Ship Target Image Segmentation Algorithm Based on Fuzzy Level Set

Yu Zhang1,*, Yuntao Li1, Yonghui Guo1 and Zheshuai Zhou2
1Space Engineering University, Beijing, China, 101416
263999 unit, Beijing, China

*Corresponding author email: 986230552@qq.com

Abstract. The effective recognition of ship target is very important for the protection of ocean rights, and the image segmentation is the precondition of the ship target recognition. To solve the two problems existing in the traditional level set graph, namely the increase of image segmentation and the increase of computation, the Fuzzy C-Means (FCM) and level set are introduced. A new algorithm for image segmentation based on fuzzy level set is proposed in this paper. The algorithm can use spatial fuzzy clustering to realize the parameter estimation and evolutionary adjustment. The algorithm is applied to optical remote sensing ship target image segmentation in complex sea environment, and the effectiveness of the proposed algorithm is verified by experiment results.

Keywords: Level set; Image segmentation; Spatial modulus and clustering method; Parameter estimation.

1. Introduction
In the information era of big data, images have become an important carrier for human perception of the world to acquire and transmit information, because images contain most of the information for human perception and cognition of the world and transformation of the world[1]. Image information must be processed to meet the needs of people’s vision, heart and practical application, and the processing of image information is often realized by computer technology. In Computer Vision, digital image processing is a process in which the image signal is represented as digital signal and processed and analyzed by computer. Image segmentation is an important part of digital image processing and analysis, and it has been widely used in the computer vision field[2]. By simplifying and changing the image representation, image segmentation makes the image easier to understand and analyze. Image segmentation is to divide an image into several non overlapping sub regions, so that each sub region has certain similarity, while different sub regions have obvious differences. Image segmentation is the basic preprocessing work of image recognition, scene understanding, object detection and other tasks.

Image segmentation is a very simple task for human vision, but it is a challenging task for computer. In the field of image processing, image segmentation has become one of the important research topics for decades, lots of research on image segmentation have been done by scholars at home and abroad, and many kinds of image segmentation methods, such as threshold image segmentation[3], region segmentation[4], boundary segmentation[5], watershed segmentation[6], level set image segmentation have been given[7][8]. Among these image segmentation methods, this paper focuses on level set image segmentation because level set image segmentation has the following advantages: (1)The level set is a knowledge point in the field of mathematics. By using the level set function formula and iterative process, the objective function of image segmentation and the segmentation process can be clearly
The level set image segmentation method can be easily combined with the knowledge of other fields, which is beneficial to the research and fusion of cross-fields in scientific research. The level set function can control the free topology of the evolution curve, split and merge, and can be extended to the evolution of three-dimensional and four-dimensional curves. The level set image segmentation method has good expansibility and is convenient to establish many kinds of energy functional models. Compared with other image segmentation methods, level set image segmentation method—which can be applied to target detection, 3D image reconstruction, target tracking and so on—has a broad application prospect.

Because of its advantages, the level set image segmentation method has received extensive research and attention in recent years. It is obvious that this image segmentation method has strong vitality. However, there are still many problems to be solved in level set image segmentation, for example, the robustness and low iterative efficiency of the level set image segmentation model which is specially used for the serious uneven gray level image processing, and a level set image segmentation model is only suitable for one type of image.

Based on the advantages of the level set image segmentation method in the field of image segmentation and its wide application and development prospect as well as some existing problems, it is necessary to study the level set image segmentation theory deeply and systematically, it is also necessary to extend it by introducing other theories or methods. This paper discusses the fuzzy level set theory in the first place, and proposes a fast level set equation—which makes the difficult level set algorithm faster—to solve the problems of too much computation and the constraints of the evolution of the level set. Then it analyzes the establishment of the mold and the level set algorithm, introduces the new mold and the level set algorithm, deduces and analyzes the theory of the new algorithm, and proposes an adaptive method to realize the adjustment of the control parameters, a large number of evolutionary iterations is achieved with a small computational resource cost. Then, a new modulus and level set algorithm is proposed to segment the ship target in optical remote sensing image, then the correct segmentation result is achieved, and the validity of the algorithm is proved.

