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Entropy-Based Global and Local Weight Adaptive Image Segmentation Models

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Abstract: This paper proposes a parameter adaptive hybrid model for image segmentation. The hybrid model combines the global and local information in an image, and provides an automated solution for adjusting the selection of the two weight parameters. Firstly, it combines an improved local model with the global Chan-Vese (CV) model, while the image's local entropy is used to establish the index for measuring the image's gray-level information. Parameter adjustment is then performed by the real-time acquisition of the ratio of the different functional energy in a self-adapting model responsive to gray-scale distribution in the image segmentation process. Compared with the traditional linear adjustment model, which is based on trial-and-error, this paper presents a more quantitative and intelligent method for achieving the dynamic nonlinear adjustment of global and local terms. Experiments show that the proposed model achieves fast and accurate segmentation for different types of noisy and non-uniform grayscale images and noise images. Moreover, the method demonstrates high stability and is insensitive to the position of the initial contour.

Key words: image local entropy; parameter adaption; image segmentation; active contour

1 Research Background

Classical region-based global active contour models dependent on a global mean can achieve satisfactory results for noise images and those with a uniform gray distribution. However, they are based on the assumption that the global model is constant based on the background of the target, which is invalid when the image is characterized by grayscale inhomogeneity. This assumption leads to segmentation errors in non-uniform images. Segmentation models based on local image information [1–8] are more effective than the global models at segmenting uneven gray-level information. For example, Li et al. [7] proposed a Local Binary Fitting (LBF) model based on image local information, LBF overcomes the shortcomings of global models in non-uniform gray-level image segmentation, but its computational complexity is high and is easy to fall into local minimum. In order to solve the LBF model’s problem of high computational complexity, Zhang et al. [8] proposed a Local Image Fitting (LIF) model, which effectively reduces the computational complexity, while maintaining the segmentation accuracy for non-uniform gray and noisy images. However, LIF still has some problems in the segmentation of complex non-uniform gray images.

The degree of gray unevenness of an image varies in different regions. While it is appropriate to use a global model with a fast convergence speed for segmentation in the regions where the image gray distribution is relatively uniform, a local model is most suitable for segmenting the image in regions where the gray-level distribution is uneven. In order to select...
suitable data items to guide the evolution of the curve according to the gray-level distribution of different regions of the image, and to combine the advantages of global and local models, a large number of models fusing local and global image information have been proposed\textsuperscript{[9-14]}. These include the Local and Global Intensity Fitting (LGIF) model proposed by Wang et al.\textsuperscript{[9]}, which considers the gray-level information of the image comprehensively, to achieve a better segmentation result.

However, hybrid methods require that a reasonable weight parameter value is selected to correctly allocate the respective proportions of the local and global items. LGIF can not automatically select the weight parameter, so it is usually implemented with fixed parameters set manually. The same is true for the other hybrid models that have been proposed thus far. In the initial stage of curve evolution, a fixed weight parameter is set to implement a linear control of global and local terms. However, the selection of this parameter often needs to be determined by repeated experiments, which means that a lot of time and energy is used to fine-tune the parameter. The final parameters are based on the results of repeated experiments and there is no quantitative selection criteria. In the process of curve evolution, the fixed parameters can not be adjusted in real time in accordance with the gray level of the image, and the selection of weight parameters will directly affect the segmentation speed and the accuracy of the evolution curve. In addition, the correct weight parameters values vary for different images, which makes their selection more complicated. Therefore, there is a need to find a method for efficiently and accurately segmenting images automatically without the costly determination of weight parameters. Based on this original intention, a more accurate and reliable indicator for measuring grayscale information of images is found and a characteristic function reflecting the image information, and is well suited as a weight parameter to adjust the respective proportions of the global and local items.

