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Soft-tissues Image Processing: Comparison of Traditional Segmentation Methods with 2D active Contour Methods

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The paper deals with modern methods of image processing, especially image segmentation, classification and evaluation of parameters. It focuses primarily on processing medical images of soft tissues obtained by magnetic resonance tomography (MR). It is easy to describe edges of the sought objects using segmented images. The edges found can be useful for further processing of monitored object such as calculating the perimeter, surface and volume evaluation or even three-dimensional shape reconstruction. The proposed solutions can be used for the classification of healthy/unhealthy tissues in MR or other imaging. Application examples of the proposed segmentation methods are shown. Research in the area of image segmentation focuses on methods based on solving partial differential equations. This is a modern method for image processing, often called the active contour method. It is of great advantage in the segmentation of real images degraded by noise with fuzzy edges and transitions between objects. In the paper, results of the segmentation of medical images by the active contour method are compared with results of the segmentation by other existing methods. Experimental applications which demonstrate the very good properties of the active contour method are given.

Keywords: Medical image processing, image segmentation, liver tumor, temporomandibular joint disc, watershed method

1. Introduction

IMAGE PROCESSING has become a very active discipline in the last few years. Methods of image processing are a tool for measuring the qualitative and quantitative parameters of industrially produced objects [1] or in medicine. Producing images of soft tissues with the aid of magnetic resonance (MR) tomography is an important area of medical diagnostics today. The processing of MR images, referred to as MRI, covers a broad spectrum of individual steps. The first of them is the pre-processing of the image (image reconstruction, brightness transformations, geometric transformations, noise filtering, edge detection, and image sharpening) [2, 3, 4, 5]. This can be followed by extracting objects from the image using segmentation methods. A physician can process the image only subjectively (manually). In the course of manual processing the results may be subject to error due to the human factor, fatigue, low degree of repeatability, physician's experience, etc. On these grounds, automatic or at least automated image segmentation after image pre-processing plays a very important role. The precision of subsequent qualitative and quantitative description or further image processing, visualization, etc. depends on the precision of segmentation. For a comparison of the segmentation properties of the methods, two sets of real medical images were chosen: a) MR images of the human liver with a tumor visible in several slices, b) MR images of the human head for the processing of the region of temporomandibular joint (TMJ).

Extensive research was conducted in the area of processing MR images of tumors 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. The topicality of the selected topic of liver tumor 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" [6], 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 [7] 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 string gives very good results. A disadvantage can certainly be seen in the many degrees of freedom of this string. A simpler approach is described in [8]. 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 mentioning of important parameters such as segmentation speed or differences in comparison with the actual/real division of tissues, for example by manually tracing the tumor edges. A similar approach, segmentation of liver tumor area by the level set method, is described in [9]. 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 tumor 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 [10], thresholding method [11] and region growing method [12]. Another possibility is the application of statistical methods such as the hidden Markov models [13]. Again, the proposed algorithm consists of image pre-processing, segmentation by a model, and post-processing of the segmented image. The development of the method for the segmentation of liver tumors follows from the previously published work [14], 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 tumor in tomographic images is required or it is necessary to choose a large number of segmentation parameters or to pre-process the images.

In the case of processing tomographic images when diagnosing a diseased TMJ we come across problems similar to those in the segmentation of liver tumor regions. 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 segmentation of this small low-contrast region is very difficult, in particular if it is to be done within a reasonable period of time and with the lowest possible level of interaction with the physician. The construction of a three-dimensional model from segmented MR slices can be found, for example, in [15]. Here, the author describes the disc segmentation using a model from the known tissue distribution in the TMJ region. The approach has the disadvantage of failing in the case of major degradation of the surrounding tissues, from which the disc position is derived. The kernel of the segmentation proper is the watershed method. It is known that with this method, it is absolutely necessary to post-process the image since the method itself gives highly over-segmented results. The segmentation of TMJ is based on the previous research into a method that can be used to extract the disc region from a complex image of the human head. Initial experiments have been made with the active contour method, which takes the image as a region that is subdivided into sub-regions with different mean intensity values. The method assumes that each actual sub-region represents an actual distribution of tissues in the MR image. This procedure usually fails because it is not possible to determine in advance how many different mean intensities are to be sought in the image. The result is either over-segmented images when a great number of phases of the segmented image was chosen or incomplete segmentation, for which image post-processing is also necessary [16].

The selected segmentation methods are based on the solution of partial differential equations. They are modern methods of image processing – based on active contours. This approach is of much advantage in the segmentation of an actual image, loaded with noise and with non-sharp edges and transitions between objects. A method for the segmentation of MR images is described in the paper, designed for the construction of a 3D model of the mandibular disc, tumors in human organs, and other applications.

