Analysis of selecting the optimal threshold in image segmentation based on the evolution of feature field

Shuqin Liu*, Jinye Peng

Information Science and Technology College of Northwestern University, 710127, China

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Abstract

In order to select the optimal threshold in image segmentation, this paper raised an image segmentation method based on the data field evolution mechanism. Integrating the local gray feature with the metric texture, it enabled to extract sufficient image information. Imaging that every pixel with multi-features was a particle with physical meaning, it built a feature field in the space of image feature. Under the supposition that the optimal threshold was the potential direction of evolution, particles would self-adapt to attract or repel each other because of the interaction in the dynamic data field among particles. In this way, the co-evolution was achieved and we further got the segmentation result. The experiment result shows that this method acquires quite good segmentation performance and is quite practical, without significantly increasing the time complexity.

Keywords: image segmentation, feature field, the optimal threshold, evolution algorithm

1 Introduction

Image segmentation is a kind of key technologies in image processing, which is successfully applied in aspects like pattern identification, target detection, analysis of medical imaging [1,2]. For lack of universal segmentation theory system, most of the present segmentation algorithm aims at specific problems so that there is no segmentation algorithms applied to image segmentation. At present, the most commonly used algorithm is edge detection, region detection and threshold acquisition, among which the last one is one of the most widely, applied technologies [3].

Segmentation of the optimal threshold for gray-scale image is just to determine the grain-scale threshold within the value ranges of gray-scale images and then to make a comparison between the gray-scale value of each pixel of image and this threshold. Based on the comparison results, the relative pixels are divided into two categories in different image regions to reach the segmentation. It is shown that the the key of segmentation is to determine the optimal threshold. Therefore, the method of multi-dimension threshold has acquired a sound development and application. So as to optimize the ability of extracting the local features and improve the time performance of algorithm, a series of improved methods of thresholding 2D image are put forward one by one, and so do a great number of modified algorithms [6].

Texture feature is also one of the innate features of objects surface. In order to acquire some more precise segmentation results, this method is supposed to combine the gray-scale with texture feature. This paper aims at the segmentation of gray-scale images and raised a method of high-pit image segmentation by taking advantage of the feature field co-evolution based on data field mechanism. This method acquires an understanding of the selection of optimal threshold from a new perspective, and establishes a feature field based on the gray-scale and texture feature of image. With multi-feature co-evolution under the influence of stress field, this method adapts more to the human visual system (HVS), and searches for the optimal threshold with heuristic adaption based on the dynamic evolution of particles in feature field.

2 Image feature field

Figure 1 is the original CS image. The binaryzation result of artificial sketch is shown in the right of Figure 1. The thresholding method based on gray-scale feature generally can not obtain effective results and it is supposed to combine some local features, such as gray-scale and texture.

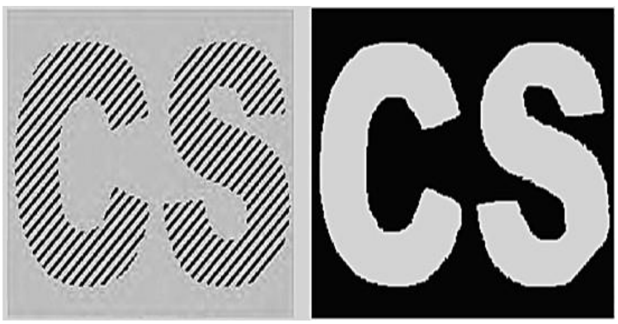

FIGURE 1 Image examples with texture

2.1 LOCAL FEATURES

From previous studies, it can be seen that human visual perception of texture at least consists of 6 measurement,

* ***Corresponding author's*** e-mail: lsqshuqin@163.com

including coarseness, contrast, directionality, linearity, regularity and roughness [7]. This paper, by introducing the former three visual measurements, integrated the local gray-scale feature to establish an image feature field. For any given images to be segmented: $f:(h,w)\to\{0,1,2,\cdots,L+1\}$, where $h\in[1,H]$, $w\in[1,W]$, and *H*, *W*, *L* is the height, width and gray-scale level respectively.

Gray-scale variance, coarseness, contrast, directionality.

