Evolution Analysis of Adaptive Distance Preserving Level Set in Image Segmentation Based on Deep Learning

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Abstract: As we know, image segmentation is the key technology from image processing to image analysis, and variational level set method has become one of the main development directions in the field of image segmentation. Adaptive distance preserving level set evolution model is one of the common methods. Although this method gets rid of the dependence of evolution curve on the initial position, it still has low segmentation accuracy and high accuracy For this reason, this paper analyzes the evolution of adaptive distance preserving level set in image segmentation based on deep learning. In this paper, convolution neural network is introduced into the evolution of adaptive distance preserving level set. Based on the adaptive distance preserving level set evolution model, a new variable weight coefficient is introduced, and a new edge stop function is defined. Experiments on different data sets are carried out to verify the reliability of the proposed method. The results show that in the traditional adaptive distance preserving level set evolution model, the average value of signal-to-noise ratio is 22.1343, and the average value of peak signal-to-noise ratio is 28.0425. In this method, the average value of signal-to-noise ratio is 24.2743, and the average value of peak signal-to-noise ratio is 29.9982. Therefore, the denoising effect of this method is better. In addition, the experimental results show that the segmentation accuracy of the proposed method is much higher than that of the traditional adaptive distance preserving level set evolution model. Therefore, this method can effectively improve the segmentation accuracy and denoising effect.

1. Introduction

Generally speaking, in an image, people are only interested in certain parts, which are generally referred to as the target or region of interest (ROI). To achieve these goals, we need to process the image. Image processing is to extract the image parts that people are interested in, and define and describe them [1-2]. Therefore, in the image, separating the target from the background for further processing is called image segmentation [3]. More specifically, image segmentation refers to the segmentation of the image into many non overlapping regions according to the gray level, color, texture, shape and other characteristics of the image. Generally speaking, the segmented regions are similar or consistent. In addition, the difference between different regions is obvious [4].

With the rapid development of science and technology, the application of deep learning in image segmentation is more and more extensive [5-6]. In recent years, variational level set method has become one of the main development directions in the field of image segmentation, and has been widely concerned by scholars at home and abroad [7-8]. In the traditional level set method, in order to keep the level set function close to the symbolic distance function in the evolution process, it is necessary to initialize the level set function periodically. This process not only consumes a lot of time, but also easily causes numerical error [9-10]. In order to solve the problem that the level set evolution model is sensitive to contour initialization and slow convergence without re initialization, this paper proposes a deep learning adaptive distance preserving level set evolution model for image segmentation based on the model, which is of great significance for image segmentation.

This paper first introduces some basic concepts and common models of deep learning, and describes the evolution model of adaptive distance preserving level set. Secondly, convolution neural network is introduced into the evolution of adaptive distance preserving level set, and a new

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variable weight coefficient is introduced to improve the model. Finally, we choose the image data set and study the proposed method. Compared with the traditional adaptive distance preserving level set evolution method, the experimental results show that the proposed method can effectively improve the segmentation accuracy and denoising effect compared with the traditional adaptive distance preserving level set evolution model.

2. Deep Learning and Adaptive Distance Preserving Level Set Evolution Model

2.1 Deep Learning

Deep learning is a process of feature learning. Its principle is to outline the characteristics of the model by learning the internal characteristics and abstract levels of the original data, and then classify the test data well. Here are some deep learning models.

(1) Deep belief neural network

Deep belief network (DBN) is a probabilistic generation model. DBN can be used not only for feature selection and classification, but also for data generation.

(2) Convolution neural network

Convolutional neural network (CNN) can be understood as a kind of feedforward neural network including data convolution calculation. It is a research hotspot in the current algorithm field, and is often used in classification, recognition, image and other major fields.

Convolutional neural network mainly uses the principles of local sensing, parameter sharing and pooling (down sampling). Local sensing is to select only a part of the data and extract local features. Many local features constitute the eigenvalues of all data. Weight sharing is to share the same parameters in the convolutional neural network, Thus, the corresponding training complexity is reduced; pooling is also known as down sampling, which reduces the dimension of eigenvalues by taking the maximum value or the mean value of eigenvalues, so as to make the convolution neural network run faster and better.