2. METHOD

The image being scanned is loaded by various types of distortion. In addition to the omnipresent noise, it may be a geometric distortion due to the optical properties of the lenses, brightness distortions, defocusing, etc. [2, 3]. The task of the pre-processing is to appropriately prepare the image for subsequent image segmentation and to effectively eliminate distortion during the scanning and the transfer of image signal to the system of further processing. According to the image processing chain, a suitably pre-processed image can be segmented – the "useful signal" can be separated from the background. In many traditional segmentation methods the result strongly depends on the quality of pre-processing. If the image being scanned is loaded by noise and segmented without prior noise filtering, the noise may partially appear also in the output image. The consequence then is a superfluous classification of non-existent objects in the noise area. This problem is solved to a considerable extent by segmentation methods, which can cope even with a partially noisy image [17]. As described in experimental applications, it is the methods of active contours that are the issue here. An advantage of these methods has already been mentioned – the segmentation can be partially independent of the image noise or interrupted edges of the objects being segmented; included can be here also the a priori knowledge of the shape of the configuration being sought, etc.

Image parameters for segmentation

When selecting a suitable method there is a range of image parameters that play an important role and which need to be assessed, be it mathematically or subjectively (by sight). An edge-based analysis needs to be made for this selection.

The first parameter in the selection of an appropriate segmentation technique is the edge sharpness. Edges in the image can be assessed either subjectively (transitions between individual regions are visible with the naked eye) or mathematically. The mathematical analysis of edges uses the edge detectors [2, 3], which are based on the convolution of the image with the convolution mask, which represents the given edge detector.

An important parameter influencing not only the segmentation result but also the effectiveness of the whole image processing chain is noise or the signal-to-noise ratio (SNR) [2]. As regards segmentation, it is necessary to bear in mind one important thing: noise, the same as image edge, is represented by the higher components of the space frequency spectrum. Eliminating the noise by suppressing the higher components of frequency spectrum will blur the edges. By contrast, enhancing the edges will simultaneously increase noise in the image. This problem is addressed, for example, by the median noise filtering, which preserves the edge sharpness while effectively suppressing noise in the image [2, 3].

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. This is of much advantage when processing images exactly by the MR method. There are many definitions for determining the level of noise [2, 3, 19, 20]. For example, the ratio of the mean brightness level S in the homogeneous region of interest to the standard brightness signal deviation N in the region with the least possible brightness level:

$$\mathrm{SNR} = 20\log\left(\frac{S}{N}\right)\ [\mathrm{dB}], \tag{1}$$

Segmented images often exhibit low contrast in the region of interest. In evaluating the image quality a parameter can be used which gives the contrast-to-noise ratio (CNR) [20, 23]. It combines the signal-to-noise ratio with the contrast of two regions, A and B. It is given by the difference of these two ratios in the given regions:

$$\mathrm{CNR} = \mathrm{SNR_A} - \mathrm{SNR_B}\ [\mathrm{dB}]. \tag{2}$$

On the assumption that the goal is to obtain a completely segmented image, i.e. with individual segments corresponding to the actual objects in the original images, it is necessary to ensure that the segmentation is not sensitive to interrupted edges and noise, which may erroneously be detected as an edge point, and it must recognize overlapping objects. One can also come across brightness degradation but an appropriately selected segmentation method should not be sensitive to these changes in brightness. The parameters for determining the segmentation method quality can be summarized in the following: resistance to interrupted edges and noise, ability to recognize overlapping objects, resistance to global linear/step changes in brightness or contrast, and the possibility of model-controlled segmentation.

