# Segmentation and Quantification of Brain Tumor

Chunyan Jiang, Xinhua Zhang, Wanjun Huang, Christoph Meinel
Department of Computer Science, University of Trier
Campus II, University of Trier, 54286, Germany
Phone: +49-651-201-2838, Fax: +49-651-201-3954, Email: jiang@ti.uni-trier.de

*Abstract* – *Nowadays, the inside situation could be obtained by medical machines, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) scanner, etc. These noninvasive diagnosis means increase the precision of the diagnoses, at the same time decrease the pain of the patients. Brain tumor diagnoses benefits from these devises very much. In the brain MR image, the tumor is shown clearly. For the treatment, the physician also needs the quantification of the tumor area. This requires the abnormal part in the image to be segmented accurately; afterward the segmented area can be measured. This task could not be handled by hands totally. The computer can give great help during this procedure.*

*In this paper we introduce one system to perform the task mentioned above. In this system, the brain tumor MR image is segmented semi-automatically. One deformable model-based method is adapted in the system. And by the graphic user interface, the segmentation can be intervened by user interactively at real time.*

*Keywords* –*MRI, segmentation, level-set, quantification, DICOM*

## I. INTRODUCTION

Since the X-ray was first used for taking the photography of human's internal information at 1895, the doctors' diagnosis relay more and more on the internal imaging techniques. Along with the developing of the techniques, there are more and more new machines can reveal the human inside in 2D or 3D. For example, Computed Tomography (CT) scanners reconstruct 3D volumetric maps of X-ray attenuation coefficients; while Magnetic Resonance Imaging (MRI) scanners differentiate various soft tissues, and functional MRI (fMRI) or Positron Emission Tomography (PET) acquire functional information modality. These assistant diagnostic devices are much helpful for the doctor during disease diagnosis and treatment, as well as decreasing the invasive pain of the patient. The plenty of acquired medical images show the inside to doctor, however, the doctors want to know more than peer images, such as emphasizing the abnormal tissue, quantifying its size, rendering its shape, and so on. If these tasks are covered by the doctors themselves, it may be inaccurate or impossible, and burdens them heavily. Thus, computer image processing is important in radiology. And there are already many computer-aided diagnosis systems are put into practice in disease monitoring, operation guiding, etc. Among all medical image processing, image segmentation is initial and important work, for example, quantification of specified area must based on accurate segmentation. But it is still not solved very well, because of the complexity of the medical image.

Therefore in the computer-aided diagnosis (CAD) system, the expert hand work for image segmentation is the gold standard. But it is too time consuming, tedious, and further more, maybe difficult for the doctor to handle it. The automatic image segmentation by computer is often doubted by the expert since the doctor's knowledge and experience is more important in the interested area determining, and computer could not simulate all the doctor's actions in the diagnosis. So the CAD system should find a good balance between manual manner and automatic manner in the segmentation procedure. To reach this goal, the system should implement the algorithm of the segmentation, which could get the most precise result as possible. In the other hand, the system should adapt good interactive mechanism that segmentation could be under the user's control and give the feedback in the real time. This paper describes our CAD system, Med-Volumeter, which is such a general-purpose segmentation quantification, and visualization tool for medical image processing and be used in brain tumor cases currently. The system is developed under telemedicine environment and can communicate with other modules according to the telemedicine standard.

This paper will be structured as follows; In Section 2 we will introduce the telemedicine and DICOM, which are environment and input data in our system; In Section 3, 4, 5 we will describe main processing procedures in our system orderly, which are visualization, segmentation and quantification. The last part, section 6, is the conclusion and future work.

## II. TELEMEDICINE AND DICOM

The definition of telemedicine [1], broadly speaking, is to incorporate the remote delivery of health services and health information via information technology. Telemedicine systems consist of integrated networks offering such services. For the health information communication, a standard method for the transmission of medical images and their associated information should be employed. DICOM (the abbreviation of digital imaging and communications in medicine) is such a standard. This standard was created by the National Electrical Manufacturers Association (NEMA) to aid the distribution and viewing of medical images, such as CT scans, MRIs, and ultrasound. It is used or will soon be used by virtually every medical profession that utilizes images within the healthcare industry. DICOM Standard [2] is an international standard for communication of biomedical diagnostic and therapeutic information in disciplines that use digital images and associated data.

