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Research of Automatic Medical Image Segmentation Algorithm Based on Tsallis Entropy and Improved PCNN

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Abstract - It needs set parameters on image segmentation based on PCNN (Pulse Coupled Neural Network) now. This paper points out the new method for medical image segmentation based on improved PCNN and Tsallis entropy. The new methods can automatically segment the medical images without selecting the PCNN parameters. It gets the best results with combining with the Tsallis entropy. The new method is very useful for PCNN application in the medical images segmentation.

Index Terms - Artificial Intelligence; PCNN; Tsallis entropy; Medical Image Segmentation.

I. INTRODUCTION

The research of ROI segmentation is the most important base for the medical image analysis [1]. Accurate, robust and fast image segmentation is the most important step for following steps (quantitative analysis and three dimension visualization and so on). It is also foundation for image guided surgery, radiotherapy plans and treatment evaluation and others clinical application. Medical images have the characters such as blurredness, edges and regional feature indistinctness because of physical thermal noise of imaging equipment, offset effect, partial effect, fast moving of myocardial and flowing of blood.

In the early research of medical image segmentation, it mostly directly used the classics method of image processing such as edge extraction and region growing algorithm based on gray. In recent years, with mathematics development on the theory and application. It brings the new segmentation algorithm combing with wavelet, mathematical morphology, fuzzy mathematics, genetic algorithm, neural network, Markov model, deformable model and model guide method [2, 3]. PCNN founded by Eckhorn is better than the traditional method of image processing which explains synchronization of neuron related the characteristic in the cat's brain vision cortex experiment [4]. It needs set the parameters in the mathematics model through several experiments to realize the best segmentation effect. This paper points out the automatic segmentation method for medical image based on PCNN, which can automatically set PCNN parameters. In addition, it can get the best result by the two dimension Tsallis entropy.

II. TSALLIS ENTROPY

As generally, entropy is the basic concept in energetic concerning with the order of irreversible process. It can be used to measure randomness in a physic system. Shannon redefined the entropy function to check the indeterminacy of information included in the system. And it quantitatively measures the amount of the information produced by a process [5].

It assumes that the system has n kinds of possible states, the possibility of each state is $p = \{p_i\}$. $0 \le p_i \le 1$ and $\sum_{i=1}^{n} p_i = 1$. And then entropy can be defined as:

$$S_{Shannon} = -\sum_{i=1}^{n} p_i \ln p_i \qquad (1)$$

But its application is limited in the effective range of B-G statistical mechanics. There are many systems in the nature which can't be described by the B-G statistical mechanics, such as long-range interaction, Long-range microscopic memory (Non-markov process), Galaxies singular speed, Levy anomalous diffusion, dissipative system and so on. Therefore, Tsallis [6] brings out the Non-extensive entropy equation.

$$S_q = \frac{1 - \sum_{i=1}^{n} (p_i)^q}{q - 1} \qquad (2)$$

In this equation, n is the amount of possible states of the system, q is Non-extensive parameter.

The statistical mechanics which is based on Non-extensive is called Non-extensive statistical mechanics or general statistical mechanics. B-G statistical mechanics is included in it when q approximate to 1 limitlessly.

$$S_{Shannon} = \lim_{q \to 1} S_q \qquad (3)$$

As the parameter in Tsallis entropy, q describes the degree of Non-extensive. When the system consists of two independent systems A and B, the system entropy $S_q(A+B)$ meets the following pseudo-additivity.

$$S_q(A+B) = S_q(A) + S_q(B) + (1-q) S_q(A) S_q(B) \qquad (4)$$

III 2D TSALLIS ENTROPY OF IMAGE

The traditional image processes think that an image can be regarded as a Markov field. For simplify the processing, it

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only think the field remember adjective units. In fact, Natural image itself owns two aspect characteristics of long-range microscopic memory and dissipative system. Non-extensive Statistical mechanics can describe image itself appropriately. After processing hundreds of images, using the Non-extensive entropy (q=0. 8) is better than Shannon entropy [7].

However, after getting the histogram of image, it can work out the Tsallis entropy by the equation (2). It is better than the Shannon entropy. As the histogram considers the gray information, it easily becomes the boundary interrupted and less segmented by using the equation (2). Considering that the two dimension histogram not only includes the gray information but also spatial information, this paper combines the Tsallis entropy with two dimension histogram.

IV 2D HISTOGRAM

An image size is $M\times N$. The gray-scale is L. $f(x,y)$ describes the gray value of pixel(x, y). $g(x, y)$ describes the neighborhood average gray value. It needs consider the boundary effect when calculating $g(x,y)$. For example, when considering 3×3 neighborhood average gray value, it needs ignore the two rows of image both top and bottom and two columns of image both left and right. The equation of image's two dimension histogram:

$$h(m,n) = P\{f(x,y)=m, g(x,y)=n\} \quad (5)$$

It can adopt the correlation frequency method to estimate, which means $h(m\ ,n)$= numel($f(x,y)$=m, $g(x,y)$=n)/(MN).