2 Related Theory

2.1 Image entropy theory

The theory of information entropy\textsuperscript{[15]} has been widely applied in the field of image processing since it was proposed by Shannon in 1948. Image entropy can be used to represent the distribution characteristics of the gray levels of an image and describe its gray-level uniformity\textsuperscript{[16]}. At any time in the image segmentation, the evolution curve divides the image into two parts: \( in(C) \) and \( out(C) \). The algorithm takes the position of the evolution curve in each iteration and calculates the local entropy of the image \( E_{in} \) inside the curve,

\[
E_{in} = - \sum_{i=1}^{N} P_i \log_2 P_i, \quad i \in in(C) \quad (1)
\]

where \( N \) represents the gray-level of the image, \( P_i \) represents the probability of the occurrence of the \( i \)-th gray level\textsuperscript{[17]}. According to the extremum of the entropy function, the entropy function obtains its maximum value\textsuperscript{[18]} when each element of the system has an equal probability. Since the grayscale value of the internal image of the segmentation curve is \([0, 255]\), when the probability of the occurrence of each grayscale is equal, the entropy function is at its maximum value, and the value range of the image’s local entropy function is calculated as \([0, 8]\). If Shannon’s information entropy is generalized to the image domain, when the gray in an image is more evenly distributed, the entropy will be larger\textsuperscript{[19]}. Therefore, image entropy can effectively measure the gray distribution of an image, and is well suited as a weight parameter to adjust the respective proportions of the global and local items.

2.2 Local image entropy

For a given image \( I : \Omega \rightarrow \mathbb{R}^2 \), based on the idea of the local model being represented as a neighborhood, for any pixel point \( x \) in the image and its neighborhood with radius \( r \) is \( \Omega_x \in \Omega \), according to the definition of image entropy, the expression of image entropy in the neighborhood of pixel \( x \) is calculated as

\[
E(I(x), \Omega_x) = \frac{1}{\log |\Omega_x|} \int_{\Omega_x} P(I(y), \Omega_x) \log P(I(y), \Omega_x) dy \quad (2)
\]

where \( I(y) \) is the pixel value of \( y \) in the neighborhood of \( \Omega_x \), \( P(I(y), \Omega_x) \) is the probability function of the gray-level distribution among the pixels in the neighborhood,

\[
P(I(y), \Omega_x) = I(y) \int_{\Omega_x} I(z) dz, \quad y \in \Omega_x \quad (3)
\]

Local entropy is the result of the interaction of all pixels in the neighborhood, and can effectively reflect the variation and dispersion degree of gray values in the
local neighborhood. At the same time, the calculation of image entropy has the ability to resist both noise interference and geometric deformation\cite{20}. In recent years, local image entropy has been widely used for image processing tasks\cite{21-23}. For these reasons, local image entropy is used in this paper to construct the feature function that guides the model’s data item ratio.

2.3 Chan-Vese model

Aiming to simplify the earlier Mumford-Shah model\cite{24}, Chan and Vese proposed a Chan-Vese (CV) model based on global image information in 2001\cite{25}. The core idea behind CV is to consider the target and image background into two types of simple problems and use a simple two-clustering idea to control the curve to the target boundary and divide the target from the background.

For the image $I$ to be segmented, the image domain is $\Omega$. Assuming that the image is composed of a target and a background with evenly distributed gray scales, the energy function of the evolution of the curve $C$ is defined as

$$E^{CV}(C, c_1, c_2) = \lambda_1 \int_{in(C)} |I(x) - c_1|^2\,dx + \lambda_2 \int_{out(C)} |I(x) - c_2|^2\,dx \quad (4)$$

where $\lambda_1$ and $\lambda_2$ are positive constants, generally taking $\lambda_1 = \lambda_2 = 1$. $C$ represents a closed evolution curve within the image domain. At any moment, the image $I$ is divided into target and background regions by the evolution curve $C$, namely $in(C)$ and $out(C)$. $c_1$ and $c_2$ represent the average gray values of the target region and background region, respectively.

The CV model can obtain global optimal segmentation, avoiding falling into local minimum values. The curve converges quickly and is insensitive to the position of the initial contour when evolved. However, since CV does not take into account changes in the local grayscale characteristics of the image, it is poor in segmenting noisy image and uneven grayscale image.

