Medical Image Segmentation Based on GA Optimized BP Neural Network

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Abstract
Medical image segmentation provides the foundation and precondition for object separation, feature extraction and quantitative measurement of parameters so as to make possible higher-level medical image understanding and diagnosis. In the applications of medical image segmentation, due to the interference factors such as noise, it is easy to lose part of boundary information, causing incomplete image segmentation when the background is complex, especially when there are several research objects overlapping in the same background. This paper adopts GA-BP in medical image segmentation, training genetic neural network and putting sample value and feature value extracted into the genetic neural network for training. Genetic neural network in the weight and threshold space, randomly searches a group of the most proper weight and thresholds and set them as the initial weight and threshold of the neural network. Then, it conducts training until the mean square error converges to the designated value or reaches the maximum number of iterations. At this time, the neural network is the optimal.

Key words: Medical Image Segmentation, Genetic Algorithm, BP Neural Network.

Segmentación de Imágenes Médicas Basada en la Red Neuronal Optimizada de GA

Resumen
En las huellas digitales asimétricas, el comerciante puede rastrear a los traidores desde una copia pirateada por medio de la huella digital única incrustada, mientras que el cliente es inmune a ser enmarcado debido a la propiedad asimétrica. En esta carta, proponemos un esquema de huellas digitales asimétricas basado en una transferencia inconsciente 1-de-n, que es eficiente desde el punto de vista del uso del ancho de banda. Primero, se explota la multidifusión que es una tecnología de transporte eficiente para la comunicación de uno a muchos, lo que puede reducir significativamente el uso de ancho de banda. En segundo lugar, el cifrado simétrico en lugar del cifrado de clave pública se realiza en el contenido multimedia, lo que puede reducir la complejidad y el costo de la comunicación.

Palabras clave: Huellas Digitales Asimétricas, Transferencia Innesesaria, Comunicación Multidifusión

1. Introduction

Generally, the images we study include light intensity (LI) image, range image (RI), magnetic resonance image (MRI) and thermal image and so on. In medical images, doctors are usually only interested in certain objects which occupy certain regions of the image and have some differences in certain characteristics (i.e. grey level, contour, color, texture etc.). These differences may be very significant or too subtle to be observed by human eyes [1]. Image segmentation refers to the process to divide the image into the components which have strong correlation with the physical objects or regions in the real world. Medical image segmentation has become a typical problem in medical image processing due to its low contrast, great variability of tissue features, fuzzy boundary between soft tissues or between soft tissues and lesions and complex distribution in small and micro-blood vessels, plus restrictions of various objective factors in the imaging process. So far, there
is neither a universal image segmentation method, nor an objective criterion to accurately evaluate the segmentation [2] [3].

Classical image segmentation methods include threshold method, edge detection method and region method. The image regions to be segmented shall be homogeneous, i.e. similar grey level and textures. The regions shall be flat inside and there exists no small cavity. For certain homogenization criteria selected, there shall be significant differences between adjacent regions. Every region boundary to be segmented shall be neat and accurate in spatial position [4]. Genetic algorithm (GA) mainly accomplishes the goal of optimization through such operations as selection, crossover and mutations. In complex image segmentation, GA is frequently used in seeking the optimal value involving multiple parameters and it greatly enhances the computation speed; so, GA has been widely applied in image threshold segmentation techniques. As BP network and error back propagation have hidden layer in the middle and the corresponding learning rules to be found, it has strong recognition capability for non-linear pattern. This paper optimizes BP network with GA, obtains the optimal segmentation threshold to segmentation the image, and separate the object from the background [5] [6].

This paper elaborates image segmentation methods, and analyzes the principles of GA and BP neural network. On this basis, it proposes an GA-BP neural network. Prior to the segmentation, the first is to extract the feature value of the foreground and the background and the second is to extract good feature value to train the genetic neural network. Through the early learning, specific objects or features can be identified. The final experiment proves that the algorithm of this paper is effective.

2. Segmentation Methods Based on Threshold

Threshold segmentation method is to simply divide the histogram of the image into several classes with one or several thresholds and the pixels with gray value in the same gray-level class belong to the same class. The process is to determine a gray value to distinguish different classes and that gray value is called as the threshold. It can be divided into global threshold segmentation and local threshold segmentation. Threshold segmentation method actually is the following transform from the input image \( f \) to the output image \( g \).

\[
g(i,j) = \begin{cases} 
1 & f(i,j) \geq T \\
0 & f(i,j) < T 
\end{cases}
\]  

Here, \( T \) is the threshold and for the elements of the object, \( g(i,j) = 1 \), while for the elements of the background, \( g(i,j) = 0 \).

