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INFRARED MOVING TARGET CONTOUR EXTRACTION MODEL BY COMBINING THE GRADIENT AND PHASE INFORMATION OF THE LEVEL SET

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Abstract

Aiming to solve the problems such as the weak edge contour of the target, the low gray deviation between targets and background as well as the weak boundaries in infrared images and the low noise-proof ability which are hard to be solved by the Distance Regularized Level Set Evolution (DRLSE), this paper purposed the Distance Regularized Level Set Evolution Mode Based on Phase and Gradient Information (PGDRLSE), and this model reconstructed indicator function of boundary by combining the gradient and phase information, and then came to the new energy function. During the process of detecting and tracking the moving target, this article detected the target by using background subtraction method together with frame difference method and obtained the minimum circumscribed rectangular frames of moving target in every infrared video frame with the mean-shift method, and utilized the PGDRLSE to obtain moving human target outline eventually.

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Experiment results showed that this method could realize the accurate extraction of weak boundary of moving target in infrared images, and accelerate the evolution speed. At the same time, it has strong noise proof ability.

Keywords: contour extraction, DRLSE model, variational level set, gradient and phase information, mean-shift.

1. Introduction

At present, schools and institutes as well as military areas are equipped with high-end laboratory equipments, in addition to the high market value of these equipments; data security is also one of the issues which drew people's great attention both at home and abroad. So how to protect the equipment and the information is one of the most vital researching areas. Infrared technology is widely used in military and industrial applications for the features such as night vision imaging, navigation, searching, and tracking. Target tracking and contour extracting based on infrared video image have gradually become the hotspot in the field of pattern recognition and computer vision [1, 2].

Aiming at the low deviation between moving targets and background and the weak boundaries in infrared images, literature [5] used threshold value segmentation and Sobel operator to detect the edge of infrared image, although the detection method is feasible, and effective, but the traditional threshold segmentation method can hardly separate the target from the interfered background; [6] employed genetic algorithms on infrared video image to detect moving target, and extract target contour, but the implementation process is too complicated; [7] proposed a infrared image feature extraction method which combined threshold value segmentation and morphological, it could improve the quality of images, but this approach's tendency to enhance background and other useless information of images failed to reach the segmentation goal.

Level set segmentation method is widely used [3] because of the advantage of automatic processing topology changes. Its basic idea is to make the contour as a function of the level set zero level set, and then the level set function is embedded into the curve evolution equation. It can get the curve evolution process [4] through the evolution of its zero level set. According to different binding, level set method is divided into level set method based on region [8-11] and boundary [12-14] based level set method. The former can handle weak border and no border issues by using the image's regional statistical information to construct constraints and drive curve evolution, but the boundary positioning is not accurate. The latter mainly constructed a kind of boundary indicator function using image boundary information to make the curves stop at the target boundaries. It's typical representative is geodesic contour model (GAC model) [13], distance regularized level set evolution model (DRLSE model) [14]. However, the information of the image used in the active contour model based on the boundary is based on gray scale. For low contrast and edge blurring phenomenon in infrared images, it cannot guarantee that the border stop function stay approximately zero on the edge of the target, therefore, the DRLSE is difficult to achieve the target contour feature extraction. The method proposed by this article has a great evolution effect on infrared video sequences with characteristics of low deviation between moving targets and background, it also accurately achieved infrared moving object contour extraction.

2. The Model of DRLSE

The DRLSE model [14] is an edge-based variational level set segmentation method. This method adds a distance regularization term in the traditional level set method, which solves the problem of re-initialization and accelerates the evolution speed. In the literature [14], the energy functional is defined as follows:

$$\varepsilon(\phi) = \mu R_p(\phi) + \lambda L(\phi) + \alpha A(\phi)$$
$$= \mu\int_\Omega p(\nabla\phi)dx + \lambda\int_\Omega g\delta(\phi)\nabla\phi dx + \alpha\int_\Omega gH(-\phi)dx. \quad (1)$$

In the formula, ϕ is the function of level set, μ, λ, α are the weighting coefficients of regularization, length, and area. H is Heaviside function, δ is Dirac function.

In the formula (1), the first function of level set ϕ is the regularization term, which could correct the error between level set function and the signed distance function, and ensure that in the entire process of curve evolution, the level set function is similar to the signed distance function at maximum extent. So, periodically initialized evolution curve in the process of evolution is not required, evolution speed was increased.

In the formula (1), function g is a stop function of the boundary based on the image gradient, it is defined as follows:

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2}. \quad (2)$$

In the formula (2), G_σ is Gaussian function, I is the image to be processed, ∇ is a gradient operator. The image gradient is small when it is in the flat area of image, and curve can be evolved; the image gradient is large when it is in edges of the image, curve stops at the target boundary. The Gaussian function is an isotropic diffusion filtering method, it can smooth noise while undermining the important edge of images.

