Texture Segmentation Based on Gabor Filters and Neutrosophic Graph Cut

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Abstract— Image segmentation is the first step of image processing and image analysis. Texture segmentation is a challenging task in image segmentation applications. Neutrosophy has a natural ability to handle the indeterminate information. In this work, we investigate the texture image segmentation based on Gabor filters (GFs) and neutrosophic graph cut (NGC). We proposed an image segmentation approach, which applies GFs to gray-level images to extract image features matrix, and it segments them into regions. First, color images are transformed to gray level images as input images. Then, input parameters of GFs are adjusted, and GFs are performed on the input images to extract features. The NGC is employed for classification of input images. Finally, experiments are conducted on various natural images to evaluate the approach. Experimental results show that the proposed approach achieves desired performance of texture segmentation. However, it cannot segment the texture-free images as well as texture images. In future works, we will try to segment both texture images and texture-free images at the same time.

Keywords— Image segmentation, texture segmentation, Gabor filters, Neutrosophic Graph Cut.

I. INTRODUCTION

The goal of the image segmentation considered as dividing an input image into several sub-images. To do this, some predefined criterions should be accepted where the sub-images are disjoint, homogeneous and meaningful. Many researchers have been working on image segmentation, and a variety of works have been published [1]. Texture segmentation is a challenging and important task in image segmentation applications. For the texture feature extraction, there exist various texture descriptors such as gray level co-occurence matrix, Gabor filters (GFs) and Markov random fields [2]. GFs have been successfully applied to many image applications such as texture segmentation [3–5], document analysis [6], edge detection [7], retina identification [8], fingerprint processing [9], image coding [10], and image representation [11].

Graph based methods are important for image segmentation applications [12]. A graph G can be defined as $G = (V, E)$ where V and E are a set of vertices and edges, respectively. On an image, vertices can be either pixels or regions, and edges connect the neighbouring vertices [13]. A weight, which is a non-negative measure of dissimilarity, is associated with each edge based on some property of the pixels that it connects. Normalized-cut, Minimal-cut and Mean-Cut can be seen in some of popular graph cut methods [14–16]. Neutrosophic set (NS) was proposed as an extension of fuzzy set [17]. In NS theory, a member of a set has a degree of truth, a falsity degree and an indeterminacy degree [18]. Therefore, it has an ability to deal with the indeterminacy information, and has attracted much attention almost in all engineering communities and subsequently a great number of works have been studied [19], [20].

In this paper, we propose a texture image segmentation algorithm which uses GFs, NS and graph cut method. Firstly, various GFs are considered which constructs a texture feature volume. Constructed volume is then projected into 2d by using principal component analysis (PCA). The projected feature image is transformed into NS domain and indeterminacy degree is calculated accordingly. Then an indeterminacy filter is constructed using the indeterminacy value on feature image which is defined by combining the spatial information and global texture feature information. The indeterminacy filter is employed to remove the indeterminacy in the intensity and spatial information respectively. A graph is defined on the image and the weight for each pixel is represented using the value after indeterminacy filtering, and the energy function is also redefined using the neutrosophic value. Finally, the segmentation results are obtained using a maximum-flow algorithm on the graph.

The organisation of the paper is as following; in Section 2 we give the methodology of the proposed method. In Section 3, some experimental works are conducted. Finally, we concluded the paper in Section 4.

II. METHODOLOGY

Briefly speaking, the proposed approach composed of 3 main building blocks. Extracting texture features from input image by using GFs is the first building block. This block constructs a texture feature volume according to the number of considered GFs. The second block employs the NS and calculates the indeterminacy degree accordingly. Then an indeterminacy filter is constructed using the indeterminacy value on feature image which is defined by combining the

spatial information and global texture feature information. This filter aims to remove the indeterminacy in the texture feature and spatial information respectively. Finally, a graph is defined on the image and the weight for each pixel is represented using the value after indeterminacy filtering, and the energy function is also redefined using the neutrosophic value. Finally, the segmentation results are obtained using a maximum-flow algorithm on the graph. The flowchart of the approach is illustrated in Fig. 1.
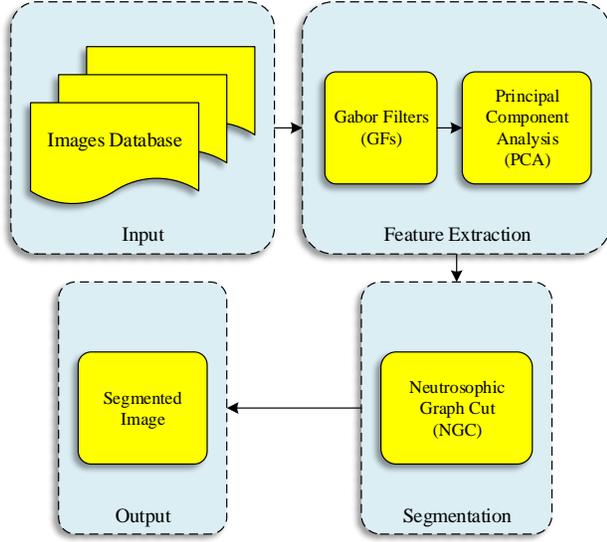
Fig. 1.   The flowchart of the approach.

