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Research on the Wood Cell Contour Extraction Method Based on Image Texture and Gray-scale Information

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Abstract

The traditional Snake model and GVF-Snake model set high requirements on noise and initial contour in wood cell contour extraction. To solve this problem, on the premise of considering the image texture and gray-scale information, the area information is directly introduced into the active contour extraction model through force equilibrium equation. Experiments show that the contour extracted with this method is not only more close to real cell contour, but also improved in anti-noise property. In particular, in the convergence of high noise and deep sunken areas, it has some advantages not found in other traditional methods.

Keywords: *Snake model; image texture; wood cells*

1. Introduction

Traditional wood recognition method has many deficiencies in the actual application process. In order to solve the problem of wood assortment identification, the computer image processing technology is adopted in this paper for the parameter extraction of wood cells. The bottleneck of identification by human experience can be solved effectively by the identification of wood in the microscopic field of cells. The method is applied mainly by: computing and analyzing the growth ring age by using the growth ring images captured, selecting part of the cells more than ten years old by growth ring age to make cell slicing and to capture growth ring images, texture images and cell images, and using the Gray Level Co-occurrence Matrix (GLCM) method to extract the relevant parameters of the texture. The extraction of wood cell contour is a prerequisite for the analysis of wood cell parameters. In this paper, according to the characteristics of wood cells, relevant improvement has been made on the traditional Snake model [1-3].

2. Snake Contour Model

The traditional Snake model can be defined by the curve $v(s)=(x(s),y(s)), s\in[0,1]$, which is the curve expression form with normalized arc length as its parameter [4-6]. The basic idea of Snake model is to transform the target contour extraction into a problem of finding closed curves that meet certain conditions in the images to achieve the minimum energy functional [7-9]. Therefore, the parameterized Snake model can be expressed as:

$$E_{snake}=\int_0^1\left[E_{\text{int}}\left(v(s)\right)+E_{ext}\left(v(s)\right)\right]d_s \tag{1}$$

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Here, E_{int} and E_{ext} are the internal energy and external energy of the contour, respectively, and E_{int} can be defined as:

$$E_{\text{int}} = \frac{1}{2}\left[w_1 \left| v^{'}(s) \right|^2 + w_2 \left| v^{''}(s) \right|^2 \right] \quad (2)$$

The internal energy E_{int} indicates the shape features of the contour curve; the first order derivative reflects the elastic energy of the curve; the second order derivative is the rigid energy of the curve. w_1 is the stress controlling the contour, which is the continuous bound term coefficient applied on two adjacent points on the Snake contour curve, mainly for adjusting the contractility of Snake. w_2 is the control weight of contour rigidity. When neither of is zero, the corresponding contour curve is a continuous smooth curve, and the weights w_1 and w_2 have an important effect on the properties of the curve.

E_{ext} is the external energy of the contour, generally indicated with the gradient or gray-scale of the images. It will attract the curve to approach the target edge and make it a true depiction of the target contour. For a given gray-scale image $I(x, y)$, the external energy is defined as in formula (3).

$$E_{ext} = -w_3 \left| \nabla (G_\sigma * I(x, y)) \right|^2 \quad (3)$$

w_3 is the corresponding weight coefficient for energy control, G_σ represents the Gaussian function with a standard deviation of σ, and * and ∇ indicate the convolution operator and gradient operator, respectively.

By variational principle, it can be seen that the target contour shall meet the Euler equation when the energy functional is minimized:

$$w_1(v^{'}(s))^{'} + w_2(v^{''}(s))^{''} + w_3 \nabla E_{img} = 0 \quad (4)$$

From the principle of the force equilibrium equation, it can be seen that formula (4) can be regarded as the formula (5) contour curve:

$$F_{\text{int}} + F_{ext} = 0 \quad (5)$$

$$F_{\text{int}} = w_1(v^{'}(s))^{'} + w_2(v^{''}(s))^{''} \quad (6)$$

$$F_{ext} = w_3 \nabla E_{img} \quad (7)$$

Among them, F_{int} indicates the endogenous effect on the Snake model, which controls the internal characteristics of the curve, such as contraction and smoothing; F_{ext} is the exogenous effect on the Snake model, guiding the convergence of the Snake model to real target contour curves. Therefore, from the perspective of the equilibrium, the Snake model can be interpreted in this way: Snake contour curve under the guidance of exogenous force continuously approaches the target contour, and the endogenous force changes with the movement of the Snake contour curves while controlling the shape of the Snake model. Finally, the sum of endogenous force and exogenous force equals to zero, and equilibrium is achieved.