2. The Principles of the Fuzzy Level Set

Level set method for image segmentation using dynamically changing boundaries. Image segmentation using active contour mean is a classical method in image segmentation. Unlike edge parameter representation, level set representation uses a time-dependent partial differential equation function \( f(t,x,y) \) to represent edges. After tracking the zero level set, you can get implicit \( \Gamma(t) \) approximate the evolution of the edges:

\[
\begin{align*}
\varphi(t,x,y) < 0 & \quad \text{in } \Gamma(t) \\
\varphi(t,x,y) = 0 & \quad \text{on } \Gamma(t) \\
\varphi(t,x,y) > 0 & \quad \text{to } \Gamma(t)
\end{align*}
\]

(1)

An implicit interface \( \Gamma \) consisting of a single or a series of Zero Contours. Then the image segmentation problem can be translated into:

\[
\bigcup S_k \cup \Gamma = I
\]

(2)

Note that the addition of the time variable \( t \) results in an increase in the dimension of the level set function \( \varphi \), which leads to additional calculations, but this approach also has many advantages. For example, by checking the level set function \( \varphi \)—which automatically adjusts as the topology of the implicit interface changes—an interface \( \Gamma \) can be determined. In particular, the evolution of \( \varphi \) is determined entirely by the numerical level set equation:
In this equation, $|\nabla \phi|$ presents the normal direction, $\phi_0(x,y)$ presents the initial contour, and $F$ represents the overall driving force, which includes internal forces from interface geometry (for example, mean curvature, contour length and surface area) and external forces from the gradient and/or artificial momentum of the image.

To prevent the evolution of the level set near the optimal solution, the edge indicator function $g$ is defined to regulate the driving force $F$.

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

In this equation, $G_\sigma * I$ presents the convolution of image $I$ and smooth gauss kernel $G_\sigma$, and $\nabla$ presents the gradient operation of image. The $g$ is close to zero at the variational boundary, and the other cases are positive. A level set partition equation is

$$\frac{\partial \phi}{\partial t} = g |\nabla \phi| \left[ \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) + v \right]$$

In this equation, $\text{div}(\nabla \phi/|\nabla \phi|)$ is an approximation of the average curvature $k$ and $v$ presents a given balloon force.

The large amount of computation is one of the biggest limitations of level set segmentation applications. The level set function transforms two-dimensional image segmentation problem into three-dimensional image segmentation problem. There are other constraints in the evolution of level sets. For example, time steps and grid spacing should meet the colan-friedrich-levie (CFL) conditions, and level set function $\phi$ should be periodically reinitialized as a symbolic distance function. In order to overcome these limitations, a fast level set equation is established:

$$\frac{\partial \phi}{\partial t} = \mu \zeta(\phi) + \xi(g, \phi)$$

The first term on the right, $\zeta(\phi)$, is the penalty momentum of $\phi$, derived from the symbolic distance function:

$$\zeta(\phi) = \Delta \phi - \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right)$$

The second $\xi(g, \phi)$ contains image gradient information:

$$\xi(g, \phi) = \lambda \delta(\phi) \text{div} \left( g \frac{\nabla \phi}{|\nabla \phi|} \right) + vg \delta(\phi)$$

In this equation, $\delta(\phi)$ represents the Paul Dirac function, the constants $\mu$, $\lambda$, and $v$ control the weights of these terms, $\xi(g, \phi)$ draws the $\phi$ towards the variational boundary, which is similar to the standard level set method. However, the penalty term $\zeta(\phi)$ forces $\phi$ to approach the real symbolic distance function automatically. Therefore, the reinitialization of the symbolic distance function, which takes a lot of
computation, is eliminated by the new algorithm, further, this method can start from an arbitrary binary region:

\[ \ldots \]

Where \( C \) is the given constant. Finally, the algorithm allows for a larger time step with stable evolution:

\[
\phi^{k+1}(x, y) = \phi^k(x, y) + \tau \left[ \mu \zeta(\phi^k) + \xi(g, \phi^k) \right]
\]

These adjustments make the level set algorithm in the application of image segmentation with a faster implementation speed.

