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Clinical Medical Image Analysis based on Computer Image Processing Technology

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Abstract: Clinical medical image analysis is helpful to find the best treatment method for clinical treatment. The existing methods ignore the calculation of discrete error of fractional equation, which can not effectively solve the uneven distribution of noise in three classes of images, which leads to poor effect of image enhancement, A new method of clinical medical image analysis based on computer image processing technology is proposed. The image was preprocessed and pathological region was marked by the coordinate of the regional points manually marked by clinical medical images. By using computer image processing technology, different fractional differential image enhancement templates are constructed, and the enhanced images are obtained by convolution. A sequential model of self-step support vector machine is established to segment the enhanced image and enhance the effect of image adhesion removal. After preprocessing, image enhancement and region segmentation, we can get the good quality clinical medical image samples, and then carry out the automatic detection of diseases. The experimental results show that the design method in this paper is higher than the existing method in the evaluation index of contrast noise ratio, and can achieve a certain de-noising effect in image enhancement, and has excellent performance in the visual effect of contrast of clinical medical images, and has good practical application effect.

Keywords: Computer image processing technology; Clinical medicine; Medical imaging; Image analysis

1. Introduction

Modern medical imaging technology can effectively realize the visual representation of the anatomical structure and physiological function of human internal organs and tissues, thus greatly improving the clinical diagnosis, detection and treatment effect evaluation level of diseases, and also plays an important monitoring role in organ transplantation and drug research and development [1]. In clinical practice, medical image analysis is usually done by some human experts, such as radiologists and physicians. However, a large number of medical images produced every day will consume a lot of manpower and time if only relying on the manual analysis of human experts, which will put a great burden on radiologists and physicians, and fatigue reading will increase the probability of misdiagnosis and missed diagnosis. Therefore, many human experts, researchers and doctors have begun to try the computer-aided diagnosis system, and obtained great benefits from it, promoting the development of medical imaging technology.

Clinical medical imaging analysis is a comprehensive knowledge and technology of various professional disciplines. In the current clinical treatment, in order to accurately diagnose the patient's condition, doctors need to conduct timely and accurate pathological analysis through some advanced medical imaging equipment, which is also a very important link in clinical treatment [2].

2. Clinical Medical Image Analysis based on Computer Image Processing Technology

2.1. Clinical medical image preprocessing

In the field of clinical medical imaging, it is difficult to analyze a large sample of millions of data samples. The reasons are various. First of all, it needs a lot of financial support to build a large sample of clinical medical image standard database, which is used to support volunteer recruitment, clinical medical image collection, image data analysis, disease classification, region of interest delineation, data storage and management, etc. Secondly, in order to obtain high-quality clinical medical imaging specimens, the project implementation personnel need to have a solid medical background knowledge and sufficient working time, and the quality detection and control is also very critical. In addition [3], privacy is a clinical problem worthy of attention. It makes it impossible for clinical medical images to be shared as easily as natural images, which also leads to the necessity of document work [4]. Fourth, the scope of clinical medical imaging analysis is very broad. It involves a lot of diseases. For different diseases, multimodal images will be collected for accurate diagnosis, reasonable treatment plan and quantifiable treatment effect verification. If we consider only the first mock exam of a disease, we need to delineate the location of the region of interest and distinguish it from benign and malignant by biopsy. If the tumor is malignant, we can further do cancer staging, quantification of cancer patients' progress in the process of treatment, and prediction of cancer patients' survival under a certain treatment regimen. Of course, for a certain disease, we can also discuss whether there is redundancy, correlation or complementary information among modes, which is conducive to provide reference for subsequent clinical data collection. Finally, whether the potential information association at gene level, molecular level or functional level can be mined from the dimension of image features is the research content of genomics [5]. Based on this, we need to preprocess the clinical medical image. With the help of BCDR-F03 clinical medical images and manually labeled tumor area point coordinates, we propose a relatively stable clinical medical image preprocessing method, namely region of interest preprocessing method, which mainly includes three steps. Firstly, we extract the region of interest manually labeled by doctors and calculate its minimum circumscribed rectangle. Based on the empirical value, the minimum circumscribed rectangle expands outward by 20 pixels, and the part in the rectangle is defined as the region of interest, that is, the mass region. This is based on two considerations. (1) Expanding the region of interest does not change the actual properties of the mass. (2) Expanding the region of interest can potentially bring the edge area between the mass and normal tissue into image analysis, which is conducive to making full use of image information. Then, OTSU segmentation algorithm is used to binarize the image, retain the maximum connected area, and carry out an open operation, a close operation and hole filling. The operation templates are all based on the disk structure with radius of 5 pixels. If the maximal connected region is a subset of the manually sketched region, we keep the manually sketched region; If the maximum connected area is larger than the manually sketched area, we keep the processed image area. The reserved image area is the input sample of the follow-up research. Finally, we use the data sample increase method, that is, to increase the number of samples by rotating and mirroring. On the one hand, data increase can reduce the over fitting problem in the process of machine learning, so as to improve the generalization performance of artificial intelligence aided diagnosis model. On the other hand, it is intuitively believed that only when the rotated and mirrored sample data can be identified consistently can the diagnosis system have certain recognition ability. After rotation and mirror, the sample size can be expanded to 8 times of the original number. On the basis of clinical medical image preprocessing, clinical medical image analysis was carried out.

