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NSCT BASED LOCAL ENHANCEMENT FOR ACTIVE CONTOUR BASED IMAGE SEGMENTATION APPLICATION

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Abstract
Because of cross-disciplinary nature, Active Contour modeling techniques have been utilized extensively for the image segmentation. In traditional active contour based segmentation techniques based on level set methods, the energy functions are defined based on the intensity gradient. This makes them highly sensitive to the situation where the underlying image content is characterized by image non-homogeneities due to illumination and contrast condition. This is the most difficult problem to make them as fully automatic image segmentation techniques. This paper introduces one of the approaches based on image enhancement to this problem. The enhanced image is obtained using NonSubsampled Contourlet Transform, which improves the edges strengths in the direction where the illumination is not proper and then active contour model based on level set technique is utilized to segment the object. Experiment results demonstrate that proposed method can be utilized along with existing active contour model based segmentation method under situation characterized by intensity non-homogeneity to make them fully automatic.

Keywords:
Segmentation, Nonsubsampled Contourlet Transform (NSCT) and Active Contour Model (AVM)

1. INTRODUCTION

In computer vision, Segmentation is a fundamental step to the further processing and analysis operation on the image. All segmentation approaches aim to segment an object of interest from the rest of the image structure regardless of type of images they operate on. The active contour models (ACM) [1], which are based on the theory of surface evolution and geometric flows have been extensively studied and successfully used in image segmentation. Contours may be represented explicitly (known as parametric active contour or snake) or implicitly as a level sets of higher dimensional scalar function, taking into account the intrinsic geometric of contour (also called Geometric active contour based on contour evolution method). Proposed ACM with gradient vector flow in [2] combine the all merit of previous snakes, more importantly; it achieves large capture range by using regularizing terms. These snakes are referred to as parametric model in some of literature [3]. Corresponding to parametric deformable models are Geometric deformable models, which was first proposed by Osher and Sethian [4]. The relationship between these two was explored in [5]. Geometric deformable models are in the form of curve evolution within level set framework. Later, geometric flows were unified into the classic energy minimization formulations for image segmentation [6, 7-9]. Generally speaking, the existing ACM methods can be classified into two types: edge-based models [1,2,7,10,11] and region-based models [6,8,9,12]. Each of them has its own pros and cons.

To stop the contours on desired edges, Image gradient is utilized as an addition constraint in edge-based model. In that case the contour is matched with previous contour as a stopping criterion. In order to enlarge the capture range of the force, a balloon force [8] term is often incorporated into the evolution function, which controls the contour to shrink or expand. However, it is difficult to choose a proper balloon force. Either a too large or too small balloon force will result in undesirable effects.

Region-based models utilize the image statistical information like image intensity or image energy to construct constraints, and have more advantages over edge- based models. First, they use image intensity instead of image gradient, and can successfully segment objects with weak boundaries or even without boundaries. Second, the initial contour can start any-where in the image, and the interior contours can be automatically detected. One of the most popular region-based models is the Chan–Vese model [6], which has been successfully used in binary phase segmentation with the assumption that each image region is statistically homogeneous. However, the C–V model does not work well for the images with intensity in-homogeneity. Vese and Chan extended their work in [12] to utilize multiphase level set functions to represent multiple regions. These models are called the piecewise constant (PC) models. Nonetheless, both the C-V and PC model have drawback described above.

Vese and Chan [12] also proposed two similar models, which were called piecewise smooth (PS) model to segment images with intensity in-homogeneities. In these methods difference of intensity and global mean was utilized as external force to stop the contour evolution. However, these methods are computationally inefficient. Li et al. [8, 9] proposed the LBF (local binary fitting) model, which utilizes the local image information as constraints, can well segment objects with intensity inhomogeneities. Furthermore, LBF model has better performance than PC and PS models in segmentation accuracy and computational efficiency.

