Design and Development of Medical Image Processing Experiment System Based on IDL Language

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Abstract: *This paper uses Interactive Data Language (IDL) as a development language to design and implement a lung tumor image processing system with a Client/Server (C/S) structure. During the development process, various business requirements related to the system have been analyzed and the system structure together with detailed business process were designed as a whole. In addition, we also established a database of patients' lung tumor images to efficiently store and query Computed Tomography (CT) images of lung tumors at various stages of the patient and the images generated during the processing of the system. Finally, the paper elaborated the implementation of the IDL-based lung tumor image processing system, and conducted a performance test and experimental analysis of the system. The system consists of five functional modules: image preprocessing, image segmentation, image reconstruction, image measurement, and image management. This system can automatically calculate quantitative indicators in the delineated area. These features can be used for further tumor differentiation tests, tumor characterization, treatment monitoring, and prognosis assessment. The experimental results show that the system is effective, and also processing speed meets the real-time requirements, and has wide applicability, friendly human-computer interaction, convenient extensibility, good portability, and so on.*

Keywords: *IDL language, Medical image, Image processing, Modular programming.*

Introduction

Since the 1970s, with the rapid development of Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and other technologies, medical imaging has gradually become an important basis for medical diagnosis and disease treatment. It has been widely used in clinical practice and has very important application value [1-4]. The acquisition and processing of medical images are closely related to the treatment of patients. Especially for patients suffering from diseases such as tumors, the accuracy of their medical imaging assessment greatly affects the preoperative treatment plan and prognosis [14, 10]. A set of excellent image processing systems can dig out features that cannot be recognized by human eyes, so as to feedback the information in the images to a greater extent and improve the utilization of the images [3]. In addition, a good system can also greatly reduce the burden on doctors, save doctors time, and free up more medical resources. Therefore, we propose to design a set of medical image processing platform system based on image processing, which can provide several functions such as image display, Region of Interest (ROI) delineation, three-dimensional reconstruction of the Volume of Interest (VOI), and visualization.

Interactive Data Language (IDL) is a fourth-generation computer language oriented to matrix computing. Its syntax is simple and the development environment is more complete, faster, and more efficient. IDL uses OpenGL graphics acceleration technology, with the ability to interactively analyze 2D and 3D data, has the ability to quickly analyze large-scale data, integrated mathematical analysis and statistical algorithm software package, and also has a sophisticated advanced image processing capabilities. Its data input and output methods are more flexible and suitable for a variety of development platforms. IDL provides users with a visual data analysis solution that allows users to interactively analyze and browse data, allows programmers to rapidly develop prototypes, and provides them with high-level cross-platform publishing programming tool. Based on these characteristics, IDL enables programmers to directly study data without writing a large amount of code. Due to the large amount of data in medical images, IDL is particularly suitable for the study of medical images. Therefore, the research and application of IDL in medical image processing and 3D reconstruction technology will certainly promote the development of imaging technology.

After more than 20 years of updating, IDL has further enhanced its image processing, analysis, and display capabilities, and is highly favored by medical image processing experts. At present, IDL has been widely used in medical image processing. It can quickly and easily implement various medical image processing. For example, IDL can process X-ray images, MR and CT images, and microscopic medical images in molecular biology. IDL can be applied to various aspects of medical image processing, such as: image fusion, image segmentation, image registration, image reconstruction and so on.

This paper studies the design and implementation of a lung tumor image processing system. It presents the design and implementation of a full-featured lung tumor image processing software aim at improving lung tumors visualization. CT image clarity, image noise reduction, segmentation of lung parenchymal images based on image segmentation techniques, extraction of features based on lung parenchymal images, and use of statistical machine learning methods to identify lung tumors, are ultimately helping physicians to improve tumor analysis and judgment capabilities.

Materials and methods

System framework structure

The block diagram of the system design is shown in Fig. 1. The system can be divided into five modules: Digital Imaging and Communication (DICOM) interpretation and image loading, image display, ROI delineation, VOI three-dimensional display and visualization. The system first reads and displays medical images such as MRI and CT. Doctors can outline the ROI on the image [7-9]. The outlined contours can be displayed simultaneously in the same position in different image sequences so that the doctor can view the ROI on multiple sequence images.