2.4 VLIF model

Zhao et al.\cite{26} introduced the term of variance between classes into the LIF model, and proposed a model based on maximum between-cluster Variance Local Image Fitting (VLIF), which takes into account the difference in fitting mean between the interior and exterior of evolutionary curve in the neighborhood to reduce false segmentation and improve segmentation accuracy. According to the idea of variance between maximal classes, the variance between two classes of mean $m_1$ and $m_2$ in a local Gaussian window is

$$\sigma_0^2 = \omega_1(m_1 - m_0)^2 + \omega_2(m_2 - m_0)^2 \quad (5)$$

where $\omega_1$ and $\omega_2$ represent the ratio of the parts belonging to $m_1$ and $m_2$ to the whole image, respectively, and $m_0$ represents the average gray value of the pixels in the Gaussian window, calculated as

$$m_0 = \omega_1 m_1 + \omega_2 m_2 \quad (6)$$

By substituting Eq. (6) for Eq. (5), the inter-class variance terms can be obtained as

$$\sigma_0^2 = \omega_1 \omega_2 (m_1 - m_2)^2 \quad (7)$$

Assuming that the neighborhood is represented by $\Omega_\epsilon$, the energy term of the variance between classes can be defined as

$$E_{\Omega_\epsilon}(x) = -\omega_1 \omega_2 \int_{\Omega_\epsilon} |m_1 - m_2|^2\,dx \quad (8)$$

The energy function of the improved VLIF model is

$$E^{VLIF}(\varphi) = \frac{1}{2} \int_{\Omega} |I(x) - I^{LIF}(x)|^2\,dx - \omega_1 \omega_2 \int_{\Omega_\epsilon} |m_1 - m_2|^2\,dx \quad (9)$$

In this model, the idea of maximum inter-class variance is introduced into the local segmentation model, and the energy term of maximum inter-class variance is added on the basis of the local model. By maximizing the difference between the target and the background in some neighborhood on the evolution curve, the pseudo-boundary points that make the evolution curve fall into the local minimum are eliminated, and the evolution curve is driven to stay at the correct target boundary.

3 Automatic Adjustment of Active Contour Model Based on Weight of Image Entropy

Our proposed method uses the VLIF model to construct the local energy term and the CV model to construct the global energy term. These two data energy terms then drive the curve to the target edge under the adjustment of the weight function.

The adjustment mechanism of the global and local terms on the evolution curve works as follows. The evolution of the curve is dominated by the local term in regions where the image gray-level distribution is uneven and in the region near the target edge. This approach is taken because the grayscale information in these regions is usually complicated, with the gray-level values varying greatly. The local term takes
the neighborhood approach to accurately capture the subtle changes in the gray-level information in the neighborhood, so that the segmentation curve can be docked accurately at the target edge. In the regions where the image gray-level distribution is relatively uniform, the evolution of the curve is dominated by the global term, because these regions are generally parts of the image background or the target interior, and the curve can be quickly evolved to reach the target edge as soon as possible.

Accordingly, the proportions of the global and local items should be different for different regions, meaning that the weight parameter must be nonlinear and adjusted for different regions based on their gray-level distribution. Choosing the appropriate weight parameters is very important for segmentation results and computational efficiency. If the weight parameter is biased toward the global term, the gray-level information changes in uneven gray-level regions will be insufficient for accurate segmentation, and the initial contour will be therefore too sensitive; if the weight parameter is biased toward the local term, the evolution of the curve will be too slow, adding unnecessary computational cost.