3. The Establishment of the Fuzzy Level Set Algorithm

The new modulus and level set algorithm uses spatial modulus and clustering to automatically initialize and configure the parameters for level set segmentation. FCM is combined with spatial restriction to determine the edge of the part of interest in the image. As shown in equation (9), the enhanced level set function can evolve directly from the results of FCM. Suppose the interest component in the FCM result is \( R_k; \{ r_k = \mu_{nk}, n = x \times N_y + y \} \). Then the level set function can be initialized to:

\[ \phi_0(x, y) = -4 \varepsilon (0.5 - B_k) \]  

Where \( \varepsilon \) is the constant that regulates Paul Dirac’s function. The Paul Dirac function is defined as follows:

\[
\delta_{\varepsilon}(x) = \begin{cases} 
0, & |x| > \varepsilon \\
\frac{1}{2\varepsilon} \left[ 1 + \cos \left( \frac{\pi x}{\varepsilon} \right) \right], & |x| \leq \varepsilon 
\end{cases}
\]

\[ B_k \] derived from the following relationships:

\[ B_k = R_k \geq b_0 \]

Where \( b_0 \in (0,1) \) is an adjustable threshold. The \( B_0 \) is able to approximate the part of interest to some extent by adjusting the \( b_0 \) by spatial injection and clustering.

The control parameters of the level set method are shown in Table 1. The level set algorithm optimizes the results of the Algorithm by properly configuring these parameters. Based on the experience and practice, some rules of thumb are given for the configuration of control Parameters: For example, a large \( \sigma \) value can result in image smoothing and loss of image detail. Large time step \( \tau \) may accelerate level set evolution, but there is a risk of boundary miss detection. In addition, if the initial \( \phi_0 \) is outside the area of interest, then the value of \( v \) is positive, and vice versa. In order to keep the evolution stable, the product of the time step and the penalty coefficient \( (\tau \times \mu) \) must be less than 0.25 and the parameter should be greater than \( 2\varepsilon \). A larger \( \lambda \) value will lead to the smoothing of the contour, and a larger \( v \) value can accelerate the evolution of the level set, but there is the risk of boundary miss detection. The above empirical parameter allocation strategy is difficult to adapt to complex image characteristics and achieve optimal image segmentation performance.

**Table 1.** Control parameters for level set segmentation.
Parameters | Meaning
---|---
$\sigma$ | Expansion of Control Gaussian smoothing function
$C$ | Control the gradient of the initial level set function
$\varepsilon$ | Normal Paul Dirac function $\delta(\phi)$
$\mu$ | The Weight Coefficient of penalty term $\zeta(\phi)$
$\lambda$ | Figure Length Coefficient of a smoothing gauge
$\nu$ | Artificial balloon force
$\tau$ | Time step of level set evolution
$T$ | The maximum iteration number of evolution of level set

Therefore, it is necessary to propose an adaptive control parameter adjustment method for a specific image. Given the initial level set function $\phi_0$ from the space modulus and cluster equation (11), the length $l$ and the area $a$ are easily estimated:

$$l = \int \delta(\phi_0) \, dx \, dy$$

$$a = \int H(\phi_0) \, dx \, dy$$

The Herviside function $H(\phi_0)$ is:

$$H(\phi_0) = \begin{cases} 1, & \phi_0 \geq 0 \\ 0, & \phi_0 < 0 \end{cases}$$

The larger the range of interest, the faster the level set evolution. In this case, the ratio:

$$\zeta = a/l$$

The ratio is also large. Therefore, in the proposed level set algorithm, the $\zeta$ can be assigned to time step $\tau$ and the penalty factor $\mu$ can be set to:

$$\mu = 0.2/\zeta$$

To ensure stable evolution, the product $(\tau \times \mu)$ should be less than 0.25. The initial level set function $\phi_0$ derived from the modulus and clustering equation (11) approximates the true boundary, and the relatively conservative $\lambda$ is selected to control the topological change.