Therefore, the key of threshold segmentation algorithm is to determine the threshold. If a suitable threshold is determined, it can accurately segment the image. After the threshold is decided, compare the threshold with the gray value of the pixels and perform pixel segmentation in parallel and the segmentation result directly gives the image region [7].

The so-called global threshold segmentation is to use the information of the whole image to obtain the threshold for segmentation and then segment the entire image based on this threshold while the local threshold segmentation is to obtain thresholds for different regions according to the corresponding regions and use these thresholds to segment various regions, namely that a threshold corresponds to a corresponding sub-region [8].

3. Specific Steps of Genetic Algorithm

Step 1. Production of initial population: it can randomly produce (represent with encoding methods) the scale of population (depends on the computation ability and complexity of the computers).

Step 2. Encoding methods: encoding methods include binary coding (only 0 and 1 are allowed), sequential coding (repeated coding is not allowed), real-number coding (it is simple in computations, but cannot reflect the characteristics of the genes) and integer coding (repeated coding is allowed) and so on.

Step 3. Fitness function: in GA, fitness function is used to distinguish the individuals of the group. It is not only the driving force of the evolutionary process of the algorithm, but also the only basis for natural selection.

Step 4. GA: for the fitness probability obtained from the fitness function, select the parents to be inherited for crossover and mutation to obtain new population and the crossover process is as follows:

1. Randomly select two crossover positions and select the crossover part for every father generation.
2. Insert the contents of the crossover part in the first father generation into the first crossover position of the second father generation. As crossover operates part of the population of chromosome, it means inserting some population of the first father generation into the second father generation.
3. Remove all repeated individuals from the original population in the offspring generation to make the previous relationship of sub-ordination give way to the newly inserted population. Therefore, there is change in
certain population of the offspring generation. They will not have the same individuals as the previous generation.

④ Change the role of two father generations and re-apply Step 2 to Step 3 to produce the 2th offspring generation.

Step 5. Selection strategy: different selection strategies will lead to different selection pressures; in another word, the individuals of the father generation in the next generation copy different relations of distribution to numbers.

Step 6. Stop criterion: the number of genetic generations or the condition to stop computations can be set by humans until GA ends.

4. BP Neural network model and its basic principle

BP neural network is the abbreviation of error back-propagation neural network, which is composed of an input layer, one or more hidden layers and an output layer, and each layer includes a number of neurons. These neurons are related to each other just like human nerve cells.

The basic BP algorithm includes two aspects: signal forward propagation and error back propagation. That is to say, the calculation of the actual output is carried out from input direction to output direction, while the correction of weight and threshold is carried out from the output direction to input direction. Its structure is shown in Figure 1.

![BP network structure](image)

**Figure 1** BP network structure

In which, \( X_j \) represents the input of the number \( j \) node in the input layer, \( j = 1, \ldots, M \);
\( W_{ij} \) represents the weight between the number \( i \) node and the number \( j \) node in the hidden layer;
\( \Theta_i \) represents the threshold of the number \( i \) node in the hidden layer;
\( \Phi(x) \) represents the excitation function of the hidden layer;
\( W_{ik} \) represents the weight between the number \( k \) node in the output layer and the number \( i \) node in the hidden layer, \( i = 1, \ldots, q \);
\( a_k \) represents the threshold value of the number \( k \) node in the output layer, \( k = 1, \ldots, L \);
\( \psi_k \) represents the excitation function of the output layer.
\( O_k \) represents the output of the number \( k \) node in the output layer.

The purpose of BP neural network learning is to use a certain learning method to find an optimal parameter combination in the ownership value and threshold parameter combination of neural network connection, so as to minimize the fitness function value. The smaller the fitness function value is, the better the network weight and threshold parameter combination will be [9] [10].

5. BP Neural Network Based on GA Optimization

Image segmentation can be regarded as a second-class classification problem. Every pixel in the image is input into the genetic neural network as a group of samples for classification to determine whether the pixel
belongs to the foreground or background. If it belongs to the foreground, its value is set to 0; otherwise, it is set to 1. The loop operation is carried out on each pixel to complete the image segmentation [11]. Here are the steps.