2.2. Image enhancement based on computer image processing technology

Because the clinical medical imaging uses the principle of low coherent light interference, it will introduce some speckle noise interference, which will make different tissues blur at the boundary, and then increasing the difficulty for the next image segmentation of tissue lesions . To solve this problem, this paper uses computer image processing technology to enhance the clinical medical image. The specific flow is shown in Figure 1.

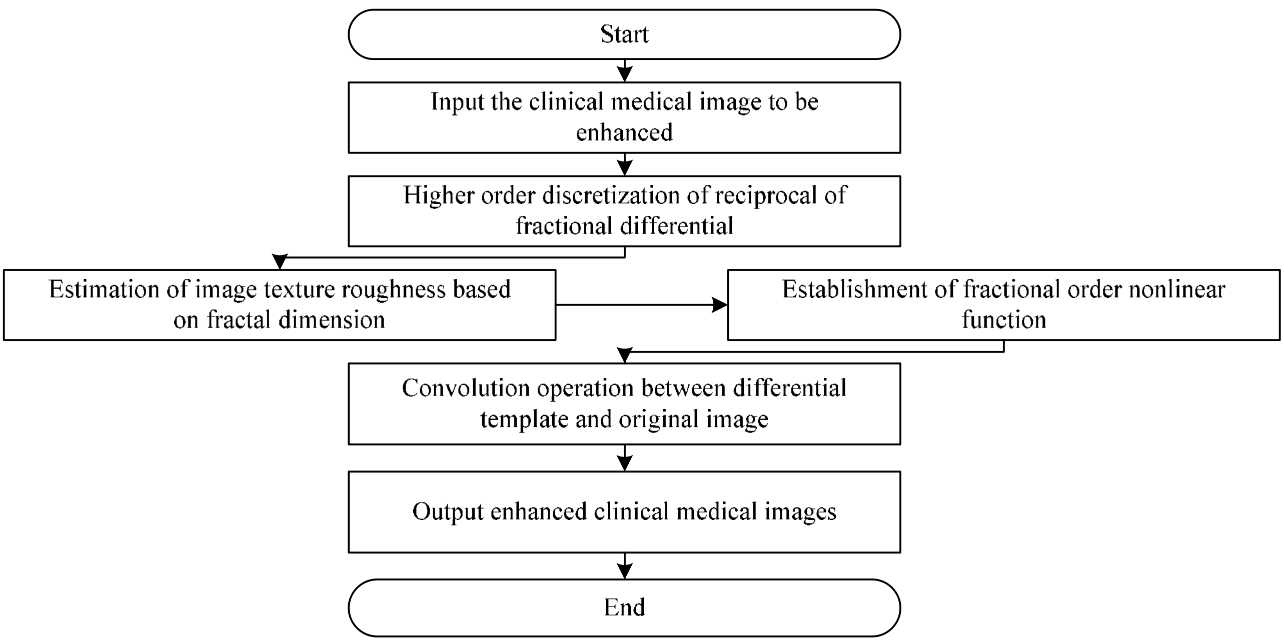

Figure 1. Image enhancement process

Previous image enhancement methods usually ignore the discussion of discrete methods. However, different discrete coefficients (i.e. elements in the fractional order template) generated by different discrete methods will form different fractional order differential image enhancement templates. Therefore, it will have a great impact on the effect of image enhancement. In this paper, the fractional derivative is discretized by the method of backward difference. Because most of the traditional image enhancement methods use the constant order fractional differential operator, that is, different regions in the image are enhanced by the same fractional order generated enhancement template. However, due to the different size of the fractional differential operator for different frequencies of the image content information enhancement effect has obvious differences, the larger the fractional order, the greater the enhancement degree of the template for the image, the biggest defect is that the high-frequency noise information is also enhanced. Therefore, how to obtain different fractional order adaptively according to the characteristics of the image itself, and then generate variable order fractional order differential template (operator) is an effective way to realize the adaptive enhancement of the image. Image texture feature is one of the most important features in image, which can reflect the slow change of object surface and periodic structure. In order to extract image texture features, power-law distribution can be used, and fractal dimension provides a description and measurement method for power-law distribution. The larger the fractal dimension, the more complex the texture or irregularity of the image. The process can be expressed as follows:

$$y=\begin{cases}0.45, w\le W_{\min}\\ 0.45+0.5(w-1.5), W_{\min}<w\le W_{\max}\\ 0.85, w>W_{\max}\end{cases} \quad (1)$$

In formula (1), y is the order of fractional derivative; w represents the fractal dimension in the range of clinical medical images; $W_{\min}, W_{\max}$ are the threshold of fractal dimension. The frequency response process of fractional differential operator can be regarded as a nonlinear filtering process in image processing. When the order of fractional derivative increases, the filtered image will pass through more high frequency, that is, the enhancement effect of boundary and noise is obvious at the same time. According to the roughness (fractal dimension) of the local texture information of the image itself, the number of times to select the fractional order is adapted, so as to generate a variable order fractional order image enhancement template, which can effectively improve the adaptability in image enhancement. In this process, the main task is to convolute the image to be enhanced, which can be expressed by the following formula:

$$P(a,b)=\sum_{u=-n}^{n}\sum_{v=-n}^{n}Q(u,v)p(a+u,b+v) \quad (2)$$

In formula (2), $P(a,b)$ represents the enhanced image; a,b represent the length and width of the image; n is the coefficient of fractional order discretization; $Q(u,v)$ represents sliding window; u,v are the length and width of the sliding window; $p(a+u,b+v)$ represents convolution operation. According to the above formula, the enhanced image is obtained.