$$\lambda = 0.1\zeta$$

The balloon force $\nu$ plays two roles in the evolution of level set. In the first place, the forward direction of the level set function is determined by the balloon force $\nu$: Contraction is positive, expansion is negative. In the second place, the bigger the $\nu$, the faster the level set will evolve. In standard level set algorithms, the control parameter $\nu$ is usually set to a global constant. If $\phi$ is far from the real boundary, the level set function should have a higher rate of evolution. In contrast, the level set function evolution should be slowed down once $\phi$ is near the boundary. In addition, the level set function should automatically change direction when passing through the boundary of interest.
4. Simulation Experiment
In this paper, an experiment is designed to evaluate the reliability of ship target segmentation in optical remote sensing image using the mode and level set algorithm. The implementation environment of the Algorithm is Matlab 2015B under Windows 7 operating system, and the computer environment running the software is Dell OptiPlex 790(CPU i7-2600@3.40GHz, 8 Gb Ram). The image sample used is shown in Figure 1.

![Image](a)
![Image](b)
![Image](c)
![Image](d)

Figure 1. Origin images.

The sample in Figure 1 is well representative, which is embodied by the complex gray texture in the target area of the ship and the obvious fluctuation of the gray level of the sea background, in particular, in Figure. 1(b), the brightness and scale of the sea wave are very close to the ship target, and the image also shows obvious noise characteristics in the optical remote sensing image.

The results of image segmentation is shown in Figure 2. The proposed method presented in this paper achieves the correct image segmentation result by adjusting the algorithm parameters. From the experimental results, it can be seen that the method can obtain the approximate boundary of the potential part of interest, so it is suitable for the initialization of image segmentation. However, considering the complex characteristics of optical remote sensing images, the standard FCM algorithm focusing only on intensity information is difficult to obtain the correct segmentation results. The enhanced spatial FCM algorithm attempts to combine the intensity and spatial information as a whole. The proposed method has been proved to be insensitive to different types of noise, so it is suitable for the initialization of the evolution of image segmentation.

The traditional image segmentation algorithm, for a specific image, the optimal parameters can only be obtained by trial and error method. And inappropriate control parameters can lead to an inadequate segmentation. The proposed method presented in this paper can automatically stabilize the implicit interface near the real boundary, and can automatically estimate the optimal control parameters according to the results of the spatial modulus and cluster. These advantages of the algorithm will greatly promote the algorithm in the application of image segmentation.
5. Conclusion
In this paper, we mainly focus on the level set image segmentation. Firstly, we introduce the traditional level set image segmentation, which uses the active contour mean, in the level set method, the edges are represented by a time dependent partial differential equation function, and the evolution of the edges can be approximated implicitly by tracking the zero level set. The dimension of the level set increases with the addition of time variables, the new algorithm eliminates the reinitialization process, which takes a lot of computation to the symbolic distance function. The new algorithm allows for a larger time step under the premise of stable evolution, it makes the level set algorithm have faster implementation speed in the application of image segmentation, and then proposes a new fuzzy level set algorithm for image segmentation, the proposed method uses spatial ambiguity and clustering to estimate the parameters and adjust the evolution of the level set segmentation proposed method, and finally realizes image segmentation. The initial level set function is given by the space fuzzy cluster equation. If the range of interest is larger, the level set will evolve faster, this method can achieve a large number of evolutionary iterations with less computational cost. The simulation experiment is used to evaluate the reliability of the fuzzy level set algorithm applied to the optical remote sensing image for ship target segmentation. The experimental results show that the mode and cluster can adaptively obtain the approximate boundary of the potential interest part, at the same time, it is not easily affected by different types of noise, which proves the reliability and effectiveness of the proposed method.

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