3. The Contour Extraction Model based on Image Texture and Gray-scale Information

The Snake model based on image gradient information is easy to fall into local minimum and sensitive to noise, and it fails to provide more information on the target area by extracting the contour evolution of the deep sunken areas [10]. In this paper, the characteristics of image texture and gray-scale information are both taken into consideration, and the area integral of the gray-scale in this area is added to the Snake model. Through the image transformation operator designed in the paper and by using the Green formula for the transformation between area integral and curve integral, the area information of the target image is transformed into area force. Afterwards, the area information is naturally and directly introduced into the active contour extraction model through the force equilibrium equation. In the paper, an active contour model based on image texture and gray-scale information is obtained. The model guides the evolution of the contour curve by simultaneously using the area information and gradient information of images, not only expanding the scope of contour initialization but also reducing the sensitivity to noise in images. Moreover, the introduction of the area information further improves the capability of the contour converging to the boundary of the target area.

3.1. Image Brightness and Texture Features

In the method of this paper, the brightness and texture features of images are used for the computation of the edge energy and edge direction probability of the area.

3.1.1. Brightness Feature: The edge energy of pixels $s=(x,y)$ in the direction of θ :

$$\begin{aligned} E_l(s,\theta) &= \left|\frac{\partial}{\partial n} I_\sigma(x,y)\right| \\ &= \left|\frac{\partial}{\partial n}\left[I(x,y)*G_\sigma(x,y)\right]\right| \end{aligned} \tag{8}$$

In the equation, the Gaussian function is G_σ, and the scale factor is σ.

3.1.2. The Edge Direction Probability of s along the Direction of θ: The edge energy $E(s,\theta)$ may flow in two directions: forward (θ) and reverse $(\theta+\pi)$. It is required to predict the probability of finding the closest edge along the two directions. The prediction is made by using the luminance information of the image at the point s, and the prediction error is defined as:

$$Error_l(s,\theta) = \left|I_\sigma(x+d\cos\theta, y+d\sin\theta) - I_\sigma(x,y)\right| \tag{9}$$

Here, d represents the offset of the centers of the two Gaussian functions (the settings of original set edge flow algorithm are used in the experiment, taking d = 4σ). A greater prediction error in a direction indicates that the edge is more likely to be found along this direction. Therefore, the probability of edge direction is in proportion to the corresponding prediction error:

$$P_l(s,\theta) = \frac{Error\ (s,\theta)}{Error\ (s,\theta) + Error\ (s,\theta+\pi)} \tag{10}$$

3.2. Texture Features

According the edge detection method, when θ = 4, 24 Gabor filters will be used to get 24 texture features. The more the dimensions of texture features are, the larger the computation amount will be. The experimental research results show that: eight texture features are extracted by using 3 × 3 DCT template for texture image contour extraction, the result of which can be compared with Gabor filters.

Let the eight DCT texture features extracted $m_k(x,y)$, similar to brightness feature, and the texture edge energy is defined as:

$$E_T(s,\theta)=\sum_{1\le i\le 8}\left|\frac{\partial}{\partial n}m_i\sigma(x,y)\right|/8=\sum_{1\le i\le 8}\left|\frac{\partial}{\partial n}\left[m_i(x,y)*G_\sigma(x,y)\right]\right|/8 \qquad (11)$$

Similarly, the computation of texture prediction error $Error_T$ and texture edge direction probability P_T is handled in the same way as in the computation of luminance characteristics.

Combine the energy and direction probability obtained according to the brightness and texture characteristics:

$$E(s,\theta)=\sum_{a\in A}E_a(s,\theta).w(a) \qquad (12)$$

$$P(s,\theta)=\sum_{a\in A}P_a(s,\theta).w(a) \qquad (13)$$

Here, attribute A = {I (brightness), T (texture)}, and $w(a)$ is the weighting coefficient of each attribute, with w (luminance) = 0.5, w (texture) = 0.3 in experiment.

