FUZZY BASED IMAGE SEGMENTATION USING SPATIAL/FREQUENCY INFORMATION

Dr. S.ANU H NAIR
Assistant Professor, Dept of CSE,
Annamalai University, chidhambaram

ABSTRACT: This article presents a multiphase fuzzy region competition model that takes into account spatial and frequency information for image segmentation. In the proposed energy functional, each region is represented by a fuzzy membership function and a data fidelity term. It measures the conformity of spatial and frequency data within each region. Gaussian densities parameters are determined jointly with the segmentation process. To efficiently solve the minimization of the energy functional, an alternate minimization procedure is adopted and Chambolle's fast duality projection algorithm is used. The proposed method is applied to synthetic and natural textures as well as real-world natural images.

Index Terms— Generalized Gaussian density, region competition, segmentation.

1. Introduction: In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images [1]. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes[2]. Various two-phase fuzzy segmentation models have also been proposed and applied successfully to a wide variety of images. In these methods, a membership function valued is adopted to measure the association of each image pixel to all regions. The introduction of fuzzy membership function has two main advantages [3]. Firstly, the optimization problem is convex with respect to the membership function which ensures that the new model is insensitive to the initialization, and that the global minimum may be possibly found. Secondly, the fast duality projection algorithm of Chambolle can be employed in the implementation to speed up the minimization process. Recently, proposed a fuzzy region competition model based on the piecewise constant functions for multiphase scalar and vector-valued image segmentation [4]. An alternate minimization method is adopted to find the optimal solution in which region parameters and fuzzy membership functions have closed form solutions. Experimental results on typical gray-scale and color images have shown very promising results. However, due to the use of piecewise constant functions, the segmentation accuracy may be degraded in the case when two different textured regions have the same average intensities but different variances[5]. Motivated by the region competition and the recent researches on texture analysis [6],a multiphase image segmentation model is proposed based on fuzzy region competition and statistical modeling techniques. In the energy functional, fuzzy membership functions are introduced to measure the association degree of each pixel to all regions, while the data term measures the conformity of spatial and frequency data within image regions to the parametric probability models[7]. Our approach gives soft segmentation results as characterized by the fuzzy membership functions and the use of frequency data provides additional region information that can enhance the overall segmentation results, justified by the experiments on different kind of images. Instead of solving the energy functional based on techniques of curve evolution via the traditional level-set formulation, which is time-consuming, we employ an alternate minimization procedure and take advantage of the fast duality projection algorithm of Chambolle [8] to find the solution of the optimization problem. Comparative experimental results on synthetic textures, natural textures, and real-world natural images reveal that our approach is very competitive to current state-of-the-art segmentation methods.

2. PROPOSED METHOD

Implementation consists of the following modules

- INITIALIZE THE FUZZY MEMBERSHIP FUNCTION U
- UPDATE THE REGION PARAMETER V AND U
- UPDATE THE AXILIARY VARIABLES V AND U
- GIVEN THE OPTIMAL FUZZY MEMBERSHIP FUNCTION OBTAINED FROM MODULE 3

2.1 Module - 1: initialize the fuzzy membership function ‘u’

In this module, each region is represented by a fuzzy membership function that measures the conformity of spatial and frequency data within each region to gaussion densities whose parameters are determined.

2.1 Updating the region parameter v and u

2.1.1Compute the spatial region estimators

In this module, the spatial region can be estimated by the following equation from the given region parameters.

$$E_{U,V}(\phi) = -\lambda_1 \sum_{i=1}^{N} \int_{\Omega} u_i \left(\frac{1}{M} \int_{W_x^M} \log P_i^s \left(I_{(y)}^s | \phi_i^s \right) dy \right) dx$$
$$-\lambda_2 \sum_{i=1}^{N} \int_{\Omega} u_i \left(\frac{1}{M} \int_{W_x^M} \log P_i^f \left(I_{(z)}^f | \phi_i^f \right) dz \right) dx. \quad (15)$$

$E_{u,v}(\phi)$ — spatial region estimator.

N — Number of regions.

P_i^f — Probability distribution for frequency region.

P_i^f — Probability distribution for spatial region.

Φ_i^s — Parameter of the distribution P_i^s

ϕ_i^f — Parameter of the distribution P_i^f

λ_1,λ_2 — fixed parameters.

U — $(U_i)i=1,2\ldots N$(Collection of fuzzy membership function)

M— Number of neighbors around specific pixel.

$I_{(y)}^s$— Spatial image at pixel y.

$I_{(z)}^f$— Frequency image at pixel z.

α_i— Scale parameter representing the standard deviation of the probability density function.

β_i— shape parameter controling the shape of the GGD

ψ(●)—Digamma function.

w_x^M— window consisting of M neighbors around pixel x.

Ω— region.