2.3. Constructing the regional segmentation model of clinical medical images

After the enhanced clinical medical image is obtained, the image is segmented. Firstly, the level set method is used to obtain the rough segmentation results of 3D MR sequences. Then, the trained self-propelled support vector machine is used to perform the fine segmentation. The 3D and 2D fusion features are constructed and input into SVM to improve the generalization ability of SVM and obtain the fine segmentation model. Finally, morphology was used for post-processing. In this paper, the idea of self-learning is used to optimize the support vector machine, and the two-dimensional and three-dimensional features of each pixel in the image are extracted to construct the input vector. The basic idea of SVM is to solve the separation hyper plane which can correctly divide the training set and define the maximum classification interval of the feature space. According to whether the training set is linearly separable, linear separable support vector machines, linear support vector machines and nonlinear support vector machines can be constructed. In reality, clinical medical image data is usually linear and inseparable. Considering the great difference between human bodies in clinical medical images, the binary self stepping regularization term is used in training, which is expressed as follows:

$$z=\min a+b\|g\|^2+f(c,h) \quad (3)$$

In formula (3), z is the binary self stepping regular term; a is the training error of the sample; b represents the mapping function; g is the relaxation coefficient; $f(c,h)$ is the pixel feature vector; c is weight; h is the decision parameter. In this way, when optimizing the parameters of decision function, the weight of each training sample is the same. The contribution of different samples to the model can be considered evenly, and the difference between images caused by human differences can be better considered by the model, and the generalization ability of the model can be better. Traditional SVM obtains classification hyper plane according to all training samples optimization, and self-step SVM is an iterative optimization process. The model supports vector machine model simply according to the initial simple sample training, and then continuously absorbs the difficult samples of the current model for learning optimization according to the difficulty degree of samples. Limited by the imaging technology of clinical medical images, the resolution of 3D images in the longitudinal direction of human body is low, which leads to the difference of continuous layers. In order to make up for the lack of resolution of the longitudinal axis, linear interpolation is used to interpolation the image sequence in the longitudinal direction. The calculation of the feature of 3D gray gradient co-occurrence matrix makes the acquired clinical medical image information more conform to the characteristics of 3D data, and plays an important role in the learning of self-supporting vector machine . The method proposed in this chapter combines the advantages of image processing and machine learning, and uses level set to get the over segmentation result quickly, which provides the region of interest for SVM. By extracting two-dimensional and three-dimensional features, the gray, texture and spatial information of three-dimensional magnetic resonance image are fully utilized to improve the image segmentation accuracy and enhance the effect of de adhesion. The self-learning idea is used to further improve the learning generalization ability of SVM on small sample data.

