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Abstract. Image segmentation is an important step in image processing and analysis, pattern recognition, and machine vision. A few of algorithms based on level set have been proposed for image segmentation in the last twenty years. However, these methods are time consuming, and sometime fail to extract the correct regions especially for noisy images. Recently, neutrosophic set (NS) theory has been applied to image processing for noisy images with indeterminant information. In this paper, a novel image segmentation approach is proposed based on the filter in *NS* and level set theory. At first, the image is transformed into NS domain, which is described by three membership sets (*T*, *I* and *F*). Then, a filter is newly defined and employed to reduce the indeterminacy of the image. Finally, a level set algorithm is used in the image after filtering operation for image segmentation. Experiments have been conducted using different images. The results demonstrate that the proposed method can segment the images effectively and accurately. It is especially able to remove the noise effect and extract the correct regions on both the noise-free images and the images with different levels of noise.

Keywords: Image segmentation, Neutrosophic set, Directional alpha-mean filter, Level set.

1 Introduction

Image segmentation is an essential process and is also one of the most difficult tasks in image processing field. It is defined as a process dividing an image into different regions such that each region is homogeneous, but the union of any two adjacent regions is not homogeneous.

Image segmentation approaches are based on either discontinuity and/or homogeneity. The approaches based on discontinuity tend to partition an image by detecting isolated points, lines and edges according to the abrupt changes of the intensities. The approaches based on homogeneity include thresholding, clustering, region growing, and region splitting and merging [1].

Neutrosophy set (NS) provides a powerful tool to deal with the indeterminacy, and the indeterminacy is quantitatively described using a membership [2]. In neutrosophic set, a set A is described by three subsets: <A>, <Neut-A> and <Anti-A>, which is interpreted as truth, indeterminacy, and falsity set. It provides a new tool to describe the image with uncertain information, which had been applied to image processing techniques [3], such as image segmentation, thresholding and denoise.

In this paper, we proposed a novel image segmentation method based on NS theory. The image is mapped into NS domain and a new filter, directional alpha-mean filter is defined in NS domain, and used to remove the indeterminance on the image. Finally, the image on NS domain is segmented using the method based on level set active contour model.

The remainder of this paper is organized as follows. The next section describes the neutrsosophic image, the directional alpha-mean filter, and the segmentation algorithm integrated with level set model. Section three reports the experiments and the relevant discussion. Concluding remarks are drawn in Section four.

2 Proposed method

2.1 Neutrosophic image

An image might have a few indeterminate regions, such as noise, shadow, and boundary. It is hard for the classic sets to interpret the indeterminate regions on images clearly. In a neutrosophic set, a subset *I*, is named as indeterminate set and employed to interpret the indeterminacy in the image.

A neutrosophic image is described by three membership sets *T*, *I* and *F*. The pixel $P(i,j)$ in the image domain is transformed into the neutrosophic set domain, denoted as $P_{NS}(i,j)$ and $P_{NS}(i,j)=\{T(i,j), I(i,j), F(i,j)\}$ (*T*, *I* and *F* are the membership values belonging to bright pixel set, indeterminate set and non-bright pixel set, respectively, which are defined as follows [4]:

$$T(i,j)=\frac{\overline{g}_w(i,j)-\overline{g}_{w\min}}{\overline{g}_{w\max}-\overline{g}_{w\min}} \tag{1}$$

$$I(i,j)=\frac{\delta(i,j)-\delta_{\min}}{\delta_{\max}-\delta_{\min}} \tag{2}$$

$$F(i,j)=1-T(i,j) \tag{3}$$

where $\overline{g}_w(i,j)$ is the mean value of intensity in the local neighborhood, whose size is $w\times w$. $\delta(i,j)$ is the absolute value of the difference between intensity $g(i,j)$ and its local mean value $\overline{g}_w(i,j)$. The value of *I* measures the indeterminacy degree of P_{NS}.

2.2 Directional α-mean operation

In [3], an α-mean operation was defined on a neutrosophic image, and it removed noise efficiently. However, it might blur the image and reduce the contrast, which could reduce the performance of the segmentation. To overcome this drawback, a directional α-mean operation (denoted as DAM) is newly proposed to remove the noise effect and preserve the edges at the same time.