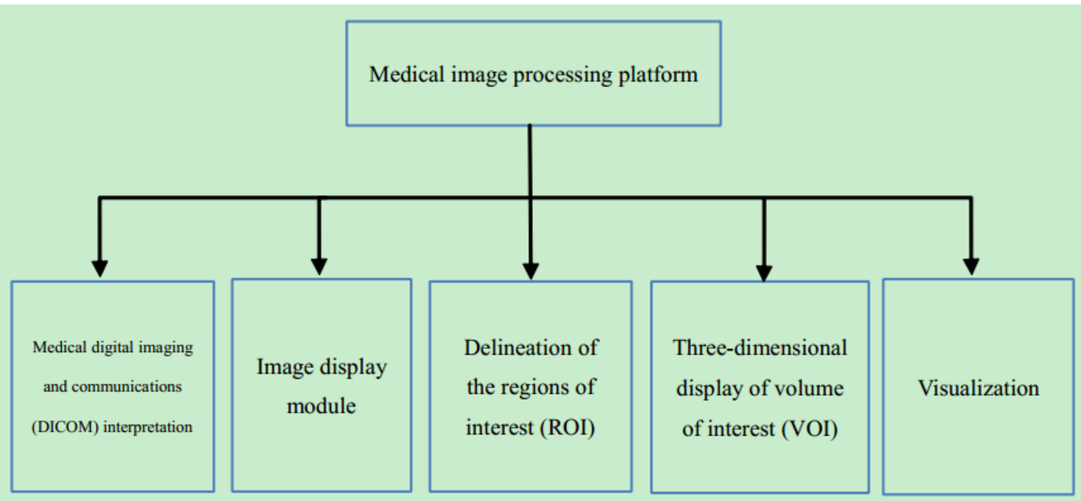


Fig. 1 System structure of the medical image processing platform

Basic methods of medical image reconstruction

Medical image processing and three-dimensional reconstruction technology is the use of image technology to process CT, MRI, and other image sequences and construct a 3D model to display human tissues and organs in a three-dimensional form on the screen. This can use existing medical equipment, as well as also greatly improves the level of clinical medical diagnosis and provides a powerful tool for medical teaching and research, assisted surgery. Currently, medical image 3D reconstruction techniques generally fall into two categories: surface rendering and volume rendering.

Surface rendering algorithm

Surface rendering 3D reconstruction is a reconstruction method that uses the surface of the object to ignore the internal information of the object. It is one of the important methods for three-dimensional visualization of medical images. The surface rendering three-dimensional reconstruction first performs surface contour extraction on a series of two-dimensional images, and then restores The three-dimensional model of the object is displayed in the form of surface contours, so as to provide the user with a more realistic 3D medical image, providing convenience for the doctor to observe and analyze the lesion from multiple angles and at multiple levels.

The two points' coordinates are denoted as (x_i, y_i, z_i) and (x_j, y_j, z_j), respectively. The vertices of the triangle matrix are found by linear interpolation as:

$$\begin{cases} x_0 = x_1 + K(x_j - x_i), \\ y_0 = y_1 + K(\mathrm{y}_j - y_i), \\ z_0 = z_1 + K(\mathrm{z}_j - z_i). \end{cases} \tag{1}$$

This method utilize that the gradient vector along the tangent direction of the equipotential surface using any point within the equipotential surface is equal to zero, so an equipotential surface can be used. The principle that the equipotential surface can represent the normal vector of the point along the gradient vector of the point can be used to determine the normal vector of the triangle, which is shown as:

$$g(x, y, z) = \nabla f(x, y, z). \tag{2}$$

Then use the linear interpolation to find the gradient of each vertex of the triangle patch, and then find the normal vector of each vertex.

Volume rendering algorithm

Volume rendering refers to the process of generating three-dimensional virtual solid images directly from volume data using voxels as the basic unit, using specified models and algorithms. The voxel model using voxel expression not only has the physical external shape information, but also includes all the internal details of the entity. Therefore, using the volume rendering method to perform volume rendering on the voxel model can express the external shape and internal details of the entity. Therefore, it is attracting increasing attention and widely used.

Implementation of tumor image processing system

Digital image contains a lot of useful information. Thus, the image processing methods need further development. The new method of medical digital image processing will improve the image processing software. It can enrich the content of stochastic software and promote the progress and improvement of imaging equipment.

Medical digital images consist of gridded pixels and are stored in a computer in the form of a matrix. The goal of medical digital image processing is to obtain more information from the original image.

Image noise assessment
Spatial spectral de-correlation noise estimation algorithm uses the characteristics of hyperspectral image spatial and spectral dimensions with high correlation. It removes signals with high correlation by multiple linear regressions, and then estimates the noise based on the obtained residual image [15]. This method is influenced by the type of ground cover, and it can be automatically executed. It is a relatively stable method for noise assessment of hyperspectral images.