The idea of image entropy, based on information entropy, can effectively reflect the gray-level distribution. The local image entropy is used to construct the feature function reflecting the gray-level change of the neighborhood in the weight function, and the proportion of the global and local items is dynamically adjusted to guide the evolution of the curve. In this way, the weight function can use the change of image entropy to obtain the distribution of gray levels in different regions of the image in real time, thus adaptively adjusting the proportion of global and local items in a non-linear way. When the gray-level distribution of the image is relatively uniform, the image entropy value will be high and the global item will dominate the evolution of the contour curve. When the gray-level distribution is not uniform, the image entropy value will be low, and the local data energy fitting term will dominate. The contour curve evolution. The energy functional definitions is

$$E(C) = (1 - s)E^{VLIF} + sE^{CV} \quad (10)$$

where $s (0 \leq s \leq 1)$ is a weight parameter, used to control the proportion of the local energy term and the global energy term, and its value is determined by the value of the entropy in the local neighborhood of the image, that is,

$$\omega = a \cdot E(I(x), \Omega_x) \quad (11)$$

where $a$ is a standardization factor, placing the value of the weight parameter within the range of $[0, 1]$. As noted above in Section 2.1, since the image grayscale has a value range of $[0, 255]$, the maximum image entropy is 8; that is, $0 \leq E(I(x), \Omega_x) \leq 8$; let $a = 1/8$, so $0 \leq E(I(x), \Omega_x)/8 \leq 1$, consistent with the weight range.

4 Energy Functional Solution

Substituting the evolution curve $C$ in Eq. (10) with the zero level set function $\varphi$, the energy functional of the level set function is defined as

$$E(\varphi) = (1 - \omega)E^{VLIF} + \omega E^{CV} =$$

$$(1 - \omega)\left\{\int_{\Omega} |I(x) - I^{VLIF}(x)|^2 \, dx \right\} -$$

$$(1 - \omega)\left\{\int_{\Omega} H_c(\varphi(x))(1 - H_c(\varphi(x)))|c_1 - c_2|^2 \, dx \right\} +$$

$$\omega\left\{\lambda_1 \int_{\Omega} |I(x) - c_1|^2 \, dx + \lambda_2 \int_{\Omega} \left|\nabla I(x)\right|^2 \, dx \right\} \quad (12)$$

where $H_c(\varphi)$ is the Heaviside function,

$$H_c(\varphi) = \frac{1}{2} \left[1 + \frac{2}{\pi} \arctan\left(\frac{\varphi}{\epsilon}\right)\right] \quad (13)$$

$\delta_\varphi(\varphi)$ is the first-order derivative function of $H_c(\varphi)$,

$$\delta_\varphi(\varphi) = H_c'(\varphi) = \frac{\epsilon}{\pi \epsilon^2 + \varphi^2} \quad (14)$$

To prevent the level set function from deviating from the signed distance function, it is necessary to add a distance penalty term, which does not need to be initialized, to ensure the stable evolution of the curve,

$$P(\varphi) = \int_{\Omega} \frac{1}{2} \left(\nabla \varphi(x) - 1\right)^2 \, dx \quad (15)$$

To make the curve as short and smooth as possible during the evolution process, a length penalty term is added,

$$L(\varphi) = \int_{\Omega} \delta_\varphi(\varphi(x)) \nabla \varphi(x) \, dx \quad (16)$$

The final energy function of the model is therefore defined as

$$E(\varphi) = (1 - \omega)E^{VLIF} + \omega E^{CV} + vL(\varphi) + \mu P(\varphi) \quad (17)$$

where $v$ and $\mu$ are weighting constants, according to the calculus of variations and the standard gradient descent flow, the expressions for the evolution of the level set are

$$\frac{\partial \varphi}{\partial t} = \delta_\varphi(\varphi) \left(F^{VLIF} + F^{CV}\right) + v \delta_\varphi(\varphi) \text{div} \left(\left[\nabla \varphi\left|\nabla \varphi\right|\right]\right)$$

$$+ \mu \left(\nabla^2 \varphi - \text{div} \left(\frac{\nabla \varphi}{\nabla \varphi}\right)\right) \quad (18)$$
where $F^{\text{VLIF}}$ and $F^{\text{CV}}$ are the local fitting force and the global fitting force, respectively,

$$F^{\text{VLIF}} = (1 - \omega)(I - I^{\text{VLIF}})(m_1 - m_2) - \omega_1 \omega_2 |m_1 - m_2|^2$$

$$F^{\text{CV}} = \omega \left[-\lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2\right]$$

The proposed algorithm is as follows.