Segmentation methods

Modern image processing methods, and not only segmentation, are based on solving partial differential equations, and are referred to as active contour methods. 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. Composing the energy function significantly influences the properties of the method which can thus be adapted to the given application. The method of active contours can be adapted such that it is not sensitive to noise and interrupted edges, and delineates problematic objects in the image even without prior pre-processing or post-processing of segmented data. Likewise, the method can be adapted such that it is resistant to global brightness changes in the image. The methods are particularly suitable for applications in which it is necessary to ensure robustness as regards the image parameters changing with time. The possibility of leaving out image pre-processing means reducing the segmentation parameters and thus simplicity of implementation. The active contour methods enable the two described approaches to image segmentation – via edge-based analysis [24, 25] as well as via statistical analysis of regions [24, 27]. There are two possibilities how to describe the curve delineating in the image the region sought. The first possibility is the curve description [24, 30]. The curve in the image is discretized using a piecewise linear curve that is formed by points – nodes, which at the time of solution change their position and thus change the shape of the curve. The number of nodes can increase or decrease at the time of solution. The result is always a closed curve. A disadvantage of parametric description is the complexity of the algorithm. Also, parametric description does not enable a simple changing of the curve topology – dividing the curve into two or more curves or uniting the curves into one curve. A more advantageous description can be obtained using the so-called level set method (LSM) [17, 24, 25, 27]. In this case the curve is represented by the intersection of the plane and the level set function, the form of the latter depending on the initial conditions and on the solution of partial differential equation over this function. An advantage of such a description is mainly the possibility of changing the topology: the curve can simply change its shape and position, it can be divided into several further closed curves or it can join several curves into one. A disadvantage of this curve description is that at each step of calculating the solution of partial differential equation a large volume of numbers enters the calculation – the level set function is defined over the whole extent of the image. The speed of solution decreases rapidly with the size of the image being processed. This problem can, however, be solved by the so-called fast LSM [29], which at each solution step changes the form of the level set function only in the close surrounding of the boundary. Active contour methods also enable segmenting an image according to a defined model of the shape of the object sought [31]. In the segmentation via region analysis, not only the most common mean brightness value of the region can be included in the mathematical model but also other statistical properties of the region such as variance or texture properties. Applications of active contours in image segmentation can be encountered that are based on local analysis [28]. These methods can be considered very robust and, in spite of iterative solution, sufficiently fast.

Design considerations

Two typical examples of application are given in the paper, which consist in the design of a sequence of image processing methods. 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 the ideal case, to segment the regions sought, without the necessity of image pre- and post-processing. In the segmentation of mandibular discs it is necessary to address the problem of low image contrast (CNR = 17.9 dB, SNR = 16.1 dB) at the site of the joint together with the very low number of pixels (41 pixels $\approx$ 9.2 mm^2), which represent the TMJ disc. Current segmentation methods fail here due to the presence of image noise and heavily suppressed region edges. The problem of manual processing lies in the very subjective view of MR images in the region of TMJ. The region of the TMJ disc changes smoothly into the region of connective joint tissue. This results in a big influence of the human factor on the results of processing and in big time demands.

By contrast, when processing MR images of human liver the segmentation of the liver tumor region is complicated by the fact that the tumor region intensity, 287.1±24.2, is very similar to the intensity of the region of the vein that supplies the tumor, 321.4±16.0. The aim of the segmentation is to separate only the tumor region from the liver and vein region. With regard to image resolution the tumor region with an intensity of 545.2±21.9 is sufficient (maximum tumor area 541.8 mm^2). The problem of processing images of human liver manually is not the low processing precision as in the case of TMJ images but rather the time demands. The paper also gives a comparison of the manual and the automatic processing from the viewpoint of the precision of volume evaluation and the viewpoint of time demands.

In view of the frequently unfavorable properties of the images being scanned, the processing of MR images goes beyond the traditional approaches. Very frequently MR images have a low contrast exactly at the site of seeking a particular pattern; the images tend to be noisy and the regions sought can be very small with respect to the size of the pixels. Methods have been described that can cope with the processing of images with such properties. These are the already mentioned active contours. Many variants of active contours have been described, the basis being always the energy functional defining the behavior of a curve or area in a 2D or 3D image. Via solving discretized equations, the shape of the curve changes iteratively from the initial solution to a steady state when in the ideal case the curve delineates the region sought. Active contours can be subdivided into two basic types according to the definition of the curve in the image: parametric representation of the curve and geometric representation of the curve [31].

Parametric representation of the curve is not of much advantage. A much better approach to the curve representation is its geometric representation [18]. In this case the curve is not given by a number of points known in advance and by their linkages but by the intersection of the plane with the distance function.

The curve, which in the image evolves from the initial solution to steady state, is defined by the relation [27]:

$$C(t) = \{(x, y) | \phi(t, x, y) = 0\}, \tag{3}$$

where $\Phi(t,x,y)$ is the so-called level set function, which evolves in time t in plane xy. A general equation describing the behavior of the level set function is given by the relation [30]:

$$\frac{\partial \phi}{\partial t} + F |\nabla \phi| = 0, \tag{4}$$

where F is the speed function influencing the behavior of the curve in the image. In the case of image segmentation the speed function will adapt the curve shape such that it delineates the region sought. The above equation [18] is a universal tool for modeling various physical phenomena. In the region of image segmentation, the function F is chosen such that it depends on image data (pixel intensity and edges in the image) and on the LS function itself.

In view of the approach of the segmentation method to image data (intensity function), the active contour method can be subdivided into two basic types – edge-based segmentation [24, 25] and region-based segmentation [24, 27]. In the medicine applications mentioned the edge approach proved to be of better use.