The function of the directional mean filter DMF is defined as [5]:

$$DMF(i,j)=\begin{cases} R_1 & |G_{Th}(i,j)-G_{Tv}(i,j)|\le\sigma \\ R_2 & G_{Th}(i,j)-G_{Tv}(i,j)>\sigma \\ R_3 & G_{Tv}(i,j)-G_{Th}(i,j)>\sigma \end{cases} \tag{4}$$

where $G_{Th}(i,j)$ and $G_{Tv}(i,j)$ are the norm of the gradient at (i,j) of the subset *T* at the horizontal and vertical direction, respectively. σ is a threshold value and selected as 0.01here.

The directional α-mean filter $DAMF$ is defined using the subset *T* and *I* as:

$$DAMF(i,j)=\begin{cases} T(i,j) & I(i,j)<\alpha \\ DMF(i,j) & I(i,j)\ge\alpha \end{cases} \tag{5}$$

2.3 Level set

Level set method was proposed in [6], and applied for image segmentation [7]. The level set method tracks the evolution of the boundaries between different objects, which are embedded as the zero level set.

The level set active contour models can be divided into two classes: edge based and region based. The edge based model tries to find a curve with the maximum edge indicator value which can minimize the energy function $J(C)$ [8]:

$$J(C)=\int |C'(s)|\,g\big(Im(C(s))\big)ds \tag{6}$$

where *g()* is an edge indicator function, *C* is the boundary, and it can be represented implicitly as the zero level set of a true positive function $\phi:\Omega\to R$, Ω is the domain of image. The evolution equation of boundary *C* can be derived as:

$$\begin{cases} \dfrac{\partial\phi}{\partial t}=|\nabla\phi|\left(div\left(g(Im)\dfrac{\nabla\phi}{|\nabla\phi|}\right)+v(Im)\right) \\ \phi(0,x,y)=\phi_0(x,y) \quad \text{in } \Omega \end{cases} \tag{7}$$

where *v()* is a term for increasing the evolution speed to reach the boundary.

The region based model uses the inside/outside mean values to compose the energy function [9]:

$$\begin{aligned} F(C,c_1,c_2)=&\mu_1 L(C)+\mu_2 S(C) \\ &+\lambda_1\int_{S_1}|Im-c_1|^2 dS_1 \\ &+\lambda_2\int_{S_2}|Im-c_2|^2 dS_2 \end{aligned} \tag{8}$$

where c_1 and c_2 are the mean intensities of the regions inside and outside the boundary *C*, respectively. *L* and *S* are the length of *C* and the area inside *C*. S_1 and S_2 are the region inside and outside of *C*, respectively. The associated level set flow can be represented as:

$$\begin{cases} \dfrac{\partial\phi}{\partial t}=\delta(\phi)\begin{bmatrix} \mu\, div\left(\dfrac{\nabla\phi}{|\nabla\phi|}\right)-v- \\ \lambda_1(Im-c_1)^2+\lambda_2(Im-c_2)^2 \end{bmatrix} \\ \phi(0,x,y)=\phi_0(x,y) \\ \dfrac{\delta(\phi)}{|\nabla\phi|}\dfrac{\partial\phi}{\partial n}=0 \end{cases} \tag{9}$$

where $\delta()$ is the Dirac function, and *n* denotes the exterior normal to the boundary $\partial\Omega$. *div()* is the divergence function on the image.

Usually, edge based approaches often suffer from noise, especially, when the image has a low signal/noise ratio; while the region based approaches are more adaptive to noise or vanishing boundaries due to considering the entire information of the regions to build an energy function.

2.4 Segmentation algorithm based on neutrosophic set and level set (NSLS)

A segmentation algorithm is proposed based on the directional α-mean filter and level set on neutrosophic image. Firstly, the image is transferred into the NS domain. Then, the DAMF is processed in the NS image. Finally, the boundary of region is segmented using the level set active contour algorithm based on the region model. The energy function is defined using the T subset after DAMF processing.