(3) Recurrent neural network

Recurrent neural network (RNN) is also a relatively common neural network, also known as recurrent neural network. It is mainly used to deal with the sequence data of some context features, which enhances the ability of the model to obtain historical information.

2.2 adaptive distance preserving level set evolution model

We know that the adaptive distance preserving level set evolution model can be obtained by introducing variable weight coefficient $v(I)$ without reinitializing the model.

$$\varepsilon(\phi)=\mu\int_{\Omega}P(|\nabla\phi|dxdy)+\lambda\int_{\Omega}g(I)\delta(\phi)|\nabla\phi|dxdy+\int_{\Omega}v(I)g(I)H|-\phi|dxdy \tag{1}$$

According to the variational principle and steepest descent method, the partial differential equation for the evolution of control level set function is obtained as follows:

$$\frac{\partial\phi}{\partial t}=\mu div(d_p(|\nabla\phi|)\nabla\phi)+\lambda\delta(\phi)div\left(g(I)\frac{\nabla\phi}{|\nabla\phi|}\right)+v(I)g(I)\delta(\phi) \tag{2}$$

In many images, the points with large gradient variation may be located at the boundary of the target or the uneven gray level, or they may be noise points. The model still has the following shortcomings: (1) the segmentation of uneven gray images is not ideal; (2) it is sensitive to noise.

3. Experimental Design

In this paper, the traditional adaptive distance preserving level set evolution model is compared with the proposed method to highlight the advantages of this method.

(1) Data set

In this paper, four types of images are selected as the experimental data set. The four types of images are balloon, toy, butterfly and pepper. The image size and pixel are the same.

(2) Experimental environment and parameter setting

In this paper, the computer hardware environment is Dell core 17, four core 3, memory 4GB.

The parameters of this paper are as follows: in the adaptive distance preserving level set evolution model, $\mu = 0.04$, $C = 2.5$, $\lambda = 8.2$. In this method, the results are as follows: $\mu = 0.04$, $\lambda = 8.2$, $m_l=0.5$,$m_h=2$. The initial level set function is defined as $\rho = 1$.

(3) Evaluation index

This paper evaluates the denoising effect and segmentation accuracy index. The denoising effect is compared from the signal-to-noise ratio and peak signal-to-noise ratio of the two methods. In the comparison of segmentation accuracy, we compare the segmentation accuracy of the two methods on different data sets.

4. Evolution Analysis of Adaptive Distance Preserving Level Set in Image Segmentation Based on Deep Learning

Image segmentation and image denoising are important parts of image processing. Image segmentation technology can better feature extraction and recognition of the target object, image denoising technology can remove the noise and restore the original characteristics of the image, so as to better analyze the image.

Before the advent of deep learning, most of them focused on regression and classification, only dealing with one-dimensional, two-dimensional and other low-dimensional structure data; data characteristics need to be artificially defined. When the data samples are limited and the number of training samples is limited, the simulation ability is very poor, and the accuracy rate obtained with test samples is particularly low, However, the classification effect is not obvious. Convolution neural network is a kind of deep learning. Convolution neural network is usually used in classification, recognition, image and other fields. Generally speaking, convolution neural network is a kind of feedforward neural network with back-propagation characteristics. Relatively speaking, it is very similar to the usual neural network. As an independent unit, each neuron responds effectively to the input data and outputs a set of values to represent the possibility of classification. Convolution neural network can achieve the purpose of adjusting the network structure. In this way, we can make full use of the data structure information to improve the network performance. At the same time, it also reduces a large number of parameters to shorten the network model training time. The processing flow of convolution neural network is as follows:

(1) In the first step, in the convolution layer, different convolution kernels are used to perform convolution operation in the input image to extract the local features, and then the features are output in the form of a two-dimensional image.

(2) In the second step, the output of the convolution layer is processed by using nonlinear activation function.

(3) In the third step, the output of nonlinear activation function is pooled by pooling layer.