2.1.2 Compute the frequency region estimators

To compute the frequency region estimators use the following equations.

$$\frac{\partial E_{U,V}}{\partial \alpha_i} = \frac{1}{\alpha_i}\int_\Omega u_i dx - \frac{\beta_i}{\alpha_i^{\beta_i+1}}\int_\Omega u_i \left(\frac{1}{M}\sum_{z\in W_x^M}\left|I_{(z)}^f\right|^{\beta_i}\right) dx = 0 \quad (18)$$

$$\frac{\partial E_{U,V}}{\partial \beta_i} = \left(-\frac{1}{\beta_i} - \frac{\psi(1/\beta_i)}{\beta_i^2}\right) + \frac{\int_\Omega u_i \sum_{z\in W_x^M}\left|I_{(z)}^f\right|^{\beta_i}\log\left|I_{(z)}^f\right| dx}{\beta_i\int_\Omega u_i \sum_{z\in W_x^M}\left|I_{(z)}^f\right|^{\beta_i} dx} - \frac{1}{\beta_i^2}\log\frac{\beta_i\int_\Omega u_i\left(\frac{1}{M}\sum_{z\in W_x^M}\left|I_{(z)}^f\right|^{\beta_i}\right)dx}{\int_\Omega u_i dx} = 0 \quad (19)$$

U — $(U_i)i=1,2\ldots N$(Collection of fuzzy membership function)

M— Number of neighbors around specific pixel.

$I_{(y)}^s$—Spatial image at pixel y.

$I_{(z)}^f$—Frequency image at pixel z.

α_i —Scale parameter representing the standard deviation of the probability density function.

β_i—shape parameter controling the shape of the GGD

ψ(●)—Digamma function.

w_x^M— window consisting of M neighbors around pixel x.

Ω—region.

2.3Module - 3: update the auxiliary variable v and u

In this module, to update the auxiliary variables V and U, which are necessary to complete the soft segmentation result. These variables mainly used to compute the segmentation curves from the specified region parameters.To update the auxiliary variables V and U use the following equation.

$$\hat{v}_i = u_i - \theta \operatorname{div} p_i$$

2.4Module - 4: The optimal fuzzy membership function obtained from module 3

In this module, given the optimal fuzzy membership function $U^{opt} = (u_j^{opt})_{j=1,2,..,N}$ obtained from step 3, the final segmentation result is constructed by assigning each pixel,x, a label j^* where $j^* = \arg\max u_j^{opt}(x)$.

3. COMPARISON WITH EXISTING APPROACHES

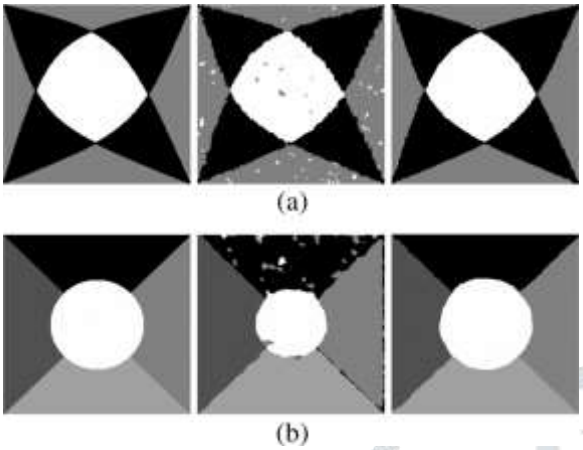

Fig. 1 Comparative segmentation results of textures of size 256X256. Left column: Ground truths. Middle column: Segmentation results using *RC* model [3]. Right column: Segmentation results using this method. Segmentation errors of the two methods: (a) (4.02%, 1.13%),(b) (11.7%, 0.55%).

Fig. 1 shows the corresponding segmentation results. As can be seen in both cases, the segmentation results of *RC* are unsatisfactory since a lot of isolated pixels and regions along the boundaries are misclassified[9,10]. On the other hand, this method has very good segmentation performance as compared with the ground truths. In terms of segmentation accuracy, the errors of *RC* and our method are (a): (4.02%, 1.13%) and (b): (11.7%, 0.55%), respectively. The *RC* model considers only spatial information and gives hard segmentation results whereas this model takes into account both the spatial and frequency information and provides soft segmentation results.

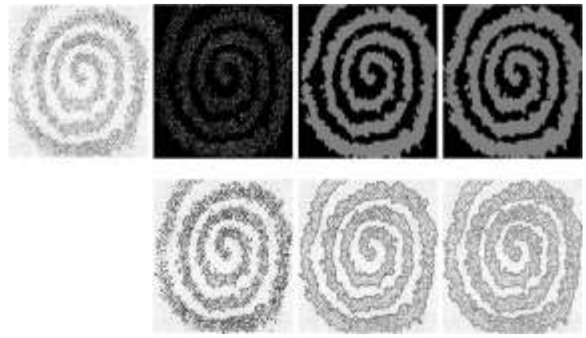

Fig.2. Comparative segmentation results of *Spiral* image of size 234x191. First column: Input image. Second column: Segmentation result using PCFRC model [16]. Third column: Segmentation result using CV model [2]. Fourth column: Segmentation result using our method.

Fig. 2 shows a *Spiral* image. As can be seen, the PCFRC method gives inaccurate result, whereas the CV and our algorithm provide very promising segmentation results. The CV method segments the image into several regions but this proposed method segments the image into two regions only, namely, the *Spiral* and the background.

4. CONCLUSION

In this research work, a multiphase image segmentation model based on fuzzy region competition and spatial/frequency information. In the proposed energy functional, fuzzy membership functions are introduced to measure the association degree of each pixel to all image regions, whereas a data fidelity term measures the spatial and frequency region information, which are characterized by the (generalized) Gaussian densities. Instead of minimizing the energy functional based on techniques of curve evolution via the level-set formulation, The energy functional is solved by the alternate minimization method with the use of Chambolle's fast duality projection algorithm. Comparative experimental results on synthetic textures, natural textures, and real-world natural images have demonstrated the efficiency and effectiveness of proposed method.

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