The edge-based segmentation method deforms via iterative solution of partial differential equation the LSM function such that the curve approximates as much as possible the edges found in the image. From this it follows that the method is preferably applicable to the segmentation of an image with more pronounced edges. The LSM equation is in this case extended to the form:

$$\frac{\mathrm{d}\phi}{\mathrm{d}t} = g(|\nabla I|)\,\mathrm{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \alpha g(|\nabla I|)|\nabla \phi| + \nabla g \cdot \nabla \phi, \tag{5}$$

where I is the input image, α is the stabilizing constant ensuring solution convergence, and g is the function that terminates the evolution of the level set function at the point where the curve reaches the edge in the image.

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.

3. Hardware used

All images were processed on a PC with the Intel Core2 Quad 2.66 GHz processor, 4 GB RAM, running on the Windows 7, 64-bit operational system. The Matlab R2008b environment with the Image Processing Toolbox was used to implement the algorithms. All the times given for the image processing correspond to this HW and SW equipment.

4. Status report

Reconstruction of temporomandibular joint disc

Changes in the position of mandibular disc belong to the most frequent diseases of the TMJ. The TMJ disc is a cartilaginous disc joining the upper joint space with the mandible head. The task of the disc is to level out the curvature of joint areas and to assist in transmitting the chewing forces. 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. Since the mandibular disc is a soft tissue, the application of MR is the preferred choice. The possibility of having images of the soft tissue of TMJ and creating its 3D model represents considerable progress and is of much benefit to both doctors and patients.

The first problem that makes obtaining MR images of the mandibular disc difficult is its small size. The shape of the tissue resembles a true disc of approx. 1 cm in diameter and a few millimeters in height. When standard tomography of the human head is applied, the disc in an MR image is thus represented by a few pixels only. Another problem is the low contrast between the mandibular disc region and the hard tissues in its surroundings. Everything indicates that using traditional segmentation methods to delineate the mandibular disc would be a complicated matter with an uncertain result. To obtain MR images, a tomographic device with a basic magnetic field induction of 1.5 T was used. Altogether, 22 images weighted by relaxation time T_1 (T_E = 8 ms, T_r = 170 ms) in the sagittal plane were obtained using the FFE (Fast Field Echo) sequence. The images are of equidistant distribution in steps of 2.3 mm, slice thickness 2 mm, and slice spacing 0.3 mm. The actual size of the area represented by one pixel is 0.46875 x 0.46875 mm, and image resolution is 320 x 320 pixels.

Reconstruction of liver tumors

Consultations with physicians from the Faculty Hospital in Brno Bohunice led to the solution of problems in the area of tumor diseases. Present-day software does not allow monitoring the evolution of liver tumors during the treatment. The diagnostic methods are based only on a subjective assessment of individual human liver images obtained by available imaging techniques. A major contribution of the described application of methods proposed for image processing is the possibility of monitoring the quantitative parameters of tumor regions in images obtained during treatment. The possibility of objectively parametrizing the tumor evolution and creating its 3D model is a significant contribution in oncology diagnostics. MR images of liver exhibit good contrast. The problem is to delineate by a smooth closed curve only the tumor region such that the curve does not delineate any other tissues. This can happen in the comparatively frequent case when the tumor is at the liver periphery; it is then important not to exceed the liver boundary.

The aim of processing is to segment the tumor in all slices, reconstruct the obtained segments back to a 3D image and calculate the tumor volume so that the tumor evolution in time can be monitored. The images were obtained using a tomographic device with a basic magnetic field induction of 1.5 T. Via the FFE (Fast Field Echo) sequence a total of 30 images were made, weighted by relaxation time T_1 (T_E = 5 ms, T_r = 117 ms) in the transversal plane. The images are of equidistant distribution in steps of 7 mm, which is identical to the thickness of one slice. The actual size of the area represented by one pixel is 0.811 x 0.811 mm, image resolution is 512 x 512 pixels.

5. RESULTS

The main advantage of segmenting the MR images of liver tumors and TMJ discs by the method of active contours based on the edge-based analysis is the obtained resultant closed curve delineating the tissue sought. The segmented image does not require any further processing. The result of segmentation without post-processing is very close to the results of manual processing.

The results of segmentation are given in Fig.1. The parameters of the proposed segmentation of images of the mandibular disc are: mathematical model of segmentation method: edge-based LSM segmentation, iteration step 10, coefficient of expansion direction and speed α = -1.5, coefficient of the smoothing of Dirac function ε = 0.1, standard deviation of the Gaussian filter 0.01, size of the Gaussian filter mask 5, number of iterations 500, initial form of LS functions: Φ = -4 inside initial curve, Φ = 4 outside initial curve.