In this paper, we propose a method to segment images having intensity in-homogeneities with used of ACM. For that, we enhanced the weak edges of desired objects while keeping strong edges. To enhance weal edges in image, Nonsubsampled contourlet transform (NSCT) is utilized and then LBF model is utilized to segment that image. The NonSubsampled Contourlet transform built upon NonSubsampled Pyramid and NonSubsampled directional filter banks, can provide a shift invariant directional multiresolutional image representation. The geometric information is gathered pixel by pixel from the nonsubsampled contourlet transform coefficients. These coefficients are added to image to enhance the weak edges falling in region of intensity having non homogeneity. The rest of paper is organized as follows. In background section, the literature surveys with their limitation were discussed. Section 3 discussed how the NSCT can be utilized along with Local Binary fitting model to compensate the demerit of above method.

2. BACKGROUND

The advantage of Chan-Vese Model [6] is it does not depend on gradient of image to stop the contour evolution. The stopping term is based on Mumford-Shah segmentation techniques. Because of that Chan-Vese model is able to detect the objects with very smooth boundary or even with discontinuous boundary.

2.1 GLOBAL REGION BASED CHAN-VESE MODEL

Let I denote a given image defined on the domain Ω and let C be closed contour represented as the zero level set of signed distance function ϕ, i.e. C={x|ϕ (x)=0}. The interior of C is specified by the following expression of the smoothed Heaviside function [6]:

$$H\phi(x,y)=\begin{cases}1 & \phi(x,y)<-\varepsilon\\ 0 & \phi(x,y)>\varepsilon\\ 1/2[1+\frac{\phi}{\varepsilon}+\frac{1}{\pi}\sin(\frac{\pi\phi(x,y)}{\varepsilon})] & otherwise\end{cases} \quad (1)$$

Similarly exterior of C is defined as $1-H\phi(x,y)$.

To specify the area just around the curve, we will use the derivative of $H\phi(x,y)$, a smoothed version of Dirac delta

$$\delta\phi(x,y)=\begin{cases}1 & \phi(x,y)=0\\ 0 & |\phi(x,y)|<\varepsilon\\ \frac{1}{2\varepsilon}\left[1+\cos(\frac{\pi\phi(x,y)}{\varepsilon})\right], & otherwise\end{cases} \quad (2)$$

Associated energy with this model is defined as

$$E_g=\int_\Omega H\phi(x,y)(I((x,y)-u)^2+(1-H\phi(x,y))(I(x,y)-v)^2\,dxdy \quad (3)$$

Minimum energy is obtained when the interior and exterior are best approximated by means of u and v. This image energy remain robust to image noise with no image smoothing because it looks at integral of image data rather than image derivative.

$$u=\frac{\int_\Omega H\phi(x,y)I(x,y)dxdy}{\int_\Omega H\phi(x,y)dxdy},\ v=\frac{\int_\Omega(1-H\phi(x,y))I(x,y)dxdy}{\int_\Omega(1-H\phi(x,y))dxdy} \quad (4)$$

This model fails to segment the object where the mean of foreground object is approximately equal to mean of background in the image. In that scenario, it is required to utilize local statistical information to segment the foreground. Shawn Lankton ad Allen Tannenbaum [13] presented such algorithm as follow.

2.2 LOCAL REGION BASED CHAN – VESE MODEL

Shawn Lankton and Allen Tannenbaum [13] presented a novel framework that can be used to localize any region based energy. They also study the significance of the parameter common to all localized statistical model. In this paper, they compared the global Chan-Vese model with their localizing version and showed some improvement.

In the localized version, they introduced a characteristic function in terms of radius parameter r

$$B(x,y)=\begin{cases}1 & \|x-y\|<r\\ 0 & \text{otherwise}\end{cases} \quad (5)$$

And minimum energy was obtained when each point on the curve has moved such that local interior and exterior about every point *y* along the curve is best approximated by local means u_x and v_x.

$$u_x=\frac{\int_\Omega B(x,y)H\phi(x,y)I(x,y)dxdy}{\int_\Omega B(x,y)H\phi(x,y)dxdy}$$

$$v_x=\frac{\int_\Omega B(x,y)(1-H\phi(x,y))I(x,y)dxdy}{\int_\Omega B(x,y)(1-H\phi(x,y))dxdy} \quad (6)$$

Associated energy with this model is defined as

$$E_L=\int_\Omega H\phi(x,y)(I((x,y)-u_x)^2+(1-H\phi(x,y))(I(x,y)-v_x)^2\,dxdy \quad (7)$$

In local Region based Chan-Vese model, there was no defined stopping criterion. Because of that, the model was running for the defined number of iteration even though the curve evolution reached to final segmentation of object prior to the defined number of iteration. From experiment, it was studied that it works best in medical applications where the mean of foreground and mean of background are approximately equal. The contour must be initialized closed to the object. For processing natural images, automatic selection of localizing radius is challenge. Even if we select the radius for particular image, then its execution time is also increase.