Step 1: Set the value of the parameter $\mu$, $\nu$, and $\sigma$;

Step 2: Given the initial contour and initialize the level set function $\varphi_0$;

Step 3: Compute $m_1(x)$ and $m_2(x)$ by Eqs. (23) and (24), respectively, and compute $c_1(\varphi)$ and $c_2(\varphi)$ by Eqs. (21) and (22); compute image entropy by Eq. (2) to obtain weight parameter $\omega$;

Step 4: Update the level set function $\varphi_n$ by Eq. (18);

Step 5: Judge whether the convergence criterion is satisfied or not, if not, go to Step 3.

The convergence criteria is $|\varphi_{n+1} - \varphi_n| \leq T$, where $\varphi_n$ is the zero level set of the $n$-th iteration, $\varphi_{n+1}$ is the zero level set of the next iteration, and $T$ is a dimensionless constant, which is set as 0.01 in our experiment.

### 5 Experimental Results and Analysis

In our experiments, we verify the effectiveness of the proposed model in reference to the following:

1. Sensitivity to the initial contour;
2. Effectiveness of the automatic selection of weight parameters;
3. Segmentation on natural images;
4. Segmentation on medical images;
5. Comparison of segmentation efficiency.

For the purposes, the proposed model was implemented in Matlab 2016a, running on the Microsoft Windows 10 64-bit OS operating system. The following parameters were set by default: time step $\Delta t = 0.1$, spatial step $h = 1$ and $\varepsilon = 1$ in the Heaviside step function and the Dirac delta function, length penalty factor $\nu = 0.003 \times 255 \times 255$, and size of Gaussian window $\sigma = 3$. Some parameters need be set according to the characteristics specific image as explained below.

### 5.1 Sensitivity experiments to initial contour

We conducted two sets of comparative experiments to verify the robustness of our model to the initial contour, as shown in Figs. 1 and 2. Figure 2 shows a synthetic image (pixel size: 434×329) of intensity inhomogeneity to test the segmentation results produced by different models with different initial images (in terms of size and location). The first column of Fig. 1 shows the original image and different initial contours, and the second, third, and fourth columns show the segmentation results, produced by the LIF model, the LGIF model, and the proposed model, respectively. For the experiment, we set $\nu = 0.007 \times 255 \times 255$ as the length parameter of the LIF model and $\nu = 0.001$ as weight parameter of the LGIF model. The weight of our model is automatically assigned by the weight function and there is no need to adjust the weight parameters manually. According to the segmentation results, the LIF model fails to segment the image correctly for all three initial contours, because it relies only on the local image information, and without the guidance of global information, it is very sensitive to the initial contour. Although the LGIF model does combine global information, it is sensitive to the selection of weight parameters, and can only segment the images correctly with particular initial contours (the third column in Fig. 1) and specific weight parameters. Our model is not limited to the size and location of the initial contour curve, and segments the images correctly with all three initial contours. This suggests that the automatic adjustment of the weight function in our model selects the appropriate proportions of the global and local items.

In the second comparative experiment, two noise-polluted synthetic images with greater intensity inhomogeneity were used and initial contours were set with different locations (the center of the image, the background, and the interior of the target) and sizes (the first row of Fig. 2). This experiment proves
Fig. 1 Results of different models with different initial contours on a synthetic image.

Fig. 2 Results of our model with different initial contours on two synthetic images. The initial contours and the final contours are plotted as blue rectangles and red contours.

the robustness of the model to the initial contour by setting different positions of the more complex initial contour. The experimental results show that the proposed model remains unaffected by the position and size of the initial contour. It is able to adjust the proportion of global items and local items automatically with the guidance of the weight function, and select the appropriate energy item ratio according to the gray scale characteristics of different regions in the image, which leads to correct segmentation results.