Image noise removal
The Wiener filter is one of the best linear filters [1, 5]. Wiener filter is used in this paper as the noise reduction method for CT images. In this section, we will analyze in detail the implementation details of the Wiener filter. First, we will introduce the data flow of the Wiener filter.

Let the image size be $M \times N$ and $f(i, j)$, and denote the gray value of the pixel as coordinates (i, j). The mean value and variance of the image gray are calculated as follows:

$$Gm = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} f(i, j)}{M \times N}, \tag{3}$$

$$Gu = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left(f(i, j) - Gm\right). \tag{4}$$

Gradient values in the image are often described by the Laplace operator. Denoting the gradient as $g(i, j)$, then it can be represented as:

$$g(i, j) = f(i+1, j) + f(i-1, j) + f(i, j-1). \tag{5}$$

Normalizing the formulation (5) as:

$$G(i, j) = INT\left[g(i, j) \times N_g / g_{\max}\right] + 1. \tag{6}$$

In the above, INT is a rounding operation, and $g_{\max}$ represents the maximum gradient. The normalized gradient image is distributed among N_g gray levels. The additive noise model is:

$$g(i, j) = f(i, j) + n(i, j), \tag{7}$$

where $n(i, j)$ represents the additive noise signal.

Implementation of image segmentation

The segmentation of CT and MRI images mainly involves three related problems: changing noise, uncertainty of pixel gray classification, and gray non-equilibrium [9]. The gray level of a single tissue in an image generally changes gradually, and its probability density is subject to a specific distribution function [7, 13]. The image region corresponding to the tissue contains a limited number of pixels (or voxels) and satisfies a partial volume average. But in the region, the gray scale of a single pixel (or voxel) is not the same as any one, and is often seen as a mixed tissue class.

Based on these assumptions, the probability of occurrence of the gray-level value i can be calculated as follows:

$$P(i) = \frac{f(i,j)}{N},\ P(i) \geq 0. \tag{8}$$

For a given optimal image threshold, the images can be defined by the following:

$$UN = 1 - \frac{\sigma_B^2 + \sigma_F^2}{C}, \tag{9}$$

where B and F denotes the background and foreground regions, and

$$C = \frac{(g_{\max} - g_{\min})^2}{2}, \tag{10}$$

where $g_{\min}$ is the minimum grey levels in the image.

Results and discussion

IDL's ability to process medical digital images

Noise removal is a conventional image processing technique (noise will reduce the image quality of medical images. The general manifestation of noise is black and white dot-to-phase noise. Some random pixels have extreme pixel values.

Median filter in IDL performs noise reduction is implemented by calculating the median (rather than the mean) of neighboring pixels. First, it can remove extreme values from the image. Second, it does not obscure image edges or features that are larger in size than the neighborhood. Obviously, noise reduction has a very good effect on images (Fig. 2).

Image segmentation is the process of extracting lung parenchyma after the CT image is processed by the Wiener filter. The data input for image segmentation is filtered CT image, and the output of image segmentation is lung parenchyma. The data flow of lung image segmentation is shown in the Fig. 3.

As it is shown in the Fig. 4, by using region-based segmentation methods combined with boundary-based segmentation methods, segmentation and extraction of regions of interest in medical images is achieved.

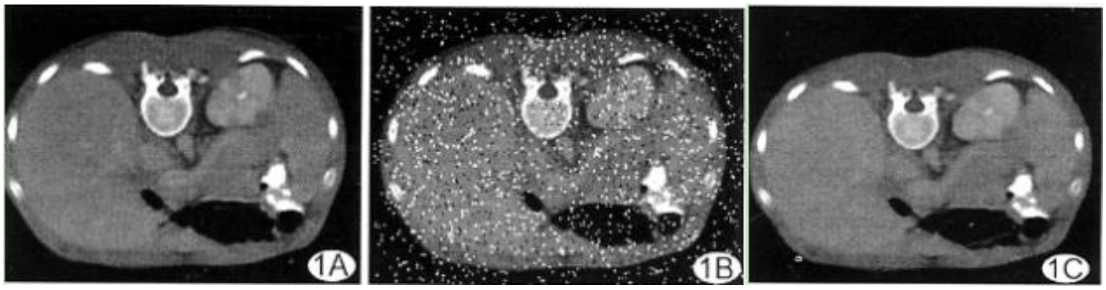


Fig. 2 Performance of image noise removal:
1A) original image; 1B) noise image; 1C) resulted processed image.