3. LOCAL BINARY FITTING MODEL WITH NSCT

3.1 LOCAL BINARY FITTING MODEL

Both local and global region based Chan-Vese model fails for the image having intensity inhomogeneity and foreground and background statistical information are same. In fact, intensity inhomogeneity occurs in many real images of different modalities. In particular, it is often seen in medical images, such as X-ray radiography/tomography and magnetic resonance (MR) images, due to technical limitations or artifacts introduced by the object being imaged. For example, intensity inhomogeneity typically appears in MR images. The inhomogeneity in MR images arises from non-uniform magnetic field produced by radio-frequency coils as well as from object susceptibility. The degree of this inhomogeneity is worse for higher field imaging.

Therefore C.Li et al. [7] proposed a novel active contour model that was able to segment images with intensity inhomogeneity. The basic idea was to introduce a kernel function to define a local binary fitting energy in a variational formulation, so that local intensity information can be embedded into a region-based active contour model. In this paper, they represented the energy function with level set function as below:

$$F^{LBF}(\phi, f_1, f_2) = \lambda_1 \int_{\Omega} \left[\int k_\sigma(x-y) \left| I(x,y) - f_1(x) \right|^2 H(\phi(x,y)dy \right] dx$$

$$+ \lambda_2 \int_{\Omega} \left[\int k_\sigma(x-y) \left| I(x,y) - f_2(x) \right|^2 (1 - H(\phi(x,y))dy \right] dx \qquad (8)$$

Where λ_1 and λ_2 are positive constants, and k is a Gaussian kernel function with localization property that $k(u)$ decreases and approaches zero as $|u|$ increases and $f_1(x)$ and $f_2(x)$ are two number that fit image intensities near point x. They called the point x the center point of above integral and above energy the local binary fitting energy.

For fixed level set function, they minimize the equation (8) with respect to the function $f_1(x)$ and $f_2(x)$ which can be expressed as

$$f_1(x) = \frac{k_\sigma(x-y) * H\phi(x,y) I(x,y)}{k_\sigma(x-y) * H\phi(x,y)},$$

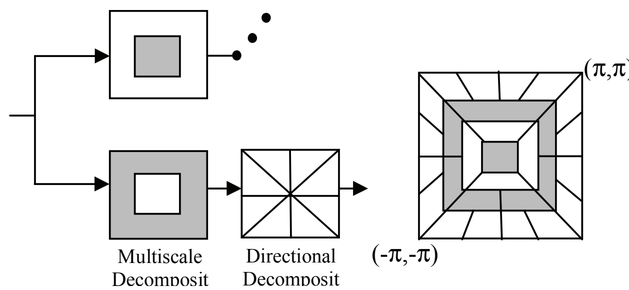
$$f_2(x) = \frac{k_\sigma(x-y) * (1 - H\phi(x,y)) I(x,y)}{k_\sigma(x-y) * (1 - H\phi(x,y))} \qquad (9)$$

Local binary fitting model was highly sensitive to kernel width. Selection of larger kernel width removes the weak edges while small kernel width also selects the undesirable edges.