A single DICOM file contains both a header and all of the image data, that header stores information about the patient's name, the type of scan, image dimensions, as well as information in three dimensions etc. This is different from the popular Analyze format, which stores the image data in one file (*.img) and the header data in another file (*.hdr). Fig. 1 shows a part of DICOM image file's header and following one image. The output of header data is generated by one free software TI-jPACS. The description of the software can be found at http://www.informatik.uni-trier.de/TI/Projekte/Telemedizin/tijpacs.html. In this example, header describes the image dimensions, size, spacing, orientation, etc. Here only part of information is shown, which are related to image rendering and some compulsory elements groups. The header also retains other text information about the scan. The size of this header varies depending on how much header information is stored. Here, the header defines an image which has the dimensions 512x512 pixels, with a data resolution of 1 byte per pixel. The image data follows the header information (the header and the image data are stored in the same file). It occupies 6088 bytes.



```
[0008,0008]  Image Type: ORIGINAL\PRIMARY\OTHER
[0008,0016]  SOP Class UID: 1.2.840.10008.5.1.4.1.1.4
[0008,0018]  SOP Instance UID:
1.3.12.2.1107.5.2.1.5603.2003073109384588400330
[0008,0023]  Image Date: 20030730
[0008,0033]  Image Time: 130728.379000
[0008,0060]  Modality: MR
[0008,0070]  Manufacturer: SIEMENS
[0018,0023]  MR Acquisition Type: 2D
[0018,0050]  Slice Thickness: 005.000000E+00
[0020,0032]  Image Position (Patient): -99.2808\-99.8447\62.1835
[0020,0037]  Image Orientation (Patient):
0.999391\0.0060602\0.0343693\0\0.984808\-0.173648
[0020,1041]  Slice Location: -04.733905E+01
[0028,0002]  Samples per Pixel: 1
[0028,0004]  Photometric Interpretation: MONOCHROME2
[0028,0010]  Rows: 512
[0028,0011]  Columns: 512
[0028,0030]  Pixel Spacing: 004.101563E-01\04.101563E-01
[0028,0100]  Bits Allocated: 16
[0028,0101]  Bits Stored: 12
[0028,0102]  High Bit: 11
[0028,0103]  Pixel Representation: 0
[0028,1050]  Window Center:   662\ 662
[0028,1051]  Window Width:   1430\ 1430
[7FE0,0010]  Pixel Data: 6088
```
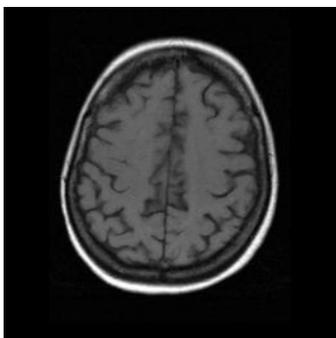
Fig. 1. An example of DICOM file's header data

Our system use DICOM file as input data so that take advantage of some information related the image in

visualization procedure, and same to measurement procedure. In the visualization procedure, the space information of the image can be used for rendering the image in the coordinate system correctly. And for constructing 3D image from a set of 2D images, the position information of every image can used for order the image data in the third dimension. The space information about pixel is used for measurement the size of interested area. That information stored in DICOM file with image data guarantee the precision of visualization and quantification procedures in our system. Furthermore, the segmented information can also be stored in DICOM file and communicated in the telemedicine system. It benefits the remote consultation on one case between several doctors. Nowadays, the DICOM standard only defines 2D image modality. There are already some supplements and proposals about 3D image data definition in DICOM [3].

## III.    VISUALIZATION

As reading a series of image data, the 3D image is built by these parallel slices. This 3D image is raw data without any extraction or deleting. However, if drawing the raw 3D image as pixel's matrix on the screen directly, only one black cube is drawn on the screen that it is the cover of the matrix. The content inside the image could not be shown. Our system applies the ray casting method to render the content of the 3D image. The basic goal of ray casting is to allow the best use of the three dimensional data and not attempt to impose any geometric structure on it or extract the surface. Surface extraction techniques fail to take into account that, particularly in medical imaging, data may originate from fluid and other materials which may be partially transparent. And surface extraction might cause the artificial fault. Ray casting doesn't suffer from this limitation.

In ray casting method, rays are cast into the dataset [4] [5]. Each ray originates at the viewing position (eye), penetrates a pixel in the image plane (screen), and passes through the dataset. The element values in the dataset are computed by interpolation at evenly spaced interval along the ray. The sample values are mapped to display properties, such as opacity and color. A local gradient is combined with local illumination model at each sample point to provide the realistic shading of the object. Compositing the opacity and color along the ray, the final pixel values are drawn on the image plane. Composition models the physical reflection and absorption of light.