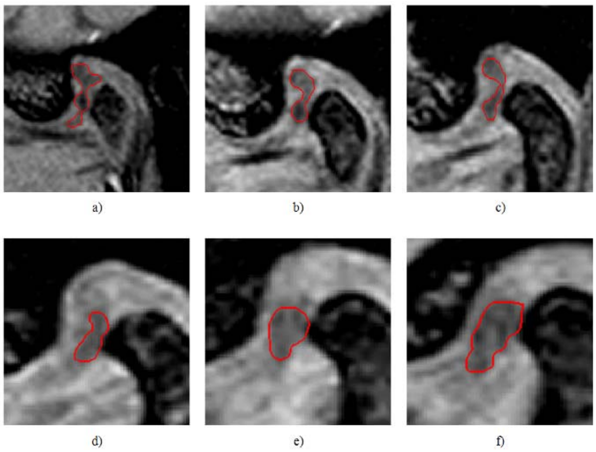

Fig.1. Result of segmentation of TMJ in six selected slices, a) – f) 1. – 6. slice through TMJ.

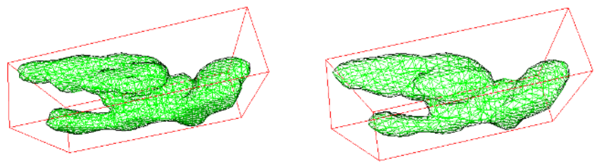

Fig.2. Three-dimensional polygonal model of TMJ disc, made of 6 segmented slices; on the left, oversampling level 3 on the right.

Individual segments can be used to reconstruct an estimate of the original three-dimensional shape of the mandibular disc. However, the quality of the reconstructed object is very low due to the small number of slices with visible disk. In the case of three-dimensional smoothing of the joint disc it is imperative to find an appropriate compromise such that image patterning (slice thickness) is not noticeable and, simultaneously, the details of the object are preserved to a maximum degree. A three-dimensional model of TMJ is shown in Fig.2. On the left is the result of modeling the disc shape with the oversampling coefficient 2, on the right with the oversampling coefficient 3. The differences due to changes in the level of smoothing can be seen on both the polygonal model and the model with smoothed surface. At a lower smoothing level, transitions are visible between individual segments but there is no simultaneous suppression of the details of TMJ, which can be a decisive factor in determining the treatment. With increased smoothing level the staggered shape of the model comes to be suppressed, with the transitions between individual model segments suppressed. The model thus appears to be smoother. But this entails an undesirable suppression of details. The problem recalls the filtering of a two-dimensional image, when a compromise needs to be found between the level of noise smoothing and edge preservation.

Fig.3 shows the results of segmenting a liver tumor 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, focusing) and which delineates only the region of the tumor 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 tumor. The proposed values of the segmentation parameters are: mathematical model of segmentation method: edge-based LSM segmentation, iteration step dt = 10, coefficient of expansion direction and speed α = 1.5, coefficient of the smoothing of Dirac function ε = 0.1, standard deviation of the Gaussian filter kernel σ = 0.1, size of the Gaussian filter mask 3, number of iterations 1000, initial form of LS function is the same as in the case of temporomandibular joint disc segmentation.

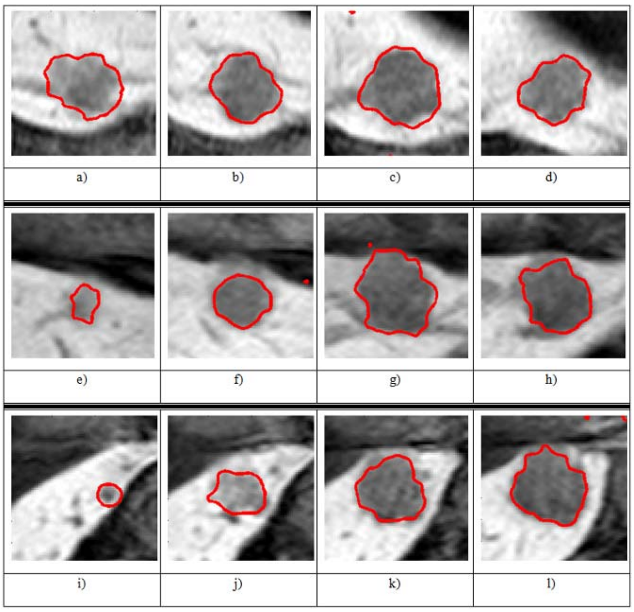

Fig.3. Results of segmenting a liver tumor by the active contour method based on edge-based analysis; a) – d) 4 slices in the sagittal plane, i) – l) 4 slices in the transversal plane.