Generally speaking, the adaptive distance preserving level set evolution model can be obtained by introducing variable weight coefficients without initializing the model. This method has many defects, such as sensitive to noise, poor noise reduction effect and low accuracy. In order to solve these problems, this paper introduces convolution neural network into it. Based on the adaptive distance preserving level set evolution model, a new variable weight coefficient is introduced, and a new edge stop function is defined.

We introduce a new variable weight coefficient and define a new variable weight coefficient

$$v(I,\beta) = (\Delta I_\sigma \beta(m))|\nabla I_\sigma| \quad (3)$$

$$\beta(m) = \begin{cases} 1, m_l \le m_h \\ 0, m < m_l, or\ m \ge m_h \end{cases} \quad (4)$$

Where m_l and m_h are constants greater than zero.
Thus, the following model can be obtained.

$$\varepsilon(\phi)=\mu\int_{\Omega}P(|\nabla\phi|dxdy)+\lambda\int_{\Omega}g(I,\beta)\delta(\phi)|\nabla\phi|dxdy+\int_{\Omega}v(I,\beta)g(I,\beta)H|-\phi|dxdy \tag{5}$$

The corresponding level set evolution partial differential equation is as follows:

$$\frac{\partial\phi}{\partial t}=\mu div(d_p(|\nabla\phi|)\nabla\phi)+\lambda\delta(\phi)div\left(g(I,\beta)\frac{\nabla\phi}{|\nabla\phi|}\right)+v(I,\beta)g(I,\beta)\delta(\phi) \tag{6}$$

Due to the introduction of variable weight coefficient, its evolution results are not affected by the initial level set function. The results are as follows: 1

4.1 Analysis of Denoising Effect

Compared with the traditional adaptive distance preserving level set evolution model, the denoising effect of the two methods is compared by comparing the signal-to-noise ratio and peak signal-to-noise ratio of the two methods. The results are shown in Table 1 and Figure 1. In order to ensure the validity of the experimental results in this paper, the experimental results are obtained through 10 independent computer experiments.

Table 1. Denoising effect of two methods

Index	The method of this paper	Traditional model
SNR average value	24.2743	22.1343
SNR variance	0.00156	0.00072
PSNR average value	29.9982	28.0425
PSNR variance	0.00156	0.00072