2.4. Design an automatic disease detection algorithm

After preprocessing, image enhancement and region segmentation, we can get the good quality clinical medical image samples, and then carry out the automatic detection of diseases. Automatic detection of diseases will locate and classify multiple organs at the same time, diagnose and find out the pathogenic factors. This automated approach helps to plan the best treatment plan and reduce the workload of clinicians. However, each type of target organ has structural complexity and different scales across subjects. Multiple tasks, that is, simultaneous location and diagnosis of all organs, are much more difficult than individual tasks. In this paper, a deep multi-scale multitask learning network is proposed, which integrates multi-scale multi output learning and multitask regression learning into a full convolutional neural network. The network integrates multi-level semantic feature enhancement module, which can effectively express the spine structure and enhance the significance of many target organs. The architecture reconstruction of multi-scale multi-output learning is the process of constructing a deep FCN and selecting multi-scale volume layer to extend to the output layer. First, we construct a FCN as the basic architecture of multi-scale multi output learning. The FCN consists of 5 convolution blocks, 5 maximum pooling layers and 3 fully connected layers composed of 16 convolution layers. Secondly, the K-means clustering method is used to select the appropriate convolution layer as the candidate layer of the output layer. Two groups of observations are used to represent the height and width of the target organ label. Then, K-means clustering is run to decompose each group of observations into K clusters, and the sum of squares in the minimum cluster is obtained. It can be expressed as:

$$S = \arg\min \sum_{i=1}^{k} \sum_{a \in o_i} \left\| i - t_i \right\|^2 \tag{4}$$

In formula (4), S means to minimize the sum of squares in the cluster; k is the total number of clusters; i is the cluster number; a is the sample observation value; o_i is cluster; t_i represents the center of the cluster. Finally, according to the clustering results, the auxiliary feature enhancement module is established, and the multi-scale output layer is generated by combining the selected convolution layers, so that all MRI scans can be adjusted to the same size as the data set in this paper. These ensure that the multi-scale and multi output learning architecture can be used for semantic representation and scale invariance of various organs. After the deep multi-scale multi task learning network is constructed, multi task regression learning is carried out. The default bounding box of the target organ is generated on the multi-scale output layer. The module is responsible for telling where to find the target that is, assuming the location of the organ to obtain accurate prediction. Before using the multi task regression model to predict more certain positions and levels, it generates the default bounding box of the target organ in the output layer. In this paper, the K-means clustering results of target organs are embedded into the size setting of the default box scheme. Specifically, the representative aspect ratio in the K-means clustering method is used as the aspect ratio of the default box, and the representative width is used as the width of the default box of the output layer. The default boxes for different output layers have the same aspect ratio, but different widths. The width of the default box is set from large to small according to the receiving effect of the output layer. The default box suggestion module in this paper sets the default box suggestions empirically according to the K-means clustering results rather than randomly. Therefore, this method can generate the best default box for further relocation and grading. The final loss includes positioning loss and classification loss. In this method, K-means clustering method is used to find the rule of organs, and the multi-scale convolution layer is extended to multi output layer to improve the scale invariance of organs. Based on the above process, the clinical medical image analysis method based on computer image processing technology is constructed.