In the formula (1), the third is weighted area item which weighted to function g, corresponding to the balloon force, and used to accelerate the evolution speed. When the initial outline is in the target's outside, α takes a positive value and speeds up contour contraction; when the initial outline is in target's inside, α takes a negative value, it speeds up outline expansion.

DRLSE model has the advantages of the simple numerical solution, fast convergence and without re-initialize the level set and so on. But, characteristics of low deviation between moving targets and background and weak boundaries in infrared video sequences cause the function g fail to reach zero value at the boundary and curves' evolving to target border unstoppable.

3. The Model in this Paper

3.1. Phase congruency analysis

Phase congruency is a relatively new feature detection method. It is not based on gray gradient, but assumes that the image points of which the Fourier components are most consistent as feature points of the image [15, 16]. Edge detection which based on the phase information is an analytical method for gray mutation in the frequency domain; the phase congruency function is defined as follows:

$$PC(x) = \max_{\varphi(x) \in (0,\, 2\pi)} \frac{\sum_n A_n \cos(\varphi_n(x) - \varphi(x))}{\sum_n A_n}. \tag{3}$$

In the formula (3), A_n represents the amplitude value of the cosine component of the harmonic, φ_n is the initial phase of the n component, $\varphi_n(x)$ represents local phase of Fourier components at the point x. Phase congruency detection gets rid of the dependence on image brightness and overcomes the defects of the low contrast and edge blur in infrared images; however, it cannot obtain a closed boundary curve, just as other edge detection algorithm. This article presents a new approach that combines the advantages of phase congruency and level set segmentation method.

3.2. Construction of new boundary indicator function ψ_p

Due to the complexity of the actual infrared images, phase congruency function values are not distributed to the $[0, 1]$. So it needs to be normalized. Through linear transformation on the function values of phase congruency, the actual PC values of the images can be mapped to $[0, 1]$, as shown in formula (4).

$$pc'(x) = T_1(pc) = \frac{pc(x) - pc_{\min}}{pc_{\max} - pc_{\min}}. \tag{4}$$

To further enhance the image contrast, we need to conduct contrast stretching transformation on the normalized phase congruency function in order to achieve the purpose of enhancing the edges, as shown in formula (5).

$$pc''(x) = T_2(pc) = \frac{1}{1 + (m / pc')^k}. \tag{5}$$

To construct a new boundary indicator function ψ_p (or called boundary stop function) which combines phase information and gradient information as a boundary stopping power. It forces the level set evolution curve stop at the target boundary. The function is defined as follows:

$$\psi_p = \frac{1}{1 + |\nabla pc''|^2}. \tag{6}$$

Among them, ∇ is the gradient operator, we get the phase gradient by conducting gradient operation on the enhanced phase congruency function. It obtains non-zero value on the smooth areas of image, prompting the curve continue to evolve. And ψ_p obtains zero at the edge of the image, forcing the curve to stop evoluting.

3.3. The level set expression in this model

According to the theory of geometric evolution and partial differential equations, we regarded the boundary indicated function ψ_p which based on the phase information as the external restraints of curve evolution, and obtained the level set segmentation model (PGDRLSE) combining the information of gradient and phase, the energy functional is defined as follows:

$$\begin{aligned}\varepsilon(\phi) &= \mu R_p(\phi) + \lambda L(\phi) + \alpha A(\phi) \\ &= \mu \int_\Omega p(\nabla\phi)dx + \lambda \int_\Omega \psi_p \delta(\phi)\nabla\phi dx + \alpha \int_\Omega \psi_p H(-\phi)dx. \end{aligned} \tag{7}$$

According to the variational theory, the Gato derivative $\frac{\partial\varepsilon}{\partial\phi}$ of the functional can be written as

$$\frac{\partial\varepsilon}{\partial\phi} = -\mu[\Delta\phi - \operatorname{div}(\frac{\nabla\phi}{|\nabla\phi|})] - \lambda\delta(\phi)\operatorname{div}(\psi_p \frac{\nabla\phi}{|\nabla\phi|}) - \alpha\psi_p\delta(\phi), \tag{8}$$

where Δ is the Laplace operator, $\operatorname{div}(\bullet)$ is the divergence operator. Using the gradient descent method to minimize the formula (8), we can obtain gradient flow equations

$$\frac{\partial\varepsilon}{\partial\phi} = \mu[\Delta\phi - \operatorname{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)] + \lambda\delta(\phi)\operatorname{div}(\psi_p \frac{\nabla\phi}{|\nabla\phi|}) + \alpha\psi_p\delta(\phi). \tag{9}$$

The gradient flow equations is the evolution equation of the level set segmentation model (PGDRLSE) combined with the phase information and gradient information.