3.2 NONSUBSAMLED CONTOURLET TRANSFORM

Local Binary Fitting model proposed by Li et al. [7] was able to segment the images with intensity inhomogeneities and was much more accurate and efficient then piecewise model proposed by Chan-Vese. But this model failed for the images having desired object edges residing in the region where the intensity of the background and objects are similar but separated by weak edges. Therefore it is required to enhance those edges and then this model can be utilized efficiently. The aim of this proposed method to improve the interpretability or perception of information in images to provide better input for automated image segmentation using active contour model. For that NonSubsampled Contourlet transform [17] was utilized to enhance such weak edges. Wavelet transform is one of the powerful tools for image edge enhancement; however wavelets are not optimal in capturing the 2-dimensional singularities found in images. Several transform has been proposed for image signals that have incorporated directionality and multi-resolution and hence, could more efficiently capture edges in the images [14]. Recently Do and Vetterli proposed an efficient directional multiresolution image representation called the contourlet transform [15]. In contourlet transform Laplacian pyramids was utilized to achieve multiresolution decomposition and directional filter banks were utilized to achieve directional de-composition. Due to directional mutiresolution decomposition the contourlet transform achieves better results than discrete wavelet transform in image analysis applications such as denoising and texture retrieval [16]. But the downsampling and upsampling process in the contourlet transform make it shift-variant. However, shift-invariance is desirable in image analysis applications such as edge detection, contour characterization, and image enhancement. Therefore to make contourlet transform shift invariant sampling process is avoided in non subsampled contourlet transform.

Thus nonsubsampled contourlet transform combines nonsubsampled pyramids and nonsubsampled DFB's as shown in Fig. 1 [17]. Nonsubsampled pyramids provide multiscale decomposition and nonsubsampled DFB's provide directional decomposition. This scheme can be iterated repeatedly on the lowpass subband outputs of nonsubsampled pyramids.



(a) (b)

Fig.1. The NonSubsaampled Contourlet Transformation: (a) Block diagram. (b) Resulting frequency division

3.3 IMPLEMENTATION AND EXPERIMENT RESULTS

In traditional Level set based active contour model, the segmentation is obtained directly on given image. Energy function in all these methods are either dependent on difference between image intensity and local statistical information or on gradient of image. For the image in which the desired object boundary is very weak, in that scenario, difference between images and mean in that region will be zero. And therefore it will not detect such weak edges. If active contour model is based on gradient of image, then also gradient at weak edges are not strong. So again it will cause the incorrect segmentation. In such situation, it is required to identify such weak edges and enhance those edges for better segmentation results. For that in proposed method NSCT is utilized.

The nonsubsampled contourlet transform provides not only multi-resolution analysis, but also geometric and directional representation. Since weak edges are geometric structure, while noises are not, we can use this geometric representation to distinguish them. The NSCT is shift invariant such that each pixel of transform subband corresponds to that of original image is in the same location. Therefore we gather the geometric information pixel by pixel from NSCT coefficients. There are three classes of pixels: strong edges, weak edges, and noises. First, the strong edges correspond to those pixels with big-value coefficients in all sub bands. Second, the weak edges correspond to those pixels with big-value coefficients in some directional subbands but small-value coefficients in other directional subbands within the same scale. Finally, the noises correspond to those pixels with small-value coefficients in all subbands. Based on this observation, we can classify pixels into three categories by analyzing the distribution of their coefficients in different subbands. One simple way is to compute the mean and the maximum magnitude of the coefficients for each pixel, and then classify pixels whether belongs to strong edge, weak edge or noise based on threshold value T.

For an image $I(x, y)$, x = 1: M, y = 1: N, Let the NSCT coefficients are given by $G_{ij}(x, y)$ Where j = 1: L (L is the directional subband level) and i = 1: d (d is direction at level j). We classified pixels as strong edge If $G_{ij}(x, y) > T$, as a noise if $G_{ij}(x, y) < T$ and as weak edges otherwise. Based on that we added this directional information to original image to enhance the weak edges which falls in the region, where intensity variation is very less. Once these edges are enhanced, this enhanced image is applied as input to the Local binary fitting model for segmentation purpose.

In proposed method, the NSCT coefficients are obtained for two level of decomposition. Then From the all Subband, the maximum coefficient pixel values are obtained. The summation of mean and variance of these maximum coefficients is utilized as threshold to classify the pixels. These pixels are enhanced and added in original image for enhancing the weak edges. The overall flow is shown in Fig.2.