1. Image reading
2. Parameter setting of self-adaptive genetic algorithm

The basic idea of self-adaptive genetic algorithm is to make \( c_p \) and \( m_p \) change automatically with fitness. When the fitness of each individual of the population tends to be consistent or locally optimal, increase \( c_p \) and \( m_p \), while decrease when the fitness of the population is relatively scattered. At the same time, for the individuals whose fitness is higher than the average fitness of the population, when compared to the lower \( c_p \) and \( m_p \), such solution can be protected to enter the next generation; individuals under average fitness, when compared to the higher \( c_p \) and \( m_p \), such solution will be eliminated. Therefore, the self-adaptive \( c_p \) and \( m_p \) can provide the optimal \( c_p \) and \( m_p \) relative to a certain solution. Such algorithm ensures the global convergence of the genetic algorithm while maintaining the diversity of the population.

The \( c_p \) and \( m_p \) of the self-adaptive genetic algorithm is adjusted according to the following formula:

\[
p_c = \begin{cases} 
\frac{k_1(f_{\text{max}} - f^{'})}{f_{\text{max}} - f_{\text{avg}}} & f^{'} \geq f_{\text{avg}} \\
\frac{k_2}{f_{\text{max}} - f_{\text{avg}}} & f^{'} < f_{\text{avg}} 
\end{cases}
\]

(2)

\[
p_w = \begin{cases} 
\frac{k_1(f_{\text{max}} - f^{'})}{f_{\text{max}} - f_{\text{avg}}} & f^{'} \geq f_{\text{avg}} \\
\frac{k_2}{f_{\text{max}} - f_{\text{avg}}} & f^{'} < f_{\text{avg}} 
\end{cases}
\]

(3)

\[
p_c = \begin{cases} 
(p_{c_{\text{max}}} - p_{c_{\text{min}}}) \times \text{iter} & , f' > f_{\text{avg}} \\
p_{c_{\text{max}}} & , f' \leq f_{\text{avg}} 
\end{cases}
\]

(4)

\[
p_n = \begin{cases} 
(p_{n_{\text{max}}} - p_{n_{\text{min}}}) \times \text{iter} & , f > f_{\text{avg}} \\
p_{n_{\text{max}}} & , f \leq f_{\text{avg}} 
\end{cases}
\]

(5)

In which, \( p_c \) is the crossover probability, \( p_{c_{\text{max}}} \) is the maximum crossover probability, \( p_{c_{\text{min}}} \) is the minimum crossover probability, \( p_n \) is the maximum variation probability, \( p_{n_{\text{max}}} \) is the maximum variation probability, \( p_{n_{\text{min}}} \) is the minimum variation probability, \( \text{iter} \) is the maximum evolutionary algebra, \( f_{\text{avg}} \) is the current evolutionary algebra, \( f_{\text{max}} \) is the average fitness value of the population, \( f' \) is the larger fitness value of the two crossed individuals, and \( f \) is the fitness value of the mutated individual [12].

3. Classification

Image segmentation is regarded as a classification process. Each pixel \((G_i)\) in the image \((G)\) is a sample to be classified. This sample is sent to the genetic neural network \((\text{sim})\) for classification, and a flag value \(V_q\) will be output, which determines the probability that such sample belongs to the first class. We can decide that if such value is greater than 0.5, it is considered foreground \((F)\), otherwise it is background \((B)\). Where, \(H\) stands for the segmented image.

\[
V_q = \text{sim}(G_i) \\
H_q = \begin{cases} 
F & V_q \geq 0.5 \\
B & V_q < 0.5 
\end{cases}
\]

(6)

4. BP neural network training samples and feature extraction
After determining the segmentation object, it is necessary to extract all kinds of samples as the initial training samples of the neural network. The second step is to extract some foreground samples and some background samples. The number of samples is not necessarily large, but its coverage must be broad enough to describe its boundary in the classification space. The network usually consists of three aspects: input layer, hidden layer and output layer. The input signal propagates forward from the input layer to the output layer layer by layer. It is assumed that the number of nodes in the input layer of the network is regarded as the research object, the number of nodes in the hidden layer is $H$, and the number of nodes in the output layer is $y_{out}$, and the nodes are connected by connection weights and output signals, in which, the output signals are activated by the sum of the input signals of the nodes by a nonlinear function. Set $x_i$ is the input of the number $i$ input node, $w_{ij}$ is the connection weight between the number $i$ node and the number $j$ hidden layer node, and $\theta_j$ is the threshold value of the number $j$ hidden node, and $h_j$ is the net input of the hidden node $j$. Suppose the activation function of the hidden layer node of the network be the Sigmoid function with threshold, and the output layer node be the linear output, then the output of the number $j$ node of the hidden layer can be expressed in equation (7).

$$o_j = f(h_j) = \frac{1}{1 + \exp[-(\sum_{i=1}^{i_i} w_{ij} x_i - \theta_j)]} \quad j=1,2,\ldots,H$$

(7)

Derivative $f'(h_j)$ is equation (8)

$$f'(h_j) = \frac{\partial o_j}{\partial h_j} = o_j(1-o_j)$$

(8)

The output of the number $k$ in the output layer is,

$$y_k = \sum_{j=1}^{H} w_{kj} f(h_j) - \theta_k \quad k=1,2,\ldots,y_{out}$$

(9)

In which, $w_{kj}$ is the connection weight between the number $j$ node in the hidden layer and the number $k$ node in the output layer; $\theta_k$ is the threshold value of the number $k$ output node.