Due to its size and contrast, the liver tumor could be segmented also manually. There are many professional medical applications that make this possible. But if the tumor is captured in several slices and, in addition, in three planes, the number of images in which it would be necessary to delineate manually increases greatly. It is therefore of advantage to choose automatic processing, which in the final result need not achieve the same or greater accuracy than manual segmentation does but is much faster and more comfortable. An example of the comparison of the liver tumor volume established by manual and automatic segmentation is shown in Table1. From the values given in Table1 it is clear that the time necessary to process one tumor by manual segmentation is much longer than when automatic segmentation is used. The total time necessary for manual segmentation in three planes was roughly 5 minutes without calculating the tumor volume while image evaluation via automatic segmentation, inclusive of establishing the tumor volume, took about 1 minute.

Table 1. Comparison of manual and automatic segmentation, and evaluation of liver tumor volume.

			Plane	
		sagittal	coronal	transversal
Number of pixels [-]		3147	2631	3171
Pixel dimension [mm]		0.811	0.777	0.811
Total area [mm^2]		2069.848	1588.411	2085.633
Slice thickness [mm]		7	7	7
Tumor vol. [cm^3]	automatic	14.49	11.12	14.60
	manual	9.70	10.00	10.10
Processing time [s]	automatic	20	25	30
	manual	80	100	120

Fig.4 gives an example of three-dimensional reconstruction of a tumor via automatic image processing. The following images were available: 4 in the transversal plane, 5 in the frontal plane, and 4 in the sagittal plane. These 13 images were segmented manually (approximate tumor boundaries were marked out using the mouse) and a three-dimensional model was created from the tumor contours in the three planes, using the TomoCon 3.0 software.

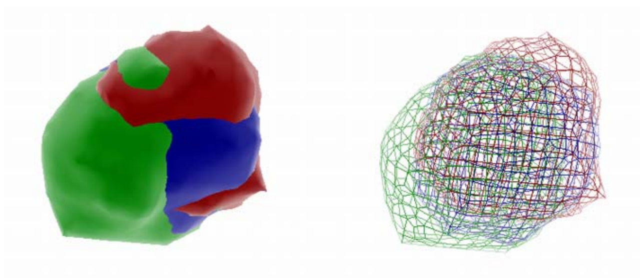

Fig.4. Result of three-dimensional tumor reconstruction with prior automatic segmentation in three planes of image scanning; surface model on the left, polygonal model on the right.

It can be seen, from the polygonal model in particular, that the tumor edges obtained from the individual scanned planes complement each other; reconstruction using images from one plane only would be inaccurate.

The results were compared with other segmentation methods that are also frequently used to process medical images. Results of the segmentation of MR images in regions of interest can be demonstrated on several examples. The image of a slice through liver tumor segmented by the active contour method is used for the comparison. The result of segmentation can be seen in Fig.3c). In this chapter a comparison of the segmentation of a selected image and other traditional segmentation approaches is shown. 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 tumor by the thresholding segmentation method [2, 3] with three different thresholds, which were established empirically (100, 125, 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 tumor were segmented while with a higher threshold level a contour was found that delineates the tumor region and goes through the tumor "edge" but this curve is not closed and penetrates farther into the liver region, out of the tumor. 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 processed further in order to obtain a complete segmentation result.

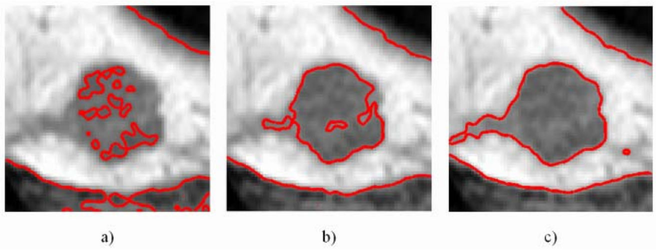

Fig.5. Result of segmenting the image of a slice through liver tumor via thresholding with thresholding levels a) 100, b) 125, c) 150, within a brightness intensity range of 0 – 255.

Fig.6 gives the result of the Sobel mask edge-based analysis [2, 3] with three different levels of thresholding the edge-based analysis image (0.05, 0.1, 0.15). The edge-based analysis yields results similar to those of the segmentation thresholding method. Choosing a low threshold value gives an over-segmented 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.

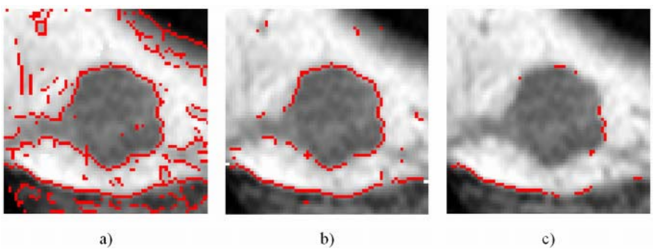

Fig.6. Result of edge-based analysis of a slice through liver tumor using the Sobel mask, with threshold values a) 0.05, b) 0.1, c) 0.15.