The GFs theory was described in Jain and Farrokhnia [21]. GFs should be in array form and it is designed with different orientations and frequencies. The step of orientation angle can be 30, 45, etc. degrees and orientations are shown as below:

$$Orients = [0, a, 2 \times a, \cdots, 180 - a] \quad (1)$$

where a is the step of orientation angle. Wavelengths have values in increasing powers of two start from minimum wavelength to maximum wavelength.

$$w_{min} = \frac{4}{\sqrt{2}} \quad (2)$$

$$w_{max} = \sqrt{im_{rows}^2 + im_{cols}^2} \quad (3)$$

where w_{min} is the minimum value of wavelength, w_{max} is the maximum value of wavelength. im_{rows} and im_{cols} are the size of rows and columns of the input image.

$$n = \left\lfloor \log\left(\frac{w_{max}}{w_{min}}\right) \right\rfloor \quad (4)$$

$$Waves = [2^0, 2^1, 2^2, \cdots, 2^{(n-2)}] \times w_{min} \quad (5)$$

The set of orientations and wavelengths are taken from [21]. Working GFs mean working with Gabor magnitude response of each filter. The size of the magnitude response is:

$$Orients_{len} \times Waves_{len} \quad (6)$$

where $Orients_{len}$ is the length of array of orientation $Orients$ in Equation (1), and $Waves_{len}$ is the length of array of wavelength $Waves$ in Equation (5).

When using Gabor magnitude responses as features, some post-processing is required. Feature smoothing and normalization is applied as post-processing. In smoothing process, the Gaussian process and normalization is applied in order to get zero mean and unit variance. Smoothing is important because some local variations in each Gabor response are not suitable for the segmentation and they can be soften by using a low-pass filtering. In addition, spatial x and y axis properties of each pixel are added to the features matrix. Spatial location information improves the segmentation process to prefer groupings that are close together spatially. After the post-processing, we apply the PCA in order to reduce dimension size of the feature vector. PCA, is a procedure which uses an orthogonal transformation [22]. The transformation is carried out with the first principle component.

After PCA, the reduced feature matrix is fed into the NS domain. A neutrosophic image I_{NS} is interpreted using three subsets T_s, I_s and F_s. Based on the texture feature value and local spatial information, the true membership and indeterminacy membership are used to describe the indeterminacy among local neighbourhood as:

$$T_s(x,y) = \frac{g(x,y) - g_{min}}{g_{max} - g_{min}} \quad (7)$$

$$I_s(x,y) = \frac{Gd(x,y) - Gd_{min}}{Gd_{max} - Gd_{min}} \quad (8)$$

where $g(x,y)$ and $Gd(x,y)$ are the gray scale texture feature value and gradient values at the pixel of (x,y) on the image, respectively. The algorithm also computes the neutrosophic membership values based on the global texture feature value distribution which considers the indeterminacy on texture feature value between different groups. To this end, NCM is used to obtain the indeterminacy values between different groups on texture feature value to be segmented [23]. Before calculation of the global texture feature value based NS memberships, the obtained local I_{NS} is filtered by indeterminate filter based on I_s. After, constructing I_{NS}, an energy function for graph model is determined and the I_{NS} is partitioned using maximum flow algorithm [24].

The algorithm of the proposed method is as following:
Step 1: Compute the GFs of input texture;
Step 2: Smoothing and normalization Gabor responses;
Step 3: Dimensionality reduction with PCA;
Step 4: Compute the local neutrosophic value T_s and I_s;
Step 5: Filter T_s using indeterminate filter based on I_s;
Step 6: Employ NCM algorithm on the filtered T_s subset to calculate T_n and I_n;
Step 7: Filter T_n using indeterminate filter based on I_n;
Step 8: Define the energy function based on the T_n' value;

Step 9: Partition the image using the maximum flow algorithm.