3.3. The Area Energy based on the Area Gray-scale of Images

In the traditional Snake model, only the endogenous and exogenous forces on the contour are considered, while the influence of image gray-scale information in the whole area is not taken into account. To effectively solve this problem, it shall be considered adding new energy to the original contour curve energy. In the image $I(x,y)$, the area surrounded by the contour curve $v(s)$ is defined as R, and then the corresponding image $I_R(x,y)$ covering R in this area is defined as:

$$I_R(x,y)=\begin{cases} I(x,y),(x,y)\in R \\ 0,(x,y)\notin R \end{cases} \qquad (14)$$

H is defined as the operator which has an effect on image $I_R(x,y)$, so the image area energy E_{region} can be defined as the two-dimensional image area integral in the following formula:

$$E_{region}=\iint_R H(I_R(x,y))dxdy \qquad (15)$$

From the total energy formula as shown in formula (1), the internal energy E_{int} is still defined as the formula (2) composed of elastic energy and bending energy, and as for the external energy, in addition to the image potential energy E_{img}, the image area energy E_{region} is also introduced. Let w_4 act as the corresponding control weight coefficient of image area energy, so the total curve energy expression of the Snake model parameterized can be represented by:

$$E_{snake} = \int_0^1 \left[E_{\text{int}} + w_3 E_{img} \right] ds + w_4 E_{region}$$
$$= \int_0^1 \left[E_{\text{int}} + w_3 E_{img} \right] ds + w_4 \iint_R H(I_R(x,y)) dxdy \tag{16}$$

3.4. The Area Force and Algorithm Principle based on the Green's Formula

The Green's Formula for the transformation between general area integral and curve integral can be expressed by formula (17), in which P and Q are defined as functions of the plane domain D. It established contact between the double integral on the plane domain D and the curve integral on the boundary curve L of this plane domain D, which makes the area information can be converted to its boundary information.

$$\iint_D \left(\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y}\right) dxdy = \oint_L Pdx + Qdy \tag{17}$$

Therefore, the double integral of the target are of the image can be transformed into the curve integral on the area boundary curve by using the Green's Formula, which allows the area information of the image to be introduced directly into the evolution of its contour curve. Thus, through the Green's formula, the image area energy (15) can be transformed into:

$$\iint_R H(I_R(x,y)) dxdy = \frac{1}{2} \oint \hat{N}_R(x,y)dx + \hat{M}_R(x,y)dy \tag{18}$$

where

$$\hat{N}_R(x,y) = -\int_0^y H(I_R(x,z))dz \tag{19}$$

$$\hat{M}_R(x,y) = \int_0^x H(I_R(z,y))dz \tag{20}$$

The physical meaning of the second type curve integral at the right end of formula (18) can be interpreted as the work of force in the direction of movement, and thus $\hat{N}_R(x,y)$ and $\hat{M}_R(x,y)$ are the component forces of the force on the x-axis and y-axis, respectively. Therefore, the image area force obtained by converting the image information of the target area can be expressed as:

$$F_{region} = w_4 (\hat{N}_R(x,y), \hat{M}_R(x,y)) \tag{21}$$

Here we define the positive direction of the contour curve $v(s)$ as: on the movement along the contour curve, the area R is always on its left. Δx and Δy are defined as the variables between the node (x, y) on the contour curve and the previous adjacent node in the x and y directions. The scale of the two dimensional image is set as $k \times l$, and the function $sign(.)$ represents the symbol functions defined below:

$$sign(x) = \begin{cases} 1; x > 0 \\ 0; x = 0; x \in R \\ -1; x < 0 \end{cases} \tag{22}$$

Through the force equilibrium equation (7) and its total energy formula (16) of the contour curve, the external force F_{ext} here is composed of two parts: one is the image force F_{img} caused by the image potential; the other is the image area force F_{region} caused by the image area energy. Thus, the force equilibrium equation (7) of the contour curve can be converted and expressed accordingly as:

$$F_{\text{int}} + F_{img} + F_{region} = 0 \tag{23}$$

where

$$F_{\text{int}} = w_1 \frac{d}{ds}\left(\frac{dv(s)}{ds}\right) + w_2 \frac{d^2}{ds^2}\left(\frac{d^2 v(s)}{ds^2}\right) \tag{24}$$

F_{int} represents the endogenous force reflecting the flexible and curving properties of the contour lines; $F_{img} = w_3 \nabla E_{img}$ indicates the image force of the image energy which reflects the gradient information. Here, the image energy E_{img} is selected as $-\left|\nabla(G_\sigma * I)\right|^2$, where G_σ represents Gaussian function of which the standard deviation is σ, and * and ∇ refer to the convolution operator and gradient operator, respectively.