Fig.7 shows the result of image segmentation of a slice through liver tumor using the watershed segmentation method [2]. 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 over-segmented and the image must practically always be adapted in an appropriate way. Fig.7b) 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 tumor reaches into the liver region since the method responds to any minute interruption of the edge by merging the regions.

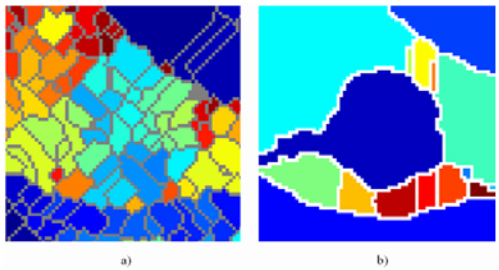

Fig.7. Result of image segmentation of a slice through liver tumor using the watershed segmentation method; a) over-segmented result without pre-processing, b) with pre-processing.

Fig.8 shows the result of image segmentation of a slice through liver tumor using the two-phase region-based segmentation method of active contours [24]. The method gives a result that is very similar to that of simple thresholding. An advantage of this method is that an appropriate threshold is found fully automatically by solving iteratively a partial differential equation, whose solution is a steady state of the curve that "moves" in the course of solution from the initial solution (primitive geometric configuration) over the image such that it divides the image into regions with the lowest possible variance of brightness values. As opposed to simple thresholding, the boundaries established by the active contour method are smoother due to the filtering properties. The result of segmentation via region-based active contours also recalls the result of watershed segmentation after the pre-processing of the input image. The segmented region of the tumor reaches also into the liver region and thus the segmentation result would anyway have to be further processed.

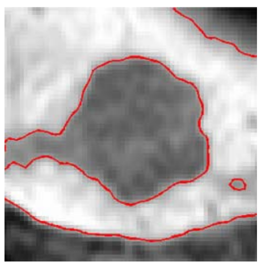

Fig.8. Result of image segmentation of a slice through liver tumor using the two-phase region-based segmentation method of active contours.

For the purposes of segmenting the tissues mentioned, which are represented by tiny regions in noisy images, these methods can be considered inappropriate. It follows from the results of processing by these simple methods that sophisticated methods of image processing need to be employed if the processing procedure is to be sped up while maintaining the required precision.

6. CONCLUSION

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.

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, with subsequent 3D reconstruction. 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. In the case of liver segmentation, good results are obtained using the thresholding, watershed, and region-based level set methods, but all these methods include in the liver tumor region also the region of the supply artery in view of its similar intensity. The application of automatic segmentation of MR images results in a pronounced acceleration of processing. The two types of processing the MR images of liver tumors were compared, with the result that the manual processing took almost four times longer than the automatic processing using active contours.

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REFERENCES

[1] Frollo, I., Andris, P., Přibil, J., Vojtíšek, L., Dermek, T., Valkovič, L., (2010). Measurement and imaging of planar electromagnetic phantoms based on NMR imaging methods. *Measurement Science Review*, 10 (3), 97-101.

[2] Jan, J. (2006). *Medical Image Processing, Reconstruction and Restoration : Concepts and Methods.* CRC Press.

[3] Hlavac, V., Sonka, M. (1992). *Image Vision*. Praha: Grada.

[4] Valkovič, L., Windiwschberger, C. (2010). Method for geometric distortion correction in fMRI based on three echoplanar phase images. *Measurement Science Review*, 10 (4), 116-119.

[5] Marcoň, P., Bartušek, K., Kořínek, R., Dokoupil, Z. (2011). Correction of artifacts in diffusion-weighted MR images. In *34th International Conference on Telecommunications and Signal Processing,* 391-397.

[6] Deng, X., Du, G. (2008). *Editorial: 3D segmentation in the clinic: A grand challenge II – liver tumor segmentation*. http://grand-challenge2008.bigr.nl/ proceedings/liver/ articles.html

[7] Seo, K.S., Chung, T.W. (2005). Automatic boundary tumor segmentation of a liver. In *Computational Science and Its Applicationas - ICCSA 2005*, LNCS 3483. Springer, 836-842.

[8] LI, B.N., Chui, Ch.K., Ong, S.H., Chang, S. (2009). In *IFMBE Proceedings (Integrating FCM and Level Sets for Liver Tumor Segmentation - ICBME 2008)*, Vol. 23, 202-205.

[9] Smeets, D., Loeckx, D., Stijnen, B., Dobbelaer, B., Vandeurmeulen, D., Suetens, P. (2010). Semi-automatic level set segmentation of liver tumors combining a spiral-scanning technique with supervised fuzzy pixel classification. *Medical Image Analysis*, 14, 13-20.