As shown in fig. 2, the elements in the dataset are named as voxels. Voxels are denoted by a vector $\mathbf{i}=(i, j, k)$, where i, j, k = 1,…,N, and the value of voxel is denoted as $f(i)$. The vector color $C(i)$ and opacity $a(i)$ of each voxel are scattered by local operators. In fig. 2, the parallel rays trace the data from the observing position and generate the image which contains P×P pixels. The pixels are indexed by $\mathbf{u} = (u,v)$ where u, v = 1,…, P. For each ray, a vector of color and opacity is computed by resampling the data at $W$ evenly spaced locations along the ray. From the colors and opacities
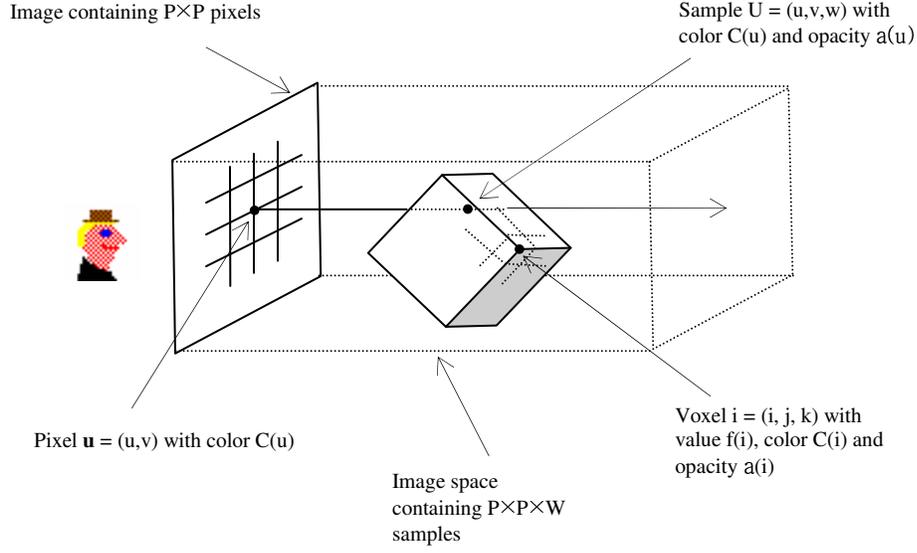
Fig. 2. Illustrated diagram of ray casting

in the eight voxels surrounding each sample location, the resample data is trilinearly interpolated. Samples are indexed by a vector $U = (u,v,w)$. Here $(u,v)$ identifies the ray. $w = 1,\dots W$, corresponds to distance along the ray where $w = 1$ is closest to the eye. The color and opacity of sample U are denoted $C(U)$ and $a(U)$ respectively. Finally, a full opacity background is generated behind the dataset. And resampled color and opacities are composited with each other, and with the background to yield a color for the ray.

In our system, the element values in dataset are mapped to different ranges, assigned with different opacity value, and rendered as color mode. Although the input data is grayscale, the object rendered as ray casting is colorized. So the specific part in the dataset is distinguished clearly from the surroundings. As shown in fig 3, in our system the 3D object can be enlarged or shrank, translated in order to facilitate the observation. And the stack of input images is shown as planar mode in three perpendicular view directions.

## IV.    SEGMENTATION

The core function in our system is the medical image segmentation since segmentation is the basic process for further quantification or analysis. It is well known that the medical image is difficult to segment automatically by the computer for its complexity. The pixel value of the interested organ in the image may vary greatly. The boundary may be blurred, or have some gaps. Thus, some low level image segmentation methods can not fulfill the complex medical image segmentation, particularly in brain tumor segmentation. Our system use level set method [6] [7] to segment the image. It is a high level segmentation that shows its flexibility and efficiency on segmentation work. It combines region-based and edge-based segmentation methods [8], and creates the

active deformable model (curve or surface) that complies with the feature of the image (volume) data. The model has no fixed parameterization so that it can change its topology needed for segmentation and describe the complex shape easily. Level set evolution with fixed propagation direction, as in boundary-driven snakes [9] [10], is either initialized inside or outside of sought objects, and the propagation force is locally opposed by a strong gradient magnitude at image discontinuities to stop propagation.