5.2 Effectiveness of automatic adjustment of weight function

To further illustrate the importance of the automatic adjustment of the weight parameters, we conducted a further experiment using the proposed model while varying the weight parameters. The test image was on an airport remote sensing map featuring a high level of
intensity in homogeneity. Figure 3a shows the original image and the randomly selected initial contour; Figs. 3b–3d show the different segmentation results on the remote sensing image produced by the proposed model using different fixed weight parameters; and Fig. 3d shows the segmentation result produced by the proposed model with the dynamic weight adjustment function. According to the experimental results, our model is unable to segment the image accurately with fixed linear weight parameters. Using the weight function constructed by local image entropy, the model analyzes the grayscale dispersion of different regions in the image and adjusts this automated nonlinear adjustment mechanism is better to assign the proportions between global and local items, thus producing more accurate segmentation results.

5.3 Segmentation on natural images

In order to further test the segmentation performance and demonstrate the practical value of the proposed model for real-world applications, an experiment was also conducted using four difficult natural images, taken from the Berkeley Segmentation DataSet (BSDS). Figure 4 shows the segmentation results on these four natural images (BSDS No. 3096, 61 060, 113 044, and 35 010) for different models. For this experiment, we used the following parameters. For the LIF model: $\sigma = 8$ for Figure 3096, $v = 0.01 \times 255 \times 255$ for Figure 61 060, and $\sigma = 8$ for Figure 113 044; for the LGIF model: $\sigma = 5$ and $\omega = 0.5$ for Figure 3096, $v = 0.01 \times 255 \times 255$ and $\omega = 0.05$ for Figure 113 044, and $v = 0.08 \times 255 \times 255$ and $\omega = 0.03$ for Figure 35 010. The default settings for other parameters are unchanged.

Figure 3096 features an image of an aircraft on an uneven background, which the LIF and LGIF models are unable to segment correctly. The grayscale distribution in the areas of the skier and the ski run in Figure 61 060 is complex and uneven. This further increases the difficulty of segmentation, meaning that neither the LIF nor the LGIF model can segment the target person accurately, and both produce false segmentation in the background area. The target horse in Figure 113 044 also has serious intensity inhomogeneity due to light reflection, and highly uneven gray levels. The grass also creates interference for segmentation. The LIF model and the LGIF model find this image almost impossible to segment. In Figure 35 010, the butterfly is affected by its own pattern and is positioned on a complex background, resulting in poor segmentation results by the LIF model and the LGIF model. However, the proposed model segments all of these different images accurately, despite the intensity.

The segmentation results can be explained as follows.

Fig. 3  Segmentation results of different weight parameters for an remote sensing image.
Fig. 4  Segmentation results of different models on natural images. The first row of Fig. 4 shows the original images (pixel size: 481×321) and the initial contour. The second, third, and fourth rows show the segmentation results produced by the LIF model, the LGIF model, and the proposed model, respectively.

The LIF model uses only the local image information and is easy to fall into the local minimum when segmenting the natural images with complex scenes, resulting in incorrect segmentation. Although the LGIF model combines global and local information to guide the curve evolution, it is too sensitive to the manual selection of appropriate weight parameters through trial-and-error. Also, the fixed weight parameters mean that the energy items for each region are the same, making it difficult for the LGIF model to segment images correctly. In our model, gray-scale distribution characteristic function is established by the local entropy to measure the degree of homogeneity of gray level in each local region, and then used to adjust the energy ratio of global items to local items dynamically. This quantitative dynamic adjustment mechanism helps the model to implement accurate segmentation results.