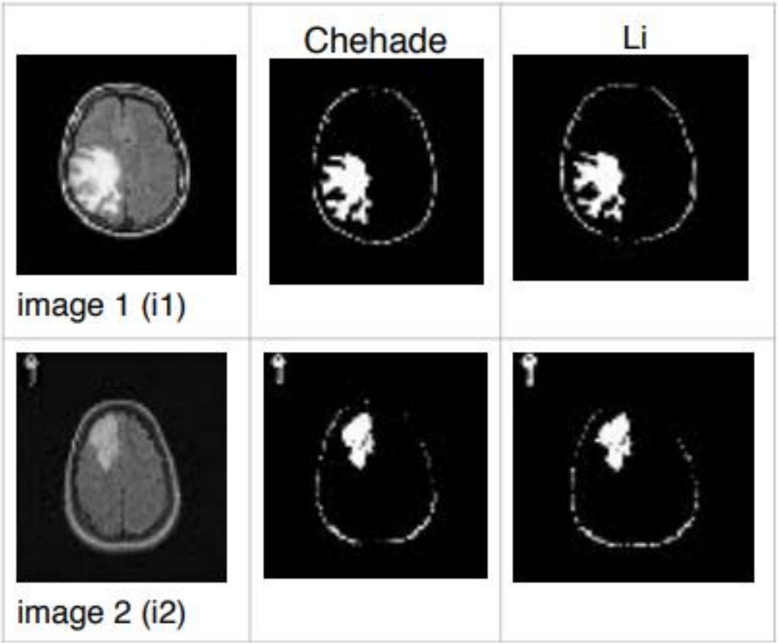
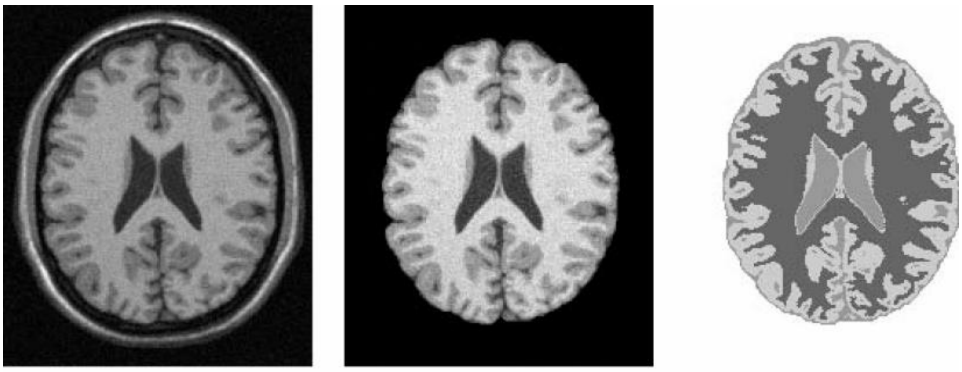


Fig. 3 The segmented MRI brain images



a) b) c)

Fig. 4 Performance of proposed algorithm in the 9% noise:
a) original image; b) after preprocessing session; c) resulted image.

Mann-Whitney test analysis results

All statistical analyses were performed using SPSS software. There are significant differences in skewness and entropy. The method of full volume histogram is used to analyze the statistical values of image pixels and the results are shown in Table 1.

Table 1. Analysis of the trial results in 15 patients with tumor using Mann-Whitney test

Parameter	*n*	Poorly	Well or moderately	*p*-value
ADC_{mean}	15	925.4 (862.7, 956.6)	1036.0 (979.6, 1107.845)	0.063
ADC5%	15	721.0 (631.7, 758.3)	832.0 (707.7, 847.5)	0.167
ADC25%	15	804.5 (731.2, 842.39)	935.0 (844.0, 948.0)	0.105
ADC50%	15	881.0 (813.7, 911.8)	999.0 (936.0, 1053.7)	0.063
ADC90%	15	1150.0 (1102.0, 1187.3)	1344.0 (1234.0, 1383.7)	0.011
Skewness	15	2.854 (2.675, 3.036)	2.726 (2.143, 3.049)	0.353
Entropy	15	14.599 (2.675, 3.036)	14.890 (10.474, 15.680)	0.486

Diffusion-weighted Imaging (DWI) is one of the most commonly used sequences in MRI, which focuses on the comparison of water diffusion between tissues. It is also one of the sequences for image analysis. It has fast imaging speed and plays a very important role in the diagnosis of many diseases. DWI uses the variation of diffusion coefficients of water molecules in the imaging plane to compare images. In this method, ADC is a quantity representing the apparent diffusion coefficient. Table 1 lists 7 parameters such as the mean of parent diffusion coefficient ADC_{mean}, ADC5%, ADC25%, ADC50%, ADC90%, skewness, entropy in poorly differentiated tumor tissues and median well-differentiated tumor tissue, with values in parentheses representing data for the 25% position and 75% position. ADC5% indicates that the data specificity is 5% under ADC threshold, which indicates the ADC diffusion and data sensitivity.