$F_{region} = w_4(\hat{N}_R(x,y), \hat{M}_R(x,y))$ is the area force of area energy acting on the contour curve.

Thus, the force equilibrium equation (23) of the contour curve can be further expressed as:

$$w_1 v''(s) + w_2 v''''(s) + w_3 \nabla E_{img} + w_4(\hat{N}_R(x,y), \hat{M}_R(x,y)) = 0 \tag{25}$$

In the equation, $v''(s)$ and $v''''(s)$ are respectively the second and fourth order derivatives of the contour curve to the arc length s, w_1, w_2, w_3 and w_4 are the corresponding control weight coefficients of different energy in the equation.

Experimental analysis shows that on the premise of the comprehensive utilization of texture features and gray-scale information, the introduction of external area force allows the convergence of the contour curve to overcome the impacts of the feature points such as fixed points and the saddle points. For real images, especially high-noise images, the introduction of area force overcomes the situation that the feature points tend to cause the local minimum of the contour line and reduces the sensitivity of the algorithm to noise; for the areas with narrow and deep sunken parts, it is avoided when the contour line is tangent to the image gradient field, there is no force pointing to the interior of the target area, thereby enhancing the convergence capability of the contour curve.

4. Analysis of the Experimental Results

4.1. The Extraction of the Image Contour with Sunken Features

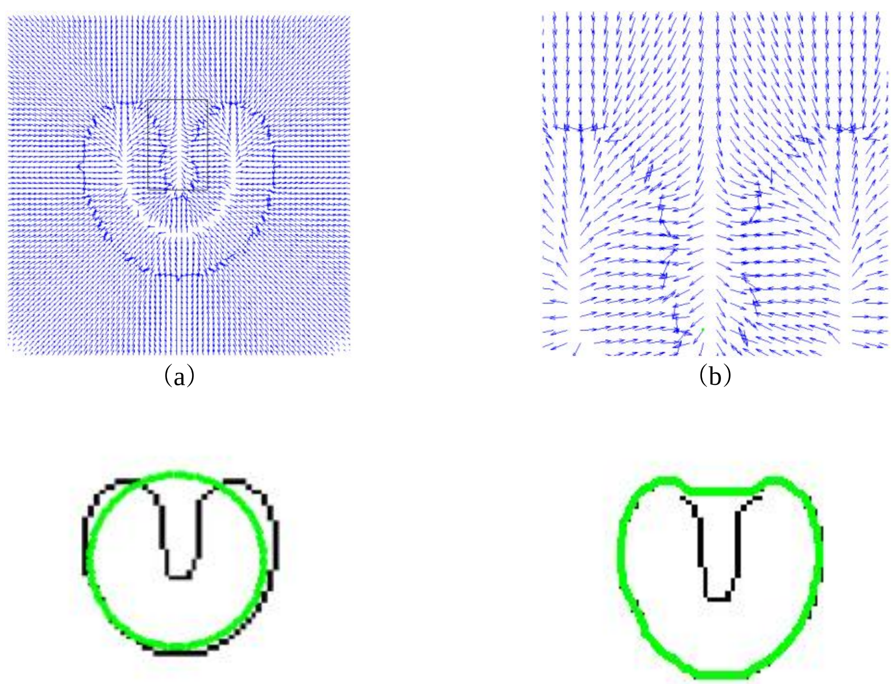
Here, the binary image with sunken features is selected for contour extraction. The original image and initial contour are shown in Figure 1 and there is a deep sunken area in the image. In order to better illustrate the potential field distribution in the sunken area, Figure 1 (a) shows the GVF gradient potential field. Figure 1 (e) - (g) are conventional Snake, GVF-Snake and results obtained by the method presented in this paper, respectively.