4. Moving Target Tracking and Contour Extraction

4.1. Moving target tracking based on mean-shift algorithm

Mean-shift algorithm is a non-parametric density estimation algorithm that can be applied to image filtering, segmentation, and target tracking. Kernel generally chooses Bhattacharyya function. With the demand of maximum similarity function, it obtains the mean-shift vector of the target, using the similarity function to measure the similarity of original frame target model and the current frame candidate model. This mean-shift vector is offset vector which shows the target from the initial position to the correct position. Because of convergence, constantly iterative calculation mean-shift vector, the final target will converge to the true position of the target (a stationary point), and finally achieve the purpose of track.

4.1.1. The description of the target model and the candidate model

Setting x_0 as the center of the target area, there are n image pixels, $\{x_i\}_{i=1,2,3,\ldots,n}$. The colour range of pixel is divided into m equal intervals, and the density estimation of the characteristic values in the target model

$$\hat{q}_u = C\sum_{i=1}^{n} k\left(\| \frac{x_0 - x_i}{h} \|^2\right) \delta\,[b(x_i) - u]. \tag{10}$$

In the formula, h is kernel bandwidth, $k(x)$ is the function of kernel contour, and C is a normalized constant:

$$C = \frac{1}{\sum_{i=1}^{n} k\left(\| \frac{x_0 - x_i}{h} \|^2\right)}. \tag{11}$$

Approximately, for the target candidate regions, assuming that central point is y, the probable density function of the u-th eigenvalue estimation in the target candidate model is

$$\hat{p}_u\,(y) = C\sum_{i=1}^{n} k\left(\| \frac{y - x_i}{h} \|^2\right) \delta\,[b(x_i) - u]. \tag{12}$$

4.1.2. Similarity function and target location

Similarity function is to show the degree of similarity between the target model and the candidate model. Bhattacharyya coefficient is used here as a correlation function which defined as

$$\hat{\rho}(y) = \rho(\hat{\rho}(y), q) = \sum_{u=1}^{m} \sqrt{\hat{p}_u(y) q_u}. \quad (13)$$

Their value is between **0 ~ 1**, the higher $\hat{\rho}(y)$ is, the closer these two models will be. In the current frame, different candidate area calculation generate different candidate models, the target location in current frame is one of the candidate areas which gets maximum $\hat{\rho}(y)$. In order to obtain the maximum $\hat{\rho}(y)$, we set the target center of current frame as the target center location y_0 in previous frame, and Taylor expansion is

$$\rho(p(y), q) = \frac{1}{2} \sum_{u=1}^{m} \sqrt{p_u(y_0) q_u} + \frac{c_h}{2} \sum_{i=1}^{n} w_i k\left(\| \frac{y - x_i}{h} \|^2 \right), \quad (14)$$

$$w_i = \sqrt{\frac{q_u}{p_u(y)}} \delta[b(x_i) - u]. \quad (15)$$

In the formula (13), only the second item changes with y, so, to achieve the maximum y, we simply make the second be the largest. So

$$f(_{N,k}) = \frac{c_h}{2} \sum_{i=1}^{n} w_i k\left(\| \frac{y - x_i}{h} \|^2 \right). \quad (16)$$

Based on mean-shift algorithm, we can derive the mean-shift vector of the center of candidate area y_0 moving to true target area

$$M_{h,G}(y) = y_1 - y_0 = \left[\frac{\sum_{i=1}^{n} w_i x_i g(\| \frac{x - x_i}{h} \|^2)}{\sum_{i=1}^{n} w_i g(\| \frac{x - x_i}{h} \|^2)} - y_0 \right]. \quad (17)$$

In (17), $g(x) = -k'(x)$, y_1 is equivalent to the new target location after iteration. At the end of iteration, setting $y_0 - y_1$ and starting the next iteration, repeating this process until the distance between y_0 and y_1 is small enough or reach a specified number. So we can find the current location of the frame target, thereby identifying the target.

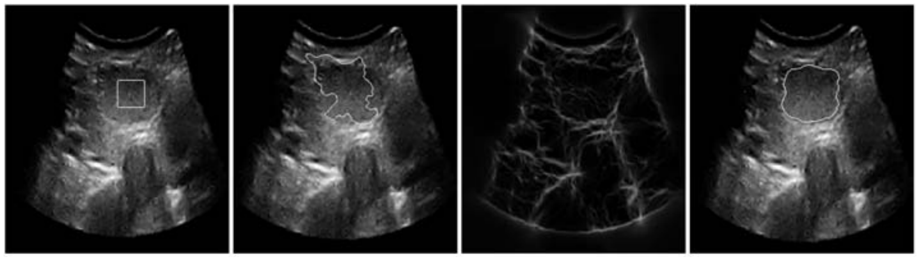
4.2. Contour extraction

In Subsection 4.1, this article obtained minimum circumscribed rectangular frames of moving target in every infrared video frame with the mean-shift method. These rectangles are the general contour of moving targets and they are set as the contour of the initial level set evolution in this paper. This article used level set model combining phase and gradient information for image segmentation, and then the moving target contour feature can be obtained.