Table 1 shows that ADC 90% of highly differentiated tissues in cervical cancer are significantly higher than those in poorly differentiated tumors of cervical cancer ($p < 0.05$), while the other 6 parameters are not significantly different.

Conclusion

IDL provides users with a solution to visual data analysis. It allows scientific researchers to interactively browse and analyze data. It also provides programmers with high-level programming tools for rapid prototyping and publishing across platforms. This study completed the design of a medical image processing platform based on image processing, and achieved information processing for medical images, including display operations on medical images such as display, enlargement, and sketching. This developed program can greatly improved the excavation of medical image information by doctors and helped improve the diagnosis and treatment of diseases.

References

1. Abbasi S., F. T. Pour (2015). A Hybrid Approach for Detection of Brain Tumor in MRI Images, Biomedical Engineering, 11, 269-274.
2. Alickovic E., A. Subasi (2015). Effect of Multiscale PCA De-noising in ECG Beat Classification for Diagnosis of Cardiovascular Diseases, Circuits Systems and Signal Processing, 34, 513-533.
3. Bhima K., A. Jagan (2017). An Improved Method for Automatic Segmentation and Accurate Detection of Brain Tumor in Multimodal MRI, International Journal of Image, Graphics and Signal Processing, 9(5), 1-8.
4. Cabria I., I. Gondra (2017). MRI Segmentation Fusion for Brain Tumor Detection, Information Fusion, 7, 1-9.

5. Eklund A., P.Dufort, D. Forsberg, S. M. LaConte (2013). Medical Image Processing on the GPU – Past, Present and Future, Medical Image Analysis, 17, 1073.
6. Jannin P., J. M. Fitzpatrick, D. J. Hawkes, et al. (2013). Validation of Medical Image Processing in Image-guided Therapy, IEEE Transactions on Medical Imaging, 21(12), 1445-1449.
7. Jonas V. Z., M. Kozlovszky, B. Molnar (2015). Semi-automated Quantitative Validation Tool for Medical Image Processing Algorithm Development, IFIP Advances in Information and Communication Technology, 450, 231-238.
8. Loiret F., J. Navas, J. P. Babau, O. Lobry (2009). Component-based Real-time Operating System for Embedded Applications, Lecture Notes in Computer Science, 5582, 209-226.
9. Mitra S., B. U. Shankar (2015). Medical Image Analysis for Cancer Management in Natural Computing Framework, Information Sciences, 306, 111-131.
10. Nakhmani A., R. Kikinis, A. Tannenbaum (2014). MRI Brain Tumor Segmentation and Necrosis Detection Using Adaptive Sobolev Snakes, Proc Spie Int Soc Opt Eng, 9034, 903442.
11. Robinson J. A. (2013). A Software System for Laboratory Experiments in Image Processing, IEEE Transactions on Education, 43, 455-459.
12. Shinde B., D. Mhaske, A. R. Dani (2012). Study of Noise Detection and Noise Removal Techniques in Medical Images, International Journal of Image Graphics and Signal Processing, 4, 51-60.
13. Scholl I., T. Aach, T. M. Deserno, T. Kuhlen (2011). Challenges of Medical Image Processing, Computer Science – Research and Development, 26(1-2), 5-13.
14. Vishnumurthy T. D., H. S. Mohana, V. A. Meshram (2017). Automatic Segmentation of Brain MRI Images and Tumor Detection Using Morphological Techniques, IEEE International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques, 9, 6-11.
15. Yokoyama T. C. K. U. (2011). Medical Image Processing System, Springer, Verlag.

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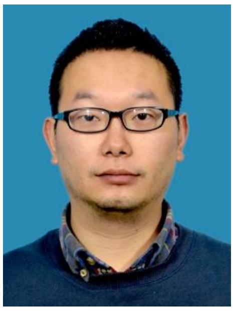

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