Level set model specifies a surface as iso-surface in the scalar data set. The surface consists of all points as the following function

$$S = \left\{ s \middle| \phi(s) = k \right\} \tag{1}$$

$\phi : U \mapsto R$ , where $U \subset R^3$ is the scalar domain of model, and $k$ is the iso-value used for iso-surface extraction. It is same to say that the set of points $s$ is the $k$-th iso-surface of $\phi$. And $\phi$ is the sampling on the rectilinear grid of scatter space. The surface may propagate according to its curvature as time varying. There are mathematical and numerical mechanisms in level set method to compute the surface deformation as iso-value $k$. It is to solve the partial differential equation (PDE) on the grid $U$, so that the surface will move as the defined manner. For defining the deformable surface as (1), $\phi(s)$ can be dynamic function as time $t$ varies, and $k$ is fixed.

$$\phi(s,t) = k \tag{2}$$

This definition can be transformed into partial differential equation so that be solved by standard numerical techniques easily. The equation (2) is differentiated with time $t$, and the chain rule is applied in the following equation (3).
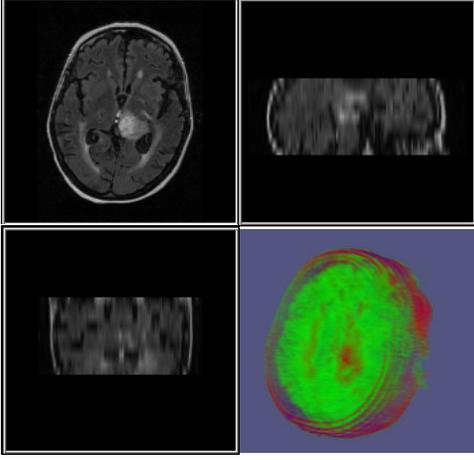
Fig. 3. The visualization of stack of input images in 2D and 3D. Left up corner: one of stack of input images, in axial view; right up corner: Coronal view from the stack of input images; left down corner: Sagittal view from the stack of input images; right down corner: 3D ray casting volume view of stack of input images

$$\frac{\partial \phi(s,t)}{\partial t} + \nabla \phi(s,t) \cdot \frac{ds}{dt} = 0 \qquad (3)$$

The equation (3) is called as "Hamilton-Jacobi-type" equation and defines an initial value problem for the time dependent $\phi$. Let $ds/dt$ be the movement of $s$ on $S$ as it deforms, which is differential expression of the implicit function $\phi$ in turn. The expression is according to the position of $s \in U$ and the geometry of the surface at that point. The PDE on $\phi : s \equiv s(t)$ is given by

$$\frac{\partial \phi}{\partial t} = -\nabla \phi \cdot \frac{ds}{dt} \equiv -\nabla \phi \cdot F(s, D\phi, D^2\phi, \ldots) \qquad (4)$$

$F$ is the speed term evaluated at $s$. It depends on the n-derivation of $\phi$, $D^n \phi$. Normally $F(x)$ includes one smoothing term that prevents the deformation of the surface disturbed by the noise data too much. Global smoothness guarantees stability in the presence of small gaps in boundaries. However, at locations of missing or fuzzy boundaries, the internal force can be strong enough to counteract global smoothness and leaks through these gaps. There are various surface-motion terms used to define $F$. One example is combination of feature attraction term (extern term) and smoothing term (inner term) with factor β.

$$F = F_{ext} + \beta F_{int} \qquad (5)$$

The first term $F_{ext}$ is to extract the surface model to the definitive feature of the data. There are several approaches to define the extractive feature, for instance [11] [12], uses region competition to define the candidate area. An alternation is the gradient magnitude that indicates the edge area in the image data. The gradient magnitude can be computed by the scale operator, e.g. the derivative of Gaussian Kernel. The initial model can propagate according to the gradient and fit into the edge of the target as the proper degree of the resolution. The attraction force is

$$F_{ext} = \nabla \left| (\nabla (G * I(x))) \right| \qquad (6)$$

In the equation (6) the data $I(x)$ is convolved with a Gaussian kernel G with $\sigma \approx 0.5$ so that the model surface moves towards maxima by positive sign, in contrast, moves towards minima by negative sign.

The smoothing term $F_{int}$ in equation (5) is defined by the vector in the direction of the surface normal **n**, which is formed by mean curvature $\kappa_M$ of level set **S**.

$$F_{int} = \kappa_M n = (\nabla \cdot n)n = \nabla \cdot \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \frac{\nabla \phi}{|\nabla \phi|} \qquad (7)$$

$F_{int}$ is weighted by the factor β so that the user can control the degree of the smoothing. The propagation of the level set terminates at the cancellation of $F_{ext}$ and $\beta F_{int}$ by each other, or the iteration number reaches the limitation.

Level set method needs the initial seed to build the propagation front, as well as level set model, curve in 2D or surface in 3D. In our system the user needs to give a coarse initialize seed near the interested area, and then the seed front converges to precise boundary in the image data.