5. Analysis of the Experimental Results

In order to verify the effectiveness of the algorithm, after achieving the minimum circumscribed rectangular frames of moving target with the mean-shift method, we employed experimental comparison of the DRLSE algorithm and the proposed algorithm in this paper. Experimental environment is: Intel(R) Core(TM) i5 CPU 2.3GHz, 2GB DDR2 memory, windows8 operating system, DELL computer, the running software is Matlab2012b. The experimental parameters were set as follows: $\mu = 1.0$, $\lambda = 1.0$, $\varepsilon = 1.0$, $\alpha = 5.0$.

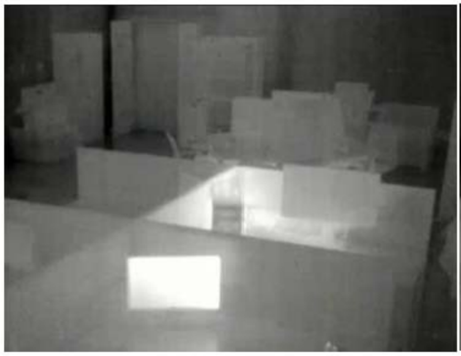
Experiment 1 verified the accuracy of the proposed algorithm in this paper. The image used in the experiment is a (280×280) thyroid ultrasound image with single nodule. Since Gaussian filter in the DRLSE model destroys the image boundary information, which seriously influences the ability to detect edges of boundary stop function. DELSE model can split out the broad contours of thyroid nodules through 500 iterations, but the edge position is not accurate and there is a certain boundary leakage, as shown in Figure 1(b). It can get the consistent feature points in the edge of the nodules when detecting edges by using phase congruency and gradient information. However, it cannot obtain a clear and obvious contour curves, which requires post-processing, as shown in Figure 1(c). Proposed model avoids the destruction of the boundary of thyroid nodules from Gaussian filter under the effect of the new boundary indicator function, which segments the thyroid nodules accurately, as shown in Figure 1(d).



(a) The initial outline; (b) DRLSE model; (c) Phase congruency detection; and (d) Model in this paper.

Figure 1. The comparison of segmentation results for single nodule thyroid ultrasound image.

Experiment 2, using infrared camera (FLIR: FC-645S) to shoot human moving video in the laboratory, parts of frame images in the video will be shown in Figure 2. Using mean-shift algorithm for target tracking, the target external rectangular was obtained, then preprocess the image, and then, using the improved level set evolution method we proposed to realize target contour feature extraction. Experimental results are shown in Figure 3.




(a1) The second frame (a2) The seventh frame


(a3) The 45th frame (a4) The 78th frame

Figure 2. Parts of frame images in video.

(a) Infrared video image mean-shift filter tracking results

(b) Target contour feature extraction by DRLSE model

(c) Target contour feature extraction by proposed model

Figure 3. Experimental results.

Experiment results show that: when the edge features are relatively clear (as the second picture in Figure 3 (b) and (c)), DRLSE achieves target contour feature the same as proposed method, but when being compared with the third picture in Figure 3 (b) and (c), because of the fuzzy boundaries, DRLSE model cannot get accurate features, it cannot guarantee the border stop function stay approximately zero on the edge of the target, therefore, the proposed model has certain advantages.

In terms of evolution efficiency, PGDRLSE inflates inside the curve depending on the balloon force, accelerates the evolution speed, and therefore time the PGDRLSE method used is less than DRLSE, it proves that PGDRLSE algorithm has the superiority and feasibility characteristics, as shown in Table 1.

Table 1. The number of iterations and the running time comparison table

	The seventh frame		The 45th frame		The 78th frame	
	Iterations	Time/s	Iterations	Time/s	Iterations	Time/s
DRLSE model	500	21.13	600	29.34	600	20.78
Model in this paper	450	16.05	450	14.96	500	17.32

In terms of noise immunity, Gaussian filter of DRLSE make serious damage to the image edge information, the peak signal to noise ratio of the image is reduced, however, under the action of new indicator function, this model can protect the image details.

6. Conclusion

This paper presents an infrared moving target contour extraction model by combining the gradient and phase information of the level set. The algorithm uses the phase congruency detection principle and constructs a new boundary indicator function combining with phase information and gradient information. It replaces the boundary stop function in DRLSE model and gets a new energy functional by using ultrasound images and infrared images to verify the proposed method. Experimental results show that the model has good noise immunity, and effectively extracted contour feature, better than the original DRLSE model.

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