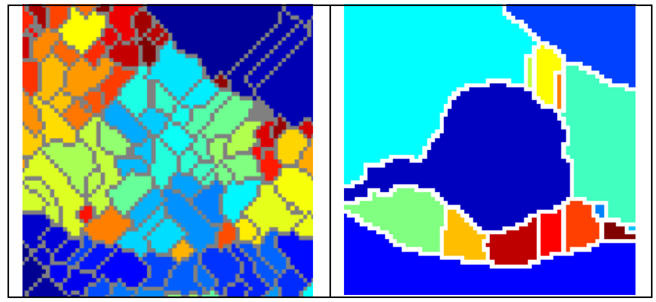

Figure 7. Result of image segmentation of a slice through liver tumour using the watershed segmentation method; a) oversegmented result without pre-processing, b) with pre-processing.

VIII. Summary

Results of image processing show that the active contour method based on the level set principle is very appropriate for the segmentation of both low-contrast images and regions with interrupted edges. An example of the first type of task, namely the segmentation of regions in low-contrast images, was demonstrated on the processing of MR images in the TMJ region, specifically the TMJ disc. The segmentation of regions with interrupted edges, on the other hand, is demonstrated by the application of active contours in the processing of MR images of human liver. In contrast to other traditional segmentation methods, the active contour method was always able to segment the given region of interest. The segmentation result is always a closed curve delineating the tissue sought.

IX. Conclusions and Future Works

The segmentation of regions of interest in MR images is an important part of the image processing chain. The quality of separating the region of interest from the background determines the quality of further processing. This may include the quantification of the delineated regions such as establishing the dimensions, area and volume or three-dimensional reconstruction and visualization of objects.

The future work will be concerned with registration of segmented images and creation of the 3D model of the region of interest and its visualization.

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