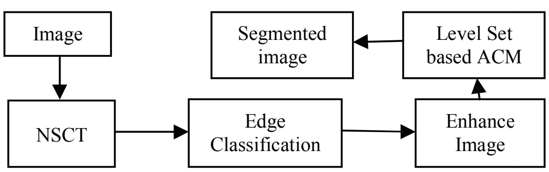
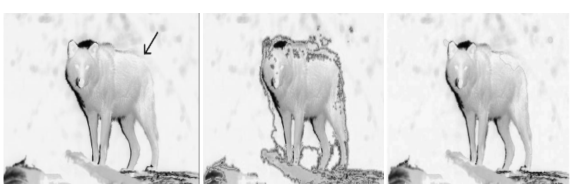


Fig.2 Flow chart for proposed algorithm

For the image shown in Fig.3, it can be noticed that part shown with arrow in image contain weak edge and also the mean value for foreground and background in the local region of that part is approximately equal. So in such situation, all above mentioned method fails to segment the object correctly as shown in Fig.3 (b-c).



(a) (b) (c)

Fig.3. (a) Original image (b) Segmentation using Chan-Vese model (c) Segmentation using LBF Model

To achieve the correct segmentation, NSCT coefficients are obtained. From the various sub bands, the maximum coefficients are calculated. Fig.4 (a) shows corresponding image of NSCT coefficients. Finally Local binary fitting model is utilized to segment for that enhanced image. Fig.4 (b) shows the results for Local binary fitting model where input image enhanced image using NSCT.

Similarly the algorithm was also verified for the synthetic image. Fig.5 shows the results. The Chan-Vese model fails o segment the image because the mean of object and background are approximately equal. Similarly for local binary fitting model results are quite good but not accurate. While same algorithm segment the object correctly for same number of iteration when enhanced image using NSCT is utilized instead of the original image as input.

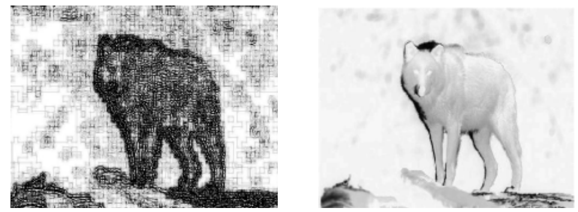
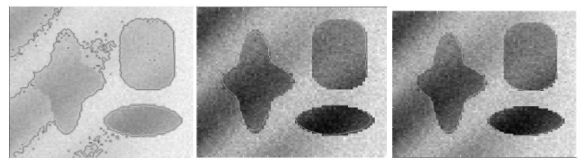


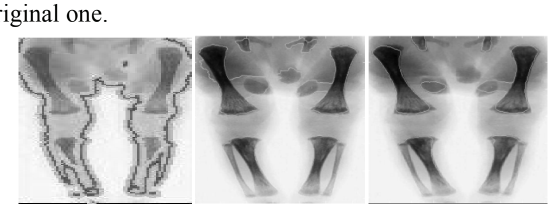
Fig.4 (a) NSCT Coefficients (b) Segmentation results for LBF with NSCT



(a) (b) (c)

Fig.5**.** Segmentation results for (a) Chan-Vese model (b) local Binary fitting model (c) Proposed method

The same algorithm was also tested for medical images. The LBF model is applied on the x-ray image of bone shown in fig.6. It is found that the LBF model is also able to segment the object correctly as our proposed method do. But to obtain the similar results for the same parameter, the LBF model requires 7000 iteration, while the same results were obtained for only 2356 iteration when enhanced image using NSCT was utilized instead of original one.



(a) (b) (c)

Fig.6**.** Segmentation results for (a) Chan-Vese model (b) local Binary fitting model (c) Proposed method

3. CONCLUSION

The main drawback of all level set based active contour model is they all are dependent on image feature like image gradient or image mean. The mean dependent ACM algorithm fails to segment the object where the mean value of segmenting object is similar to background. Similarly in gredient dependent ACM the Gaussian kernel is utilized, which reduces the strength of edges and thus weak edges will be nullified in such cases and algorithm fails to segment the object correctly.

This paper presents a solution for this problem. Nonsubsampled contourlet transform is utilized to find weak edges correspond to desired object and the weak edges were enhanced. The enhanced image are utilized instead of original image with level set based ACM gives better results and also time required for segmentation is less compared. Effect of filters utilized to design the contorlet transform are not well studied here. Therefore proper choice of filter may give the more accurate results for all types of images. This is still open topic for further study. Once the relation will established with filter response and ACM, all model can be made fully automatic.

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