5.4 Retinal vascular image segmentation

We also conducted experiments on medical images, specifically images of retinal blood vessels. Traditional models cannot segment such images correctly due to the complex structure, large quantity and small size of retinal blood vessels, their uneven gray-scale, and the blurred contour of blood vessel boundaries. The vessels in the optic disc are especially affected by the uneven gray-scale, which has always presented a problem for retinal blood vessel segmentation. The color fundus retinal images used in the experiment were taken from the STARE database, with green channel images with low noise and high blood vessel contrast being selected. The segmented regions of retinal blood vessels were 343 pixel × 343 pixel in size. This group of experiments show that the model proposed in this paper can overcome the influence of noise and uneven gray-scale, and is able to segment retinal vessels with
complex structure quickly and accurately.

Figure 5 shows the segmentation of retinal blood vessels produced by different models. We selected representative regions in the retinal blood vessel image, as identified in Figs. 5a–5d (where Figs. 5c and 5d are blood vessels in the optic disc). The weight parameters of the LGIF model are set as $\omega = 0.06$, $\omega = 0.5$, $\omega = 0.0001$, and $\omega = 0.0005$, respectively.

For Fig. 5e, the segmentation results show that the LIF model produces a large area of redundant curves; while the LGIF model is greatly disturbed by the optic disc in the upper right corner, resulting in segmentation
failure, but the proposed model can get the correct segmentation results. For Fig. 5f, the results show that the proposed model can segment all fine blood vessels, while the LIF model is not completely segmented and the LGIF model produces the incorrect segmentation in the upper right corner.

For Figs. 5g and 5h, the LIF model and LGIF model cannot achieve the correct segmentation because the blood vessels in the optic disc are greatly disturbed by uneven gray levels. LIF model falls into local minima when segmenting blood vessels, resulting in insufficient segmentation and false segmentation of blood vessels; LGIF model cannot adaptively adjust the proportion of global terms and local terms, thus producing unsatisfactory segmentation results. The proposed model effectively uses the inter-class difference terms to reduce false segmentation for these complex images with uneven background. It can also obtain the pertinent gray-level information in real time and make a timely adjustment of the weight parameters to obtain accurate segmentation results.

5.5 Number of iterations and CPU time

In order to intuitively illustrate the segmentation efficiency of the proposed model, the iteration times, and the CPU time required for natural image and retinal vascular image segmentation are listed in Tables 1 and 2 for comparison.

Table 1 shows the number of iterations and running time required by the three models to segment the four natural images taken from the BSDS data set. The LIF model uses more iterations and takes longer to execute than the LGIF model, which is in turn less efficient than our model on both measures. Both LGIF and the proposed model use the global term of the image to speed up the evolution of the curve, but the weight parameters of the LGIF model are fixed in across regions, while the proposed model varies the weight across regions with inconsistent gray-level uniformity. In regions with uniform gray levels, the global term is assigned a larger proportion, thus greatly accelerating the evolution rate of the curve and improving the overall segmentation efficiency.

Table 2 shows the same efficiency measures for segmentation of retinal vascular images by the three different models. The proposed model returns the lowest number of iterations and the fastest execution time, and chooses the most appropriate parameters for each local area through the adaptive non-linear adjustment mechanism of the weight function, realizes the optimal balance of the proportion of local and global terms, and improves the efficiency of segmentation.

5.6 Segmentation accuracy comparison

In order to more intuitively and accurately reflect the superiority of the model proposed in this paper compared with other model methods, two similarity measures, the Dice Similarity Coefficient (DSC)\(^9\) and the Jaccard Similarity (JS) coefficient\(^{[27]}\), are used to quantitatively compare the results of each model. Their respective definitions are

\[
DSC = \frac{2N(S_g \cap S_m)}{N(S_g) + N(S_m)} \quad (26)
\]

\[
JS = \frac{N(S_g \cap S_m)}{N(S_g) \cup S_m} \quad (27)
\]

Table 1 Number of iterations and the CPU time to segment of Fig. 4 when using the LIF model, the LGIF model, and the proposed model.