III. EXPERIMENTS

Experiments are conducted on various natural images from Berkeley Segmentation Dataset (BSD) to evaluate the approach. Four images are selected randomly to show the performance of the method. These images are "Cheetah", "Lady", "Plane" and "Zebra", respectively. As shown in Fig. 2, each of figure which includes these images has four types of images. First image is original gray-level and second image is after Gabor filtered and PCA image. Third image is segmentation result of NGC of the first. Fourth image is border result of NGC of the first.
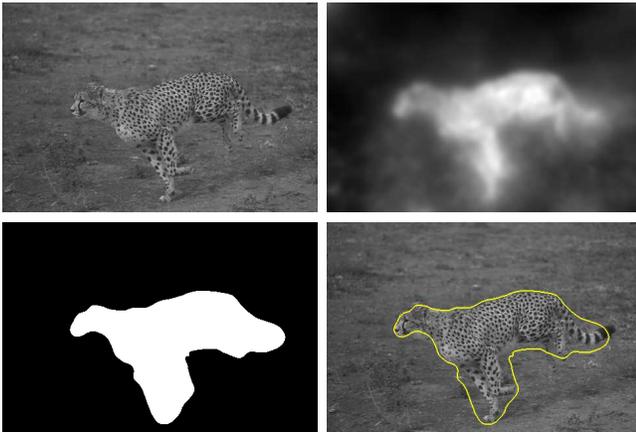
Fig. 2. Top-left: Cheetah image, top-right: result image after GF and PCA, bottom-left: segmentation of NGC, bottom-right: border of segmentation.

GFs are applied to the input images to extract texture features. To use GFs as features, the orientations and the wavelengths should be selected and calculated. We consider the "Cheetah" image in Fig. 2 to examine the process of feature extraction. As seen in Fig. 2, the input image is a gray-level image. Its size is 321×481 pixels. Minimum wavelength is mentioned at upper section and it is 2.8284. Maximum wavelength is calculated via size of the input image. Maximum wavelength is $\sqrt{321^2 + 481^2} = 578.2750$. The wavelengths that send to Gabor magnitude as input parameter, start in increasing powers of two from minimum wavelength up to maximum wavelength. For the "Cheetah" image, the wavelengths have six values: {2.8284, 5.6569, 11.3137, 22.6274, 45.2548 and 90.5097}.

Orientation angle called theta begins with 0 degree and continues with 45 degrees increase thus it has four values for the "Cheetah" image: {0, 45, 90 and 135}.

The related illustrations are given in Figs 2-5. As can be seen in these figures, the proposed method produced reasonable segmentation results. The objects in the input images are well segmented from the background. However, the boundaries of the object are rough and need further post-processing. Especially, for woman image, the head of the woman is not correctly segmented. In addition, several over-segmentations are clear.
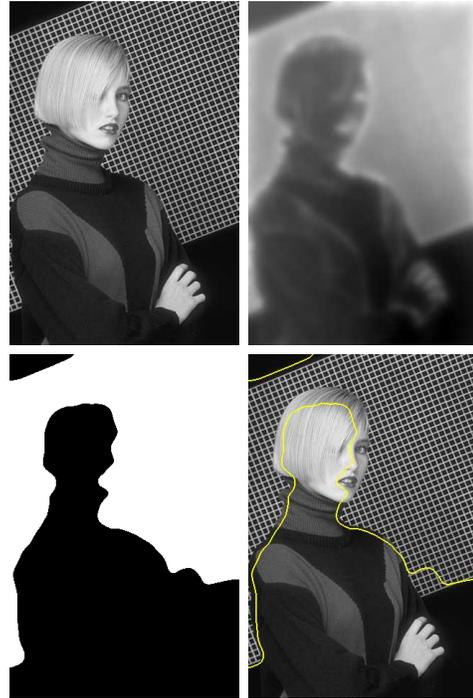
Fig. 3. Top-left: Lady image, top-right: result image after GF and PCA, bottom-left: segmentation of NGC, bottom-right: border of segmentation.

Fig. 4. Top-left: Plane image, top-right: result image after GF and PCA, bottom-left: segmentation of NGC, bottom-right: border of segmentation.

IV. CONCLUSIONS

This paper presents a texture image segmentation using GFs and NGC method. Before the image is described in NS domain, GFs are applied on the image to extract texture features. The experimental results show that the NGC method can segment the images properly and the proposed approach achieves desired performance of texture segmentation. The disadvantage of the proposed method is rough segmentation. To overcome this disadvantage, in the future works, a boundary preserving filtering method will be adopted.

REFERENCES

[1] Pal, N. R., & Pal, S. K. (1993). A review on image segmentation techniques. Pattern recognition, 26(9), 1277-1294.
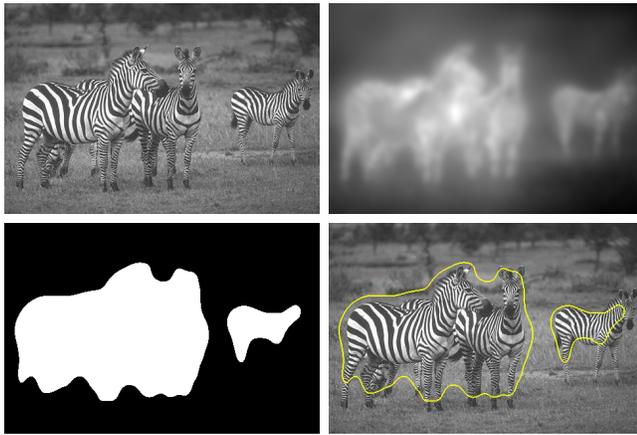
Fig. 5. Top-left: Zebra image, top-right: result image after GF and PCA, bottom-left: segmentation of NGC, bottom-right: border of segmentation.