Set the input-output relationship of the training sample in the network application as:

$$y^d(t) = g(x^d(t)) \quad t=1,2,\ldots,n_t$$

(10)

In which, $x^d(t)=[x_1^d(t),x_2^d(t),\ldots,x_n^d(t)]$ is the input of the training sample; $y^d(t)=[y_1^d(t),y_2^d(t),\ldots,y_{out}^d(t)]$ is the corresponding sample desired output of the sample input $x^d(t)$ under the function of unknown non-linear function.

Then the fitness function of the network learning can be defined as:

$$E = \sum_{t=1}^{n_t} \sum_{j=1}^{y_{out}} (y_j^d(t) - y_j(t))^2$$

(11)

(5) Training of genetic neural networks

The training of genetic neural network is an extremely important step, which reflects the difference from the traditional segmentation algorithm. It is a learning process and a training process. Through continuous learning and training, the understanding of the segmentation problem can be strengthened by the genetic neural network and thus naturally distinguish all types [13].

(6) Image segmentation adopting genetic neural network

The trained neural network is used to segment any image conforming to such problem. Firstly, the segmentation problem is regarded as a problem of classifying a group of variables. Therefore, we need to
transform the image into a group of random variables, and a set of target values is output after classification by genetic neural network, and then such set of target values can be restored into one image, in this way, the image segmentation is completed [14].

6. Test Experiment and Analysis

In medical image segmentation, in many cases, the gray value of the background is not a constant, and the contrast of the object and the background also changes in the image. In this case, a threshold that works well in one area of the image may work poorly in other areas. In addition, when there is shadow, burst noise, uneven illumination, uneven contrast or background gray level change in the image, the segmentation effect will be affected due to the inability to take into account the situation of all parts of the image in case that only a fixed threshold value is used for threshold processing of the whole image. In these cases, the selection of threshold value is not fixed, but selecting a function value that changes slowly with the position in the image is more appropriate. The traditional segmentation method is to calculate the theoretical optimal segmentation threshold by analyzing the histogram. However, the GA-BP algorithm in this paper completely breaks this concept and turns the segmentation problem into a classification problem. First, the image histogram is analyzed to find an optimal threshold that can separate the foreground and background. Determine the range of foreground color and background color, and then put the foreground color and background color in an array in order, and the generated array is the training sample array, and then create an array of the same size T to save the sample category. Set the foreground category as 0, and the background category as 1. We take the MRI image of brain section as an example, the brain gray matter is the part of the brain cavity in the image. For such an image, the brain gray matter needs to be extracted separately for image analysis, that is, the training sample. The comparison the segmentation performance of GA-BP neural network and traditional BP neural network is shown below in Figure 2.

![Image of brain MRI with different segmentation results](image-url)
In the above image, from the image to be segmented, the original test image itself has more target areas, and the contrast of some areas is weak. Traditional segmentation methods are based on histogram analysis to calculate the optimal segmentation threshold in theory. The GA-BP algorithm in this paper breaks this concept and transforms the segmentation problem into a classification problem. From the segmentation results, the GA-BP algorithm retains the image details perfectly, accurately segments the target area, and the shape of the target is better and the edge is clear. GA-BP algorithm retains image details more perfectly, and accurately segments the target image. In terms of the search process, the optimal threshold of BP algorithm fluctuates greatly each time, while that of GA-BP algorithm is relatively stable. At the same time, the optimal threshold of image segmentation can be obtained with a smaller iteration algebra. The results of 5, 10 and 15 iterations do not change much. The stability and convergence of the algorithm in this paper are good.

7. Conclusions

In medical image segmentation, the image space is divided into some meaningful regions corresponding to various objects in the image. By describing the segmentation results, the information contained in the image can be understood. In this paper, GA-BP neural network method is applied to medical image segmentation. The test experiments show that, with high convergence speed, strong robustness and a broad application prospect, the genetic algorithm is introduced to greatly improve the efficiency of neural network training, and vital information can be obtained by the efficient processing of image segmentation, and thus better effect will be achieved by applying such genetic algorithm to the object segmentation of complicated medical images.

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