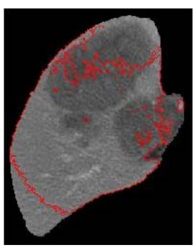
$$F(C,c_1,c_2)=\mu_1 L(C)+\mu_2 S(C) +\lambda_1\int_{S_1}|T'-c_1|^2 dS_1 +\lambda_2\int_{S_2}|T'-c_2|^2 dS_2 \tag{10}$$

3 Experimental results and discussion

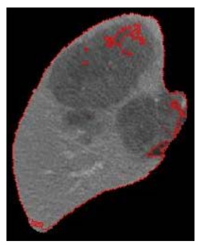
To test the performance of the proposed method, a few of images and images with different noise levels are employed. The NFLS method is compared with that of the segmentation algorithm based on the traditional level set [9], which is noted as TLS.

(a) Original image.

(b) Segmentation result of NSLS at 800 iterations.

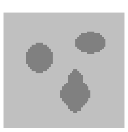


(c) Segmentation result of TLS at 800 iterations.

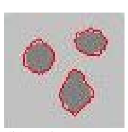


(d) Segmentation result of TLS at 1500 iterations.

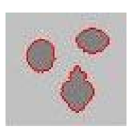
Figure 1: Comparison result on the "liver tumour" image with different iterations.



(a) Original image.



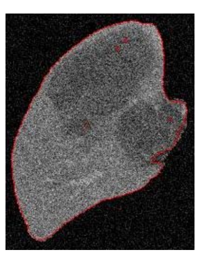
(b) The segmentation result of NSLS at 50 iterations.



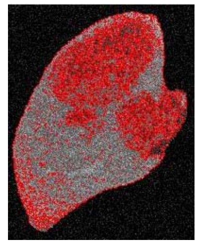
(c) The segmentation result of TLS at 50 iterations.

Figure 2: Comparison result on the "cells" image with same iterations.

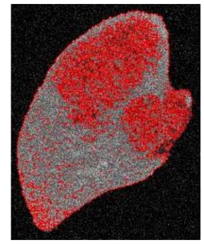
(a) Image with Gaussian noise (variance = 25).



(c) Segmentation result of NSLS at 1000 iterations.



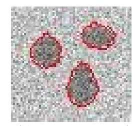
(d) Segmentation result of TLS at 1500 iterations.



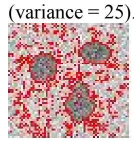
(e) Segmentation result of TLS at 2000 iterations.

Figure 3: Comparison result on the noisy "liver tumour" image with different iterations.

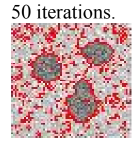
(a) Image with Gaussian noise (variance = 25).



(b) Segmentation result of NSLS at 50 iterations.



(c) Segmentation result of TLS at 50 iterations.



(d) Segmentation result of LS at 200 iterations.

Figure 4: Comparison result on the noisy "three cells" image with different iterations.

An experiment is performed to compare the time consumption of NSLS and LS methods. The NSLS takes less than 33 seconds per image on average for an AMD Phenom(tm) 9500 Quad-core Processor, 2.2 GHz. Table 1 compares the computational time on different images for different algorithms. The NSLS takes less iteration and fewer CPU times than the TLS method.

Image	TLS		NSLS	
	Iteration	CPU time (s)	Iteration	CPU time (s)
Liver tumour	1500	99.57	800	53.03
Cells	50	2.88	50	4.56
Noisy liver tumour	2000	255.34	1000	66.01
Noisy cells	200	13.19	50	4.56

Table 1: Comparison of the CPU times on images with and without noise.

From the comparisons, it can be seen clearly that the NFLS method has better performance on the image segmentation than the traditional level set method with high segmentation accuracy and low iteration time.

On noisy images, the NFLS segments the most objects with entire shape, while the performances of the traditional method are affected by the noise and some objects are divided into several regions. The results by the NSLS are smoother and more connected. Furthermore, the boundary' position and orientation are more accurate. The outperformance benefits from the fact that the NSLS approach handles the indeterminacy of the images well and DAMF operation remove the effect of noise and other indeterminant information, and preserve the determinant information in NS domain.

4 Conclusion

In this paper, a novel image segmentation approach is proposed based on neutrosophic filtering and level set theory. The image is transformed into neutrosophic set domain, and described using three membership sets (*T, I* and *F*). The directional alpha-mean filter (DAMF) is employed to reduce the image's indeterminacy, and the image is segmented on the *T* subset after DAMF processing using level set algorithm. The experimental results show that the proposed method can perform better on clear images and noisy images, due to the fact that the proposed approach can handle the indeterminacy of the images well. The proposed method can be used widely in many image processing applications.

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