[2] Clausi, D. A. (2001). Comparison and fusion of cooccurrence, Gabor and MRF texture features for classification of SAR seaice imagery. Atmosphere-Ocean, 39(3), 183-194.

[3] Dunn, D., Higgins, W. E., & Wakeley, J. (1994). Texture segmentation using 2-D Gabor elementary functions. IEEE Transactions on Pattern Analysis and Machine Intelligence, 16(2), 130-149.

[4] Weldon, T. P., Higgins, W. E., & Dunn, D. F. (1996). Efficient Gabor filter design for texture segmentation. Pattern Recognition, 29(12), 2005-2015.

[5] Şengür, A. (2009). Color texture classification using wavelet transform and neural network ensembles. Arabian Journal for Science and Engineering, 34(2), 491.

[6] Jain, A. K., & Bhattacharjee, S. (1992). Text segmentation using Gabor filters for automatic document processing. Machine Vision and Applications, 5(3), 169-184.

[7] Mehrotra, R., Namuduri, K. R., & Ranganathan, N. (1992). Gabor filter-based edge detection. Pattern recognition, 25(12), 1479-1494.

[8] Daugman, J. G. (1993). High confidence visual recognition of persons by a test of statistical independence. IEEE transactions on pattern analysis and machine intelligence, 15(11), 1148-1161.

[9] Leung, M. T., Engeler, W. E., & Frank, P. (1990, September). Fingerprint image processing using neural networks. In Computer and Communication Systems, 1990. IEEE TENCON'90., 1990 IEEE Region 10 Conference on (pp. 582-586). IEEE.

[10] Kunt, M., & Ebrahimi, T. (1991). Image compression by Gabor expansion. Optical engineering, 30(7), 873-880.

[11] Porat, M., & Zeevi, Y. Y. (1988). The generalized Gabor scheme of image representation in biological and machine vision. IEEE Transactions on Pattern Analysis and Machine Intelligence, 10(4), 452-468.

[12] Gonzalez, R. C., & Woods, R. E. (2002). Digital Image Processing, 2nd ed.: Prentice Hall.

[13] Wu, Z., & Leahy, R. (1993). An optimal graph theoretic approach to data clustering: Theory and its application to image segmentation. IEEE transactions on pattern analysis and machine intelligence, 15(11), 1101-1113.

[14] Shi, J., & Malik, J. (2000). Normalized cuts and image segmentation. IEEE Transactions on pattern analysis and machine intelligence, 22(8), 888-905.

[15] Wang, S., & Siskind, J. M. (2003). Image segmentation with ratio cut. IEEE Transactions on Pattern Analysis and Machine Intelligence, 25(6), 675-690.

[16] Ding, C. H., He, X., Zha, H., Gu, M., & Simon, H. D. (2001). A min-max cut algorithm for graph partitioning and data clustering. In Data Mining, 2001. ICDM 2001, Proceedings IEEE International Conference on (pp. 107-114). IEEE.

[17] Smarandache, F. (1999). A Unifying Field in Logics: Neutrosophic Logic. Philosophy, 1-141.

[18] Smarandache, F. (2005). A Unifying Field in Logics Neutrosophic Logic. Neutrosophy, Neutrosophic Set, Neutrosophic Probability: American Research Press.

[19] Guo, Y., & Şengür, A. (2014). A novel image edge detection algorithm based on neutrosophic set. Computers & Electrical Engineering, 40(8), 3-25.

[20] Guo, Y., & Şengür, A. (2014). A novel image segmentation algorithm based on neutrosophic similarity clustering. Applied Soft Computing, 25, 391-398.

[21] Jain, A. K., & Farrokhnia, F. (1991). Unsupervised texture segmentation using Gabor filters. Pattern recognition, 24(12), 1167-1186.

[22] Jolliffe, I. (2002). Principal component analysis. John Wiley & Sons, Ltd.

[23] Guo, Y., & Şengür, A. (2015). NCM: Neutrosophic c-means clustering algorithm. Pattern Recognition, 48(8), 2710-2724.

[24] Yuan, J., Bae, E., Tai, X. C., & Boykov, Y. (2010, September). A continuous max-flow approach to potts model. In European conference on computer vision (pp. 379-392). Springer Berlin Heidelberg.