Through the analysis of the experimental results, the traditional Snake method does not perform well for the extraction of image contours with sunken features, and though the GVF-Snake method can complete the contour convergence of the sunken area, the contour is far from a real depiction of the curve contour. Therefore, from the experimental analysis, it can be seen that on the premise of considering the image texture and gray-scale information, through the introduction of area information, a better image contour with sunken features can be obtained with this method.

4.2. The Extraction of Image Contours Affected by Different Noises

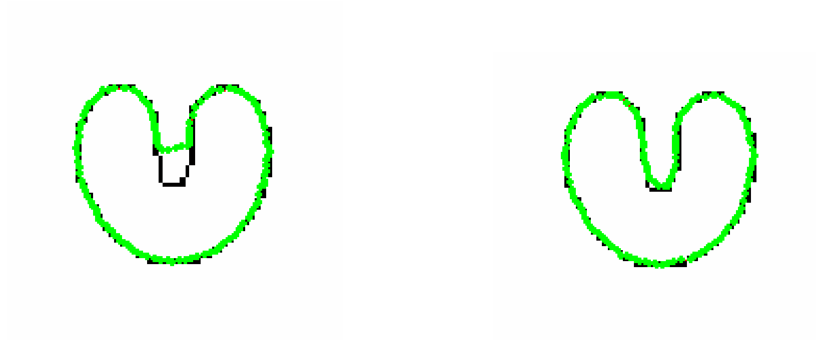
To analyze the noise sensitivity of this method, Gaussian noise (zero mean and variance of 0.01) has been added to the images used in the experiment by using Matlab, as shown in Figure 2 (a), the analysis of the experimental results shows that under the influence of the noise, neither of the traditional Snake method and GVF-Snake method can get accurate target contours.

Compared with traditional Snake method and GVF-Snake method, the method presented in this paper is less affected by noise, and can provide satisfactory results for different images with noise. Therefore, on the premise of comprehensively considering the image texture and gray-scale information, the external area force is introduced, which allows the extraction of curves much closer to real contour by using this method, and the experiment result is less affected by noises.



(a) (b)

(c) (d)

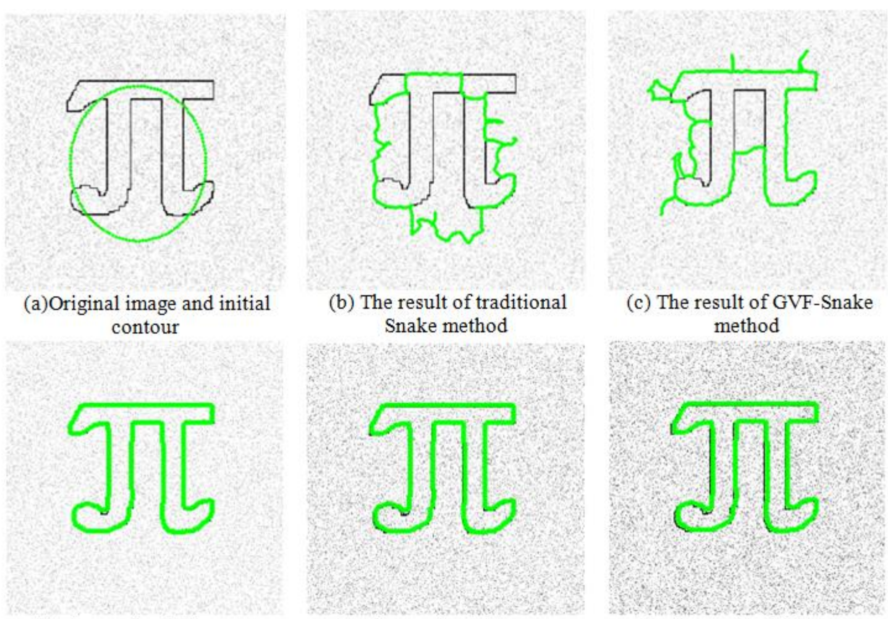


(e) (f)

Figure 1. The Contour Extraction Results of Binary Image: (a) GVF-Snake potential field gradient; (b) the area of black box in image (a); (c)the contour results of original image and initial contour; (d)~(f) traditional Snake method, GVF-Snake method and this paper method

4.3. The Extraction of Wood Slice Microscopic Cell Image

Here, the wood slice microscopic cell image is selected for the contour extraction experiment, and Figure 3 (b) ~ (f) are the results of contour extraction obtained by using the traditional Snake, GVF-Snake and the method of this paper, respectively. As shown in Figure 3, the image noise makes the traditional Snake method trapped in local minimum, and the GVF-Snake method also fails to get a good contour of the target area; while a satisfactory cell area contour curve is obtained with the method presented in this paper.