V 2D TSALLIS ENTROPY

Supposed that image f has been segmented into the goal set O and the background set B, the image's two-dimensional Tsallis entropy is defined as [6]:

$$S_q(f) = S_q(O) + S_q(B) + (1-q)S_q(O)S_q(B) \quad (6)$$

In this equation, S_q(O) and $S_q(B)$ correspond goal O and the background B Tsallis entropy respectively, the definitions are as follows:

$$S_q(O) = \frac{1-\sum_{i=1}^{L}\sum_{j=1}^{L}\left[h_{ij}(O)\right]^q}{q-1} \quad (7)$$

$$S_q(B) = \frac{1-\sum_{i=1}^{L}\sum_{j=1}^{L}\left[h_{ij}(B)\right]^q}{q-1} \quad (8)$$

VI THE BASIC MODEL OF PCNN

The pulse coupling neural network is an artificial neural network, which was founded in the last century 90's, completely different from artificial neural networks. Eckhorn and his colleagues found that the synchronized shake phenomenon appeared in the local areas of different positions caused by similar stimulus input [4] in the study of the cat visual cortex. Later, in the experiments on monkeys they gained the same result [8]. Then Eckhorn bring out pulse coupling neural network model · Because this model is highly nonlinearity and complex reciprocity, it is difficult to use mathematical methods to control and interpret the results of neuronal behaviour. So in 1999Johnson transformed Eckhorn's model into PCNN model [9].

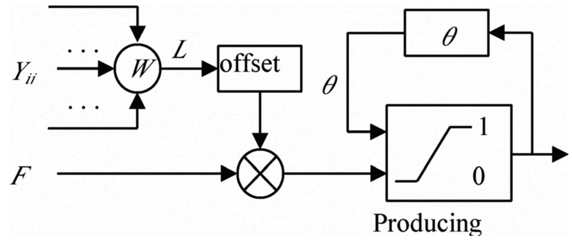

Fig.1 Neuron Model of PCNN

Figure 1 shows a PCNN neuron model, which is made up of receive part, modulation and pulse generator parts. Its discrete mathematics equation description is as follows:

$$F_{ij}[n] = \exp(-\alpha_F)F_{ij}[n-1] + V_F\sum M_{ijkl}Y_{kl}[n-1] + I_{ij} \quad (9)$$

$$L_{ij}[n] = \exp(-\alpha_L)L_{ij}[n-1] + V_L\sum W_{ijkl}Y_{kl}[n-1] \quad (10)$$

$$U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \quad (11)$$

$$Y_{ij}[n] = \begin{cases} 1 & U_{ij}[n] > \theta_{ij}[n-1] \\ 0 & U_{ij}[n] \le \theta_{ij}[n-1] \end{cases} \quad (12)$$

$$\theta_{ij}[n] = \exp(-\alpha_\theta)\theta_{ij}[n-1] + V_\theta Y_{ij}[n-1] \quad (13)$$

Equation (9) ~ (13) describes the PCNN neurons. i, j are the neuron markings, n is the iterations, I is neurons external stimulation, F is feedback input, L is connecting input, U is internal activity items, θ is dynamic threshold; M and W are connection weight matrixes (typically $M= W$); V_F, V_L, V_θ are amplitude constants for F, L, θ respectively ; V_F, V_L, V_θ third party α_F, α_L, α_θ are corresponding attenuation coefficients respectively; β is connection coefficient; Y is PCNN binary output. Receive part accepts the input of others neurons or external parts, After receiving the input, the receive part transmits them through two channels. One is the F channel, the other is L channel. When PCNN is used for image processing, the input of F channel is the gray of correspond pixel, the input of L channel is the output of neighborhood neuron generally. I_{ij} represents the gray value of corresponding pixel. After multiplying L_{ij} from L channel adding the plus offset with the F_{ij} from F channel, the modulation part gets the internal state U_{ij}. Input the U_{ij} into the pulse generation part. If U_{ij} is bigger than θ_{ij} , this neuron outputs a pulse, meanwhile, θ_{ij} is increased through the feedback. On the other hand, θ_{ij} is exponentially damped with the time growing.

When PCNN is used for image segmentation, it is the single two dimension local connection network. The neuron is corresponding with the pixel one by one. Each neuron is connected with the corresponding pixel which is also connected with the neighbor neuron. Input each gray value of pixel into corresponding F channel. The L channel of each neuron is connected with other neuron's output in neighborhood and receives their outputs. Each neuron only has two states, outputting pulse or not.

VII Improved PCNN Algorithm

Traditional PCNN model use the activity characteristics of biological neuron and threshold exponentially damped characteristics. The amplitude changeable rule based on exponentially damping is according to the need of gray response from human eyes, which is nonlinear. But the aid of medical image segmentation is to extract the ROI tissue or focus rather than the image clarity. Between the ROI tissue and background or different ROI tissue, it is difficult to segment because the bad comparability of pixel gray. The threshold exponentially damped method is not suitable for the realization of image processing algorithm [10-14]. So this paper improved this algorithm.