3. Experiment

3.1. Experimental preparation

In this paper, Tomo Therapy was used to collect MVCT images of 10 volunteers with 6MV energy. The image size is 512×512 and the layer thickness is 5mm. Five of the volunteers also received KVCT images, and the spiral CT scanner produced by Siemens was used to collect KVCT images of the five volunteers at 120KV energy. The image size is 512×512 and the layer thickness is 4mm. In this paper, the sequences of five people with MVCT and KVCT image pairs are used for training, and the images of the remaining five people are used for testing. In this paper, the experiment is completed on a desktop computer using Python 3.6, and the model construction and training are performed using Tensor flow. 5.0. NVIDIA 1070GPU, CUDA 9.0 and Cudnn v7.1.4 are used for acceleration. The configuration of desktop computer is Intel Core i7-9700K CPU, 3.6GHz, 64G memory. Because the same person uses different devices to collect images at different times, there are some differences in size and soft tissue shape between KVCT image and MVCT image. After artificial pairing, two kinds of images of the same volunteer KVCT image sequence and MVCT image sequence were selected to form KVCT-MVCT data pairs, and 200 pairs were obtained for training. In addition, by adjusting the size of KVCT-MVCT images, the contour of KVCT and MVCT images in a pair of data can be as consistent as possible. After matching, the contour of KVCT-MVCT images used for training is approximately the same, which reduces the difference between the two modal images. In view of the small amount of training sample data, the experiment uses image blocks for model training, which can reduce the influence of incomplete pairing model convergence between two kinds of modal images while increasing training samples. Some black edges are removed from KVCT-MVCT images, and a 64×64 sliding window is used for block extraction. At the same time, some hole images were removed, and 2874 pairs of 64×64 KVCT-MVCT images were obtained for training.

3.2. Experimental results and analysis

In order to test the application effect of the clinical medical image analysis method based on computer image processing technology, this paper compares with the existing image analysis methods. In order to evaluate the effect of image enhancement, contrast to noise ratio is selected as the evaluation index to measure the performance of different methods in image enhancement. The calculation formula of contrast to noise ratio is as follows:

$$C = \frac{|a_1 - a_2|}{m} \tag{5}$$

In formula (5), C represents the signal-to-noise ratio of contrast; a_1 represents the mean value of gray values of all pixels in the foreground area of the image; a_2 represents the average gray value in the background area; m is the standard deviation of the two. Theoretically, the higher the contrast to noise ratio is, the better the image quality is. In this experiment, the weights of reconstruction loss were set as 0.01, 0.1 and 0.2, respectively. The experimental results are shown in Table 1-3.

Table 1. Test results with reconstruction loss weight of 0.01

Serial number	Existing method 1	Existing method 2	Design method of this paper
1	1.4872	1.5254	1.9523
2	1.4956	1.5177	1.9636
3	1.5217	1.5382	1.9754
4	1.5178	1.5444	1.9677
5	1.4925	1.5366	1.9562

Table 2. Test results with reconstruction loss weight of 0.1

Serial number	Existing method 1	Existing method 2	Design method of this paper
1	1.2563	1.2658	1.7835
2	1.2436	1.2784	1.7943
3	1.2547	1.2847	1.8275
4	1.2574	1.2775	1.8185
5	1.2658	1.2822	1.7964

Table 3. Test results with reconstruction loss weight of 0.2

Serial number	Existing method 1	Existing method 2	Design method of this paper
1	1.0327	1.0621	1.6825
2	1.0282	1.0763	1.6684
3	1.0474	1.0676	1.6747
4	1.0257	1.0785	1.6872
5	1.0392	1.0857	1.6764

According to the test results in table 1-3, with the increase of reconstruction loss weight, the contrast to noise ratio of the three methods decreases, and the quality of the generated image gradually deteriorates. When the reconstruction loss weight is 0.01, the average contrast to noise ratio of the proposed method is 1.9630, and the average contrast to noise ratio of the existing methods are 1.5030 and 1.5325. Under the condition that the reconstruction loss weight is 0.1, the average contrast to noise ratio of the design method is 1.8040, and the average contrast to noise ratio of the existing methods are 1.2556 and 1.2777. When the reconstruction loss weight is 0.2, the average contrast to noise ratio of the proposed method is 1.6778, and the average contrast to noise ratio of the existing methods are 1.0346 and 1.0740. The above results show that the design method in this paper is higher than the existing methods in contrast to noise ratio, can achieve a certain de-noising effect in image enhancement, and has excellent performance in contrast visual effect of clinical medical images, with good practical application effect.

4. Conclusion

Although the method proposed in this paper has good effect on image enhancement, there are still some shortcomings in the research work, which need further improvement and improvement. In this paper, 61 dimension features are extracted when training SVM. In this paper, all features are fused together to construct feature vectors. The importance of each feature is not further discussed. It is necessary to further explore the importance of each feature in SVM. Selecting a small number of important features for classification can reduce the time of feature extraction and improve the efficiency of clinical assistant diagnosis.

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