Image local gray-scale variance reflects the statistical feature of gray-scale. Local gray-scale variance for any pixel (h,w) is calculated as following:

a) Calculate the average gray-scale value of pixel in image region where the pixel centers on (h,w) and pixel is 3×3 in dimension.

$$Avg(h,w)=\sum_{i=h-1}^{h+1}\sum_{j=w-1}^{w+1}\frac{1}{9}f(i,j), \tag{1}$$

where $f(i,j)$ is the pixel gray-scale value at (i,j).

b) Calculate the gray-scale variance of pixel in (a) and take the result for local gray-scale feature.

$$C^1(h,w)=\sum_{i=h-1}^{h+1}\sum_{j=w-1}^{w+1}\frac{1}{8}(f(i,j)-Avg(h,w))^2. \tag{2}$$

Any coarseness feature in which the pixel centers on (h,w) and pixel is $k\times k$ in dimension is to calculate the difference between the coarseness measurement of this pixel and the average coarseness, that is:

$$C^2(h,w)=\left|k_{best}(i,j)-Avg(h,w)\right|. \tag{3}$$

Local contrast is the measurement of different brightness levels between the bright white and the dim dark in local regions of light and shade within the image. The feature of contrast is a statistic of gray-scale in image regions where the pixel centers on (h,w).

$$C^3(h,w)=C^1(h,w)/M_4(h,w)^{1/4}. \tag{4}$$

Directionality is realized by making a statistic of direction angles distribution for gradient vectors. Its feature is the difference between the direction angle of pixel (h,w) and the average direction angle which centers on (h,w), that is:

$$C^4(h,w)=\left|\theta'(i,j)-Avg(h,w)\right|. \tag{5}$$

2.2 FEATURE FIELD

Any attribute changes in the particles of data field will lead to the evolution of data field, and then lead to the production of dynamic data field [3]. Under the influence of stress field, the basic attributes for data particles include position vector $p_x(t)$, mass $m_x(t)$, force $\varphi_x(t)$ and velocity vector $v_x(t)$. They are all changing along with the passage of time. The particle's migration is inclined to be balanced and the data field gradually reaches stability.

If every pixel is a particle with mass, its mass has strong correlation with several local features. In the space of image feature, there is an influence field around every particle. Any objects within the field will receive the joint effects from other objects. Interaction among all particles has formed a data field in the feature field, also called the image feature field [9]. The force of *i* particle at the moment of *t* is $\varphi_i(t)=\sum_{j=1}^{N_x}m_j(t)e^{-\left\|p_i(t)-p_j(t)\right\|^2}$, where $\|\cdot\cdot\|$ presents the 2-norm.

The four dimensional feature is selected to promote the integration of local features to some extent, and the local features from samples is taken for the initial value of dynamic data particles. Given the position vector for *i* data particle at the moment of *t* is $p_i(t)=(p_i^1(t),p_i^2(t),p_i^3(t),p_i^4(t))$. The available information about the position vector for any dimension $p_i^d(t)(d=1,2,3,4)$ all belongs to the set $[0,L-1]$, corresponding the gray-scale variance, coarseness, contrast and directionality after normalization respectively. The initial status for data particle is $p_i(0)$; the velocity vector for *i* particle at the *d* dimension is marked as $v_i^d(t)$ and the initial value is zero.

The gradient according to the force function is the *d* measurement from the field force imposing on *i* particle at moment of t, under the strong function of force field.

$$F_i^d(t)=\frac{2}{\sigma^2}\sum_{j=i}^{N_x}(p_j^d(t)-p_i^d(t)m_j(t)e^{-\left\|p_i(t)-p_j(t)\right\|^2}. \tag{6}$$

Equation (6) shows a higher fitness with a bigger mass, and a stronger attraction to be produced. Any particle tends to move forward the particles with higher fitness, while those with low mass are easy to repel. When there are no norms for guidance, the image feature field is inclined to be stable with the continual iteration of particle and the destination of particles' motion is the optimal threshold. During the process of every iteration, the local optimum threshold is trying it best to come close to the whole optimal threshold. Given $T(t)$ is the local optimal threshold at the moment of *t*, set $T(0)=\left(L/2,L/2,L/2,L/2\right)$. During the process of every iteration, any particle has a certain fitness compared to the present local optimal threshold.

3 Methods proposed

Given that the moment *t* and *t*+1 is two adjacent moments when the iteration interval $\Delta t=1$, the movement of every particle can be closely considered as the constant acceleration movement. According to Newton's laws of motion, position and velocity of particles in feature field are updated as follows:

$$\begin{aligned} v_i^d(t+1) &= v_i^d(t) + a_i^d(t) \\ p_i^d(t+1) &= p_i^d(t) + v_i^d(t) \end{aligned}, \quad (7)$$

where $a_i^d(t) = F_i^d(t)/m_i(t)$ and in the update of $T(t+1)$, so as to reach a balance between the time complexity and diversity of particles, research is enhanced in width in the initial stage of iteration, and particles are widely distributed in the whole image feature space. When it comes to the further stage, search in width will be decreased gradually while it will be enhanced in depth. The algorithm tends s to seek for refinement.