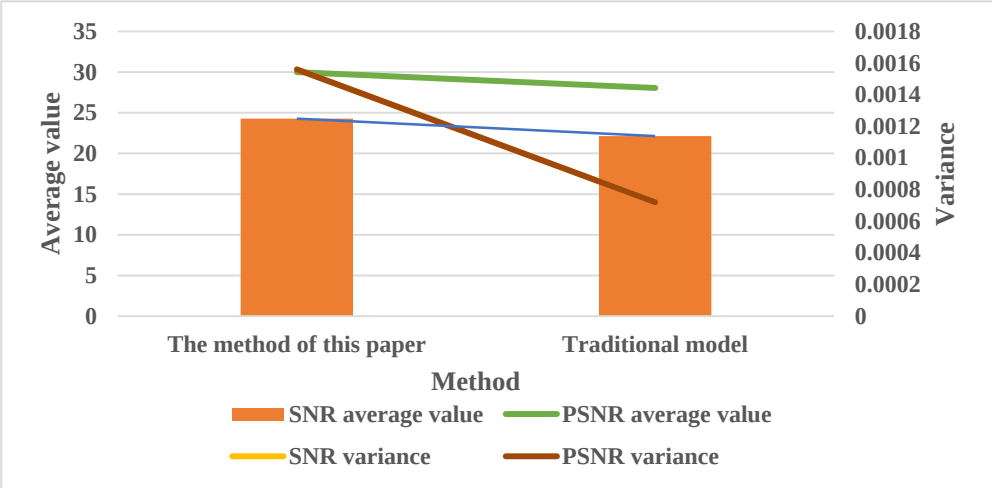

Figure 1. Comparison and analysis of denoising effect of two methods

It can be seen from Table 1 and Figure 1 that in the traditional adaptive distance preserving level set evolution model, the average value of signal-to-noise ratio is 22.1343, the variance is 0.00072, the average value of peak signal-to-noise ratio is 28.0425, and the variance is 0.00072. In this method, the average value of signal-to-noise ratio is 24.2743, the variance is 0.00156, the average value of peak signal-to-noise ratio is 29.9982, and the variance is 0.00156. Therefore, the signal-to-noise ratio and peak signal-to-noise ratio of the proposed method are higher than those of the traditional adaptive distance preserving level set evolution model, that is to say, the noise reduction effect of the proposed method is better. This method makes up for the defect that the traditional adaptive distance preserving level set evolution model is sensitive to noise and improves the noise reduction robustness. This method can protect the object boundary and smooth the noise area in the process of noise reduction. With the increase of iteration times, the method can preserve the object boundary completely, and the difference between the denoised image and the original

image is small, so it is an effective noise reduction model.

4.2 Comparative Analysis of Segmentation Accuracy

From the segmentation accuracy of different data sets, the segmentation accuracy of the two methods is compared, and the results are shown in Figure 2.

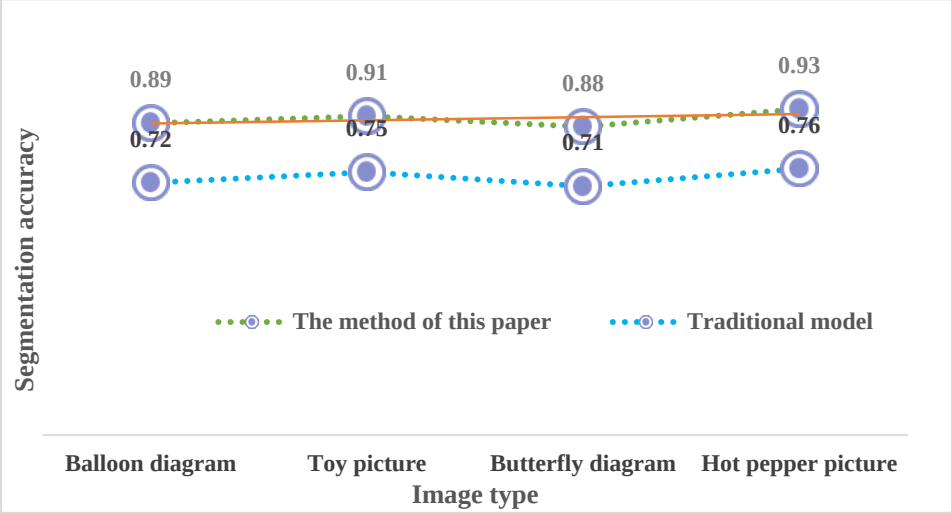

Figure 2. Comparative analysis of segmentation accuracy

It can be seen from Figure 2 that in the traditional adaptive distance preserving level set evolution model, the segmentation accuracy of balloon image is 0.72, that of toy image is 0.75, that of butterfly image is 0.71, and that of pepper map is 0.76. In the image segmentation, the segmentation accuracy of balloon image is 0.89, that of toy image is 0.91, that of butterfly image is 0.88, and that of pepper image is 0.93. It can be seen that in the four kinds of images, the image segmentation accuracy of the proposed method is much higher than that of the traditional adaptive distance preserving level set evolution model. Moreover, the convergence speed of the proposed method is fast, and the segmentation effect is accurate.

5. Conclusions

Image segmentation technology is a basic and key technology for low-level image processing and correct understanding of image through image analysis. The function of image segmentation is to divide the target regions with different structural features according to the real situation of the object. The quality of the segmentation results will directly affect the recognition and processing effect of the subsequent images. Adaptive distance preserving level set evolution model can get rid of the dependence of evolution curve on initial position. It is a very good image segmentation method, but it also has the defects of low segmentation accuracy and too sensitive to noise. Therefore, this paper proposes an in-depth learning adaptive distance preserving level set evolution model for image segmentation. In this paper, convolutional neural network is introduced into image segmentation. Based on the adaptive distance preserving level set evolution model, a new variable weight coefficient is introduced, and a new edge stop function is defined. The method is compared with the traditional adaptive distance preserving level set evolution model. The results show that the proposed method can effectively improve the image quality Image segmentation accuracy, improve the noise reduction effect.

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