[10] Stawiaski, J., Decenciere, E., Bidault, F. (2008). Interactive liver tumor segmentation using graph-cuts and watershed. *MiDAS Journal (MICCAI 2008 Workshop : Grand Challenge Liver Tumor Segmentation)*. http://www.insight-journal.org/ browse/journal/45

[11] Abdel-Massieh, N.H., Hadhoud, M.M., Amin, K.M. (2010). Automatic liver tumor segmentation from CT scans with knowledge-based constraints. In *5th Cairo International Biomedical Engineering Conference*.

[12] Qi, Y. et al. (2008). Semi-automatic segmentation of liver tumors from CT scans using Bayesian rule-based 3D region growing. *MiDAS Journal (MICCAI 2008 Workshop : Grand Challenge Liver Tumor Segmentation)*. http://www.insight-journal.org/ browse/journal/45

[13] Häme, Y., Pollari, M. (2011). Semi-automatic liver tumor segmentation with hidden Markov measure field model and non-parametric distribution estimation. *Medical Image Analysis*, 16 (1), 140-149.

[14] Mikulka, J., Gescheidtova, E., Bartusek, K. (2010). Processing of MR slices of human liver for volumetry. In *Proceedings of PIERS 2010*, 22-26 March 2010. Xi'an, China, 202-204.

[15] Smirg, O., Liberda, O., Sprlakova, A., Smekal, Z. (2011). Creating a 3D model of the temporomandibular joint disc on the basis of segmented MRI slices. In *34th International Conference on Telecommunications and Signal Processing - TSP 2011*, 18-20 August 2011. Budapest, Hungary, 369-375.

[16] Smekal, Z., Liberda, O., Bartusek, K., Mikulka, J. (2009). Data processing in studying the temporomandibular joint, using MR imaging and sonographic techniques. In *16th International Conference on Digital Signal Processing - DSP 2009*. Santorini, Greece, 100-106.

[17] Osher, S., Fedkiw, R. (2003). *Level Set Method and Dynamic Implicit Surfaces*. New York: Springer-Verlag.

[18] Fukunaga, K. (1990). *Introduction to Statistical Pattern Recognition*. Academic Press.

[19] Bushberg, J.T. et al. (2006). *The Essential Physics of Medical Imaging*. Philadelphia: Lippincott Williams & Wilkins.

[20] Rabbani, H. (2011). Statistical modeling of low SNR magnetic resonance images in wavelet domain using Laplacian prior and two-sided Rayleigh noise for visual quality improvement. In *Measurement Science Review*, 11 (4), 125-130.

[21] Peli, E. (1990). Contrast in complex images. *Journal of the Optical Society of America*, 7 (10), 2032-2040.

[22] Michelson, A.A. (1995). *Studies in Optics*. Dover Publications.

[23] Xiaomei, S. et al. (2004). Automated region detection based on the contrast-to-noise ratio in near-infrared tomography. *Applied Optics*, 43 (5), 1053-1062.

[24] Aubert, G., Kornprobst, P. (2006). *Mathematical Problems in Image Processing : Partial Differential Equations and the Calculus of Variations* (2nd ed.) New York: Springer.

[25] Li, Ch., Xu, Ch., Gui, Ch., Fox, M.D. (2005). Level set evolution without re-initialization: A new variational formulation. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition - CVPR'05*. IEEE, 430-436.

[26] Osher, S., Sethian, J.A. (1988). Fronts propagation with curvature-dependent speed: Algorithms based on Hamilton-Jacobi formulations. *Journal of Computational Physics*, 79, 12-49.

[27] Vese, L.A., Chan, T.F. (2002). A multiphase level set framework for image segmentation using the Mumford and Shah Model. *International Journal of Computer Vision*, 50 (3), 271-293.

[28] Lankton, S., Tannenbaum, A. (2008). Localizing region-based active contours. *IEEE Transactions on Image Processing*, 17 (11), 2029-2039.

[29] Shi, Y., Karl, W.C. (2008). A real-time algorithm for the approximation of level-set-based curve evolution. *IEEE Transactions on Image Processing*, 17 (5), 645-655.

[30] Xu, C., Yezzi, A., Prince, J. (2000). On the relationship between parametric and geometric active contours. In *34th Asilomar Conference on Signals, Systems and Computers*, 483-489.

[31] Tsai, A., Yezzi, A., Wells, W., Tempany, C., Tucker, D., Fan, A., Grimson, W.E., Willsky, A. (2003). A shape-based approach to the segmentation of medical imagery using level sets. *IEEE Transactions on Medical Imaging*, 22 (2), 137-154.

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