The requirement for stopping the co-evolution in feature field can be determined by observing the threshold difference in iteration $\left|T^d \mid (t+1) - T^d(t)\right|$. This paper set a convergence constant $\xi = (1,1,1,1)$. It means when this requirement $\left|T^d \mid (t+1) - T^d(t)\right| < \xi^d \, (d = 1,2,3,4)$ is met, we can consider the optimal threshold satisfied with convergence and the algorithm terminates then. Next, the optimal threshold $T_{opt} = T(t^* + 1)$ at that time will be output as the image segmentation optimal threshold.

4 Analysis of experimental results

4.1 EXPERIMENT PREPARATION

In order to prove the effectiveness of methods in this paper, several methods like hDDF, CTS integrating gray-scale and texture, NC and RACM based on the improved level of region [10] came out by the Matlab programming. And segmentation was conducted by two experiments, including the ordinary images of nature and time complexity. Machine configuration included processor AMD X2 Dual Core 2.31GHz, 2.0GB internal storage, and Windows XP operating system. For there is a lack of default parameters in the NC method, it was needed to make careful choices as many as possible based on visual validation, and pick up the best result; and the methods CTS and RACM could be directly put into experiment based on default parameters.

4.2 RESULT ANALYSIS

Experiment 1: ordinary images of nature: name the ordinary images of nature as Real 1-5 successively. The segmentation result is shown in Figure 2, among which the first column was the firsthand image, and then were methods of Hddf, NC, CTS and RACM successively.

FIGURE2 Comparison of visualization in images of nature

Results in Figure 2 showed that there was mainly too much inhomogeneous gray-scale information but little texture information in the former two images. So NC and RACM methods acquired good segmentation results, while the quality for segmenting in CTS method was quite poor. On contrary, there was too much texture information in the latter three images and RACM method appeared impotent in image segmentation or even basically amounted to a mistake, while the methods of NC and CTS acquired some results basically accessible. On the whole, hDDF method could effectively integrate ray-scale and texture and obtained a better segmentation performance.

Experiment 2 operation duration: this experiment focused on the operation duration and efficiency in the hDDF method, and made a comparison with the NC and RACM methods. There were width and height of image, and the operation duration of these three methods in Table 1, as well as the output optimal thresholds when hDDF method converged, which was applied to segment images based on evolution of feature field.

TABLE 1 Comparison among operation duration by hDDF method(measured in s)

image	W	H	Threshold in hDDF	hDDF	NC	RACM
CS	220	192	(56,36,52,36)	4.869	5.222	12.282
Real 1	241	161	(59,34,58,44)	4.591	22.752	24.114
Real 2	241	161	(33,26,28,17)	17.920	43.269	12.202
Real 3	161	241	(46,39,48,30)	18.084	26.699	12.021
Real 4	161	241	(56,42,51,34)	17.964	30.085	18.949
Real 5	256	181	(74,48,71,77)	20.610	32.373	21.895

Results in Table 1 showed that hDDF was close to RACM, far superior to NC, also superior to the quick three dimensional Otsu in line with time consumption. However, the experiment results showed that RACM terminated after 100 times of iteration in segmenting the above images on average, and the result was inferior to that from hDDF to some extent. Method raised in this paper was quite rational and effective from the perspective of operation.

5 Conclusion

With an aim to select an optimal threshold in image segmentation, this paper introduced some ideas of dynamic data field and also put forward the new method integrating gray-scale image and texture. It regarded the pixel in feature space as the particle in data field, and realized the selection of optimal threshold through the adaptive movement of particles in data stress field. In terms of the ordinary images of texture synthesis, hDDF enjoys the segmentation performance, which is close to the traditional CTS method integrating gray-scale and texture, and far superior to the RACM method simply utilizing the gray-scale information. In terms of those ordinary images of nature, hDDF enjoys the segmentation performance, which is close to the traditional NC and RACM, and far superior to the CTS for it takes no account of gray-scale information. This means that the visualization appraisal index takes a predominant position obtained from the method of selecting the optimal threshold by image segmentation based on the evolution of feature field. There is no need observing some subtle segmentation differences.

Segmentation experiments in different images show that method raised in this paper receives outstanding segmentation performance, which is able to converge rapidly. The time it spends on operation fell within acceptable limits. It is able to satisfy the need of engineering application and adapt itself to selecting the optimal threshold in most image segmentation.

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Authors

Shuqin Liu, 1986, Hunan Province, China.

University studies: master's degree in image processing, artificial intelligence of Northwestern University.
Scientific interests: graphics learning.

Jinye Peng, 1964, Hunan Province, China.

Current position, grades: professor
University studies: doctor's degree in information engineering, Northwestern Polytechnical University in 2002.
Scientific interests: graphics learning