(a)Original image and initial contour

(b) The result of traditional Snake method

(c) The result of GVF-Snake method

(d)The result of this paper method ($\nu = 0.01$)

(e) The result of this paper method ($\nu = 0.03$)

(f) The result of this paper method ($\nu = 0.05$)

Figure 2. The Contour Extraction Results of Noise Images

4.4. The Analysis of the Effect of the Algorithm

The gray-scale figure 3 and high noise Figure 2 are selected here as test images. In the paper, Table 1 is the comparison of the results obtained by using this method and the traditional Snake method and GVF-Snake method.

The quantitative evaluation method adopted in this paper is: the accuracy of the algorithm is evaluated quantitatively by using the relative deviation D between the area of the region surrounded by the contour line S and the area of the target region $S^{'}$, namely:

$$D=\left(\left|S-S^{'}\right|/S^{'}\right)\times 100\% \qquad (26)$$

From Table 3-2, through analysis, it can be seen that the experiment results of contour extraction by using the traditional Snake method and GVF-Snake method are not as ideal as that obtained with the method presented in this paper.

4.4.1 For gray-scale image (Figure 3), the experimental results obtained by using traditional Snake method and GVF-Snake method are similar, but in contour extraction they are far less accurate than the method presented in this paper.

4.4.2 For the images containing noise, GVF-Snake method compared to traditional Snake method has the indication range of contour enlarged, but it is very sensitive to the influence of noise, so that from the experimental results we can see both of them fail to provide accurate target curve contour due to the influence of noise. The method presented in this paper is not sensitive to noise, so there is little change to the target contours of different noise images extracted with this method, which are all close to the real contour curves.

By analyzing the experimental results, it can be seen that on the premise of considering the image texture and gray-scale information of images and by introducing the external area force, more accurate extraction of target contour can be realized with the method presented in this paper, and there is less impact of noise on the experimental results. The algorithm is better in stability.

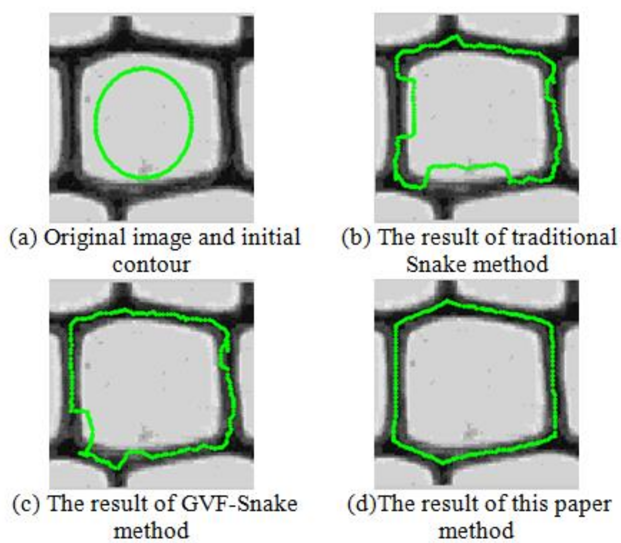


Figure 3. The Contour Extraction Result of Wood Section Microscopy Cell Image

5. Conclusion

The research is mainly carried out with the wood slice microscopic cell images as the research objects. Based on the traditional Snake model and on the premise of comprehensively considering the image texture and gray-scale information, through the combination of the Green's Formula for transformation between regional integral and curvilinear integral, the area force containing image area information is derived by using the image transformation operator involved in the paper. The area information is directly introduced into the active contour model by using the force equilibrium equation, to extract an active contour model based on image texture and gray-scale information. This method not only expands the scope of contour extraction, but also is less sensitive to noise, especially for the deep sunken and narrow images. Through a lot of experiments and the experimental analysis of real wood cell images, it proves that the method presented in this paper performs better in adaptability and robustness.

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