For the medical image processing, it is not in strict with the true nature of biological neurons. From the target and precision of the medical image segmentation, using the inhibitory properties of neurons, it adopts the search method of the traditional threshold segmentation technology, which means adopting the single increasing threshold function from smaller to bigger. It also simplifies PCNN model, as shown:

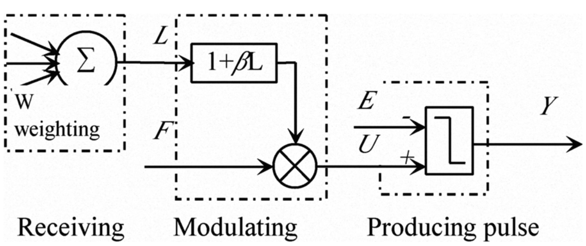

Fig.2 improved PCNN neuron model

$$F_{ij}[n] = I_{ij} \tag{14}$$

$$L_{ij}[n] = V_L \sum W_{ijkl} Y_{kl} \tag{15}$$

$$E_{ij}[n] = E[n] = \begin{cases} g[n]E_0, & Y_{ij}[n-1] = 1 \\ E_0, & Y_{ij}[n-1] = 0 \end{cases} \tag{16}$$

Using the improved PCNN model for the medical image segmentation, the neuron output is associated with the pixel value of the medical image, that is $F_{ij}[n]=I_{ij}$. Each neuron receives the neuron connection input, whose distance is within R. W that is the internal weigh coefficient matrix, and each element's value is reciprocal of Euclidean distance from the central pixel to around each pixel. $G[n]$ is the function increasing with the time growth.

Using this algorithm for medical image segmentation, each neuron can only be activated once. Concrete steps are as follows:

1) Set the initial values of PCNN parameters, which means that all threshold values are set to be zero. The aim is that all pixels can be activated.
2) Generate the next iteration threshold according to equation (16).
3) do the circulate iterating according to equation(14)-(16): When in the neighborhood where W(internal weight coefficient matrix) is there appears the pixel whose gray value is similar with others, and some pixel's gray value is less than the input threshold. These pixels output the pulse one by one; other around neurons whose gray values are similar can output pulse. Then produce the pulse sequence Y[n].

The output image produced by PCNN is the output sequence $Y[n]$. Through the principle of two dimension Tsallis entropy maximum, it makes two dimension Tsallis entropy in equation (6) is max to get the best value in the output sequence $Y[n]$. This value is the best segmentation result of the image.

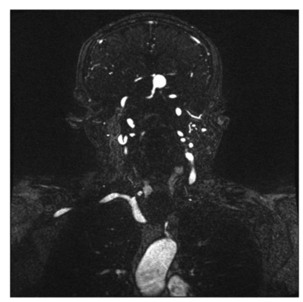

Fig.3 the human head blood vessel

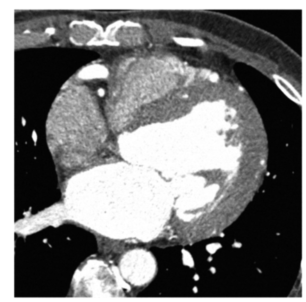

Fig.4 the human bosom

VIII Simulation results analysis

In this section, All algorithms were run on a Dell OptiPlex 170L PC. This choice was motivated by the fact that a PC is much cheaper and more widely available. The PC employed in this study had a main memory of 1024 MB and one hard disk unit of 80 GB. Its CPU was an Intel Pentium IV microprocessor running at 2.8 GHz. All programs were written in the C++ programming language and were compiled under Microsoft Visual C++ 6.0 and run under Windows XP (32-bit) operating system. All image data were first stored on the hard disk.

Two data sets were employed for this paper. The first data consisted of MRI images of the human head (see Fig. 3). The images had a spatial resolution of 448×576×120 and a dynamic range of 12 bits. The second data consisted of CT X-ray images of the human bosom (see Fig. 4). The images had a spatial resolution of 512×512×355 and a dynamic range of 12 bits. Fig 3 is the MRI original image of human head. Fig 4 is the CT original image of human bosom. Fig 5 and fig 7 are the unsegmented 3D reconstruction results.Fig 6 and fig8 are the segmented results by this paper's algorithm. From the fig6 and fig8, the vessels and heart are segmented effectively, and the details are perfect.

Fig.5 the human head vessel reconstruction result

Fig.6 the segmentation result of human head blood vessel

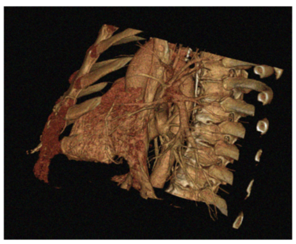

Fig.7 the human bosom reconstruction result

Fig.8 the segmentation result of bosom reconstruction

For medial image segmentation, this paper improves the changeable threshold function in PCNN, which combined with 2-D Tsallis entropy to segment the image automatically. As a result, this algorithm has the following advantages: the better image segmentation precision, the stronger adaptability. Especially this algorithm's superiority is obvious when the edge of image forward is faintness.

Based on this paper's algorithm, next step is how to segment more complicated medical images and how to improve the algorithm run speed, which strengthens the PCNN application in the medical image segmentation.

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