In our system, the gradient magnitude in the image is the extern attraction for level set model. The image can be departed into two parts according to the grayscale. One part is the target object; the other part is the background. And the boundary of the target object is the gradient magnitude maxima. Our system offers user the visualized threshold setting of the image pixel value to set up the aimed object which needs to be separated from its background. The threshold setting is shown as fig. 4 middle. The different color shows the inner part and outer part where level set model will propagate to reach the boundary as time changes. This manual setting is as much as possible to satisfy the user's requirement of the interested area specification. And it is easy to handle so that it doesn't need too much manual work.

## V. QUANTIFICATION

Quantification is very important feature for a CAD system, or one goal in the diagnosis. Therefore segmentation procedure is just the way to this destination. For the brain tumor diagnosis, doctor needs to know the precise size of the tumor from MRI, and compare the images obtained in different period. Size is one character of measuring the illness. Of course, the other characters are also important for diagnoses, such as the tumor's shape, position, and so on. These characters can be observed by the doctor during the
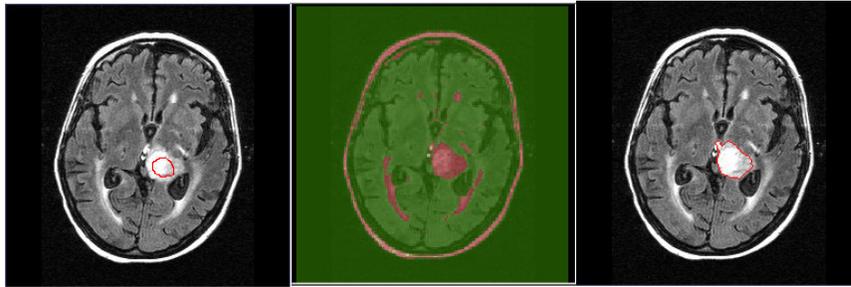
Figure 4. Segmentation procedure of the tumor in brain MRI. Left: target image with initial coarse contour; middle: intensity range of interested area shown as red part; right: after level set segmentation, the red contour is the accurate contour of interested area

visualization part of the CAD system. But the accurate size of the tumor could not be measured only in mental or by hand. This task should be handled by computer system.

The precision of interested area quantification relies on the accurate segmentation of this area. After the segmentation, the contour of the interested area is found. So that the pixel number inside the contour can be counted. In our system, the quantification of segmented object is both in pixels numbers and in physical size. Since our system processes the DICOM file, some image related properties are included in the file header (see fig. 1), such as patient name, gender, and so on. Among them, the pixel spacing can be exploited to compute the physical size of segmented part area. The physical voxel size is computed from multiplying the spacing parameters in three dimensions. Therefore the volume of the interested part in the 3D image data can be obtained. The segmentation operation is performed slice by slice in the image stack. And the target volume is constructed by the segmented contours in the stack of images. For the segmentation on each slice, the user can adjust the parameters to fit the requirement in the specified image in order to get the satisfied result. By the quantification procedure, the user can know the tumor size varying in different images in the stack.

## VI. CONCLUSION AND FUTURE WORK

In this paper, we introduce our medical image processing system, Med-Volumeter, which is a user interactive tool for image visualization, segmentation and quantification tool. The system is semi-automatic tool that it needs user to give the initial seed contour for segmentation, and the result is adjustable. The system renders the 3D volume by ray casting method to look through the row dataset. The target area is segmented under level set frame. And at last, the size of segmented part can be obtained both as pixel number and as physical measure. This system is applied in brain tumor segmentation and quantification. The evaluation of this tool from the doctors, whom the project is cooperated with, is quite positive. The segmentation procedure is controllable and the manual work is not so tedious. The precision and the quantification of the result are acceptable. This tool helps the

doctors in diagnosis, treatment plan making and state of the tumor monitoring.

In the future, the system should be improved by adapting more segmentation algorithms to suit the different medical image segmentation aims. For setting the deformation region in level-set method, the intensity range can reveal some target area. However, the brain tumor case is complex. We need more sophisticated strategy to set deformation region where the level set model's propagation terminates in. In order to balance the expert hand work and computer automatic work, the system should enhance the precision of the algorithm computation, and also improve the user interface to facilitate the user control. This tool can be used in the segmentation and quantification of many types of medical images. For the brain tumor case, we should add some other features for the aid in the diagnoses. For example, the smoothness of the tumor contour can reflect the character of the tumor. It has been shown that the smooth contour is normally appeared in benign tumor. In contrast, the coarse contour will appear in malign tumor. Our system will introduce the smoothness of the segmented contour in the future in order to give a quantitative measurement at this point. And there are other possibilities that the tool could give the help during diagnosis. It needs further investigation and development.

## ACKNOWLEDGMENT

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