| Image No. | LIF model | | | LGIF model | | | | Proposed model | | |
|-----------|-----------|---|---|-----------|---|---|-----------|---|
|           | Number of iterations | Time (s) | | Number of iterations | Time (s) | | Number of iterations | Time (s) | |
| 3096      | 150       | 112.2594 | | 70         | 15.6747 | | 30         | 13.2625 | |
| 61,060    | 100       | 44.3438  | | 100        | 36.3045 | | 30         | 13.6563 | |
| 113,044   | 100       | 57.0469  | | 80         | 50.2685 | | 50         | 21.4688 | |
| 35,010    | 140       | 62.9531  | | 80         | 34.8533 | | 40         | 18.1719 | |

Table 2 Number of iterations and the CPU time to segment of Fig. 5 when using the LIF model, the LGIF model, and the proposed model.

| Image     | LIF model | | | LGIF model | | | | Proposed model | | |
|-----------|-----------|---|---|-----------|---|---|-----------|---|
|           | Number of iterations | Time (s) | | Number of iterations | Time (s) | | Number of iterations | Time (s) | |
| Image (e) | 300       | 11.3875 | | 250        | 9.6327 | | 180        | 7.1243 | |
| Image (f) | 750       | 25.2926 | | 300        | 11.8362 | | 210        | 8.2776 | |
| Image (g) | 550       | 17.3501 | | 500        | 15.7093 | | 350        | 10.2383 | |
| Image (h) | 540       | 16.2937 | | 480        | 14.4516 | | 350        | 10.8243 | |
where \( S_g \) and \( S_m \) represent the segmentation results and the ground truth, and \( \mathcal{N}(\cdot) \) denotes the number of pixels in the partitioned area. The nearer the results of DSC and JS are to 1, the closer the segmentation results of the model are to the standard segmentation, and thus the more accurate the segmentation is.

In this paper, the accuracy of the image segmentation shown in Fig. 5 is compared using DSC and JS, with the results shown in Table 3. Compared with the other models, the proposed model returns larger DSC and JS values, and its segmentation index is significantly better. These results show that the proposed model can achieve stable segmentation in various types of noisy and uneven gray-level images with a high segmentation accuracy.

### 6 Conclusion

This paper has presented an improved model for image segmentation. In order to fully integrate the local and global information of the image, an improved model for obtaining the local information is combined with the global information of the image to jointly drive the evolution of the curve curve. Drawing on the advantages of the global model combined with the improved local model, image segmentation accuracy is improved, the sensitivity to the initial contour is reduced, and the convergence speed of the evolution curve in uniform gray-level regions is improved.

Our proposed method uses the local image entropy to establish an accurate and reliable index to measure the image’s gray-level information. The gray-level distribution is judged by calculating the entropy value of the image in real-time on each iteration, with the weight parameters conforming to the current gray-level distribution updated in real time. The non-linear adjustment mode used to adaptively guide the matching of global items and local items in the model realizes fully automatic segmentation. Compared with the traditional linear adjustment mode with fixed weight parameters, the model proposed in this paper can better balance the proportion of global and local terms, and improves on the operation speed and unsupervised adaptive performance of the active contour model. Several groups of experiments were carried out to verify the superiority of the proposed model in dealing with various types of noisy and uneven gray-level images, showing that it not only has a low sensitivity to the initial position of contour curves, but also improves the segmentation accuracy, and significantly reduces the operation time and number of iterations required to perform segmentation.

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| Image | LIF model | LGIF model | Proposed model |
|-------|-----------|------------|----------------|
|       | DSC JS    | DSC JS     | DSC JS         |
| Image (e) | 0.8216 0.8152 | 0.8358 0.8008 | 0.9427 0.9325 |
| Image (f) | 0.6512 0.6493 | 0.8945 0.8867 | 0.9683 0.9617 |
| Image (g) | 0.8694 0.8612 | 0.9216 0.9123 | 0.9358 0.9304 |
| Image (h) | 0.7965 0.7842 | 0.8129 0.8119 | 0.9646 0.9617 |
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