http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 10 (3): 607-610, 2011
ISSN 1812-5638 / DOI: 10.3923/itj.2011.607.610

Novel Fuzzy Clustering-based Image Segmentation with Simultaneous Uneven Illumination Estimation

[1,2]Wei Wei-Yi, [1,2]Li Zhan-Ming and [1,2]Zhang Guo-Quan
[1]College of Electrical Engineering and Information Engineering,
Lanzhou University of Technology, Lanzhou 730050, China
[2]Key Laboratory of Gansu Advanced Control for Industrial Processes, Lanzhou 730050, China

Abstract: The Fuzzy c-Means (FCM) is often used for image segmentation. However, it does not take into account the influence of spatial intensity variations caused by uneven illumination, the precision of image segmentation based on FCM was degraded badly. So, propose a novel robust FCM method free from uneven illumination in this correspondence, which models the uneven illumination influence as a linear combination of a set of basis function and introduce the model into objective function in FCM. So the image segmentation and the uneven illumination estimation are simultaneous achieved. The experiments show that the method proposed is efficient for influence of uneven illumination and can estimate the uneven illumination fields.

Key words: Image segmentation, fuzzy clustering, uneven illumination, illumination estimation, basis function

INTRODUCTION

Image segmentation is the process of sub-dividing an image into its constituent regions or objects based on attributes such as intensity or continuity is one of the most difficult and challenging problems in the image processing which is widely used in a variety of applications such as robot vision, object recognition, geographical imaging and medical imaging (Chaira and Ray, 2003; Wei-Yi *et al*., 2010). In the last decades, fuzzy segmentation methods, especially the fuzzy c-means algorithm (FCM), have been widely used in the image segmentation (Hoppner and Klawonn, 2003; Liew *et al*., 2005). It can retain more information from the original image. However, one disadvantage of FCM is its sensitivity to noise and other imaging artifacts. One of the most commonly used methods is to modify the objective functions (Liew *et al*., 2005). Mohamed *et al*. (1999) used a modified fuzzy FCM algorithm for image segmentation. They considered the dissimilarity measure as the resistance of pixel to the cluster center and modified the dissimilarity measure such that the pixel can be dragged closer to the cluster center if it is in homogeneous regions. Pham (2001) proposed a robust fuzzy clustering based image segmentation method for noisy image (RFCM) which is presented to achieve the unimodal property of its membership functions.

However, besides the influence of noises, the spatial intensity variations caused by uneven illumination are another obstacle in image segmentation based on FCM. To compensate for this drawback of FCM, the obvious way is to smooth the image before segmentation such as homomorphic (Brinkmann *et al*., 1998). But it is only on images with relatively low-contrast. Some researchers reported undesirable artifacts with approach (Dawant *et al*., 1993). A different approach used to segment images with intensity inhomogeneity is to simultaneously compensate for the uneven illumination effect while segmenting the image (Pham and Prince, 1999). In their proposed energy function, a term was introduced to ensure the smoothness of the computed uneven illumination. Xu *et al*. (1997) proposed a new adaptive FCM technique to produce fuzzy segmentation while compensation for uneven illumination. But it is also computationally intensive due to the introduction of the uneven illumination field smooth term. Mohamed proposed a modified FCM algorithm for bias field estimation and segmentation (Ahmed *et al*., 2002); however, it did not took into the characteristics of uneven illumination account. In general, the uneven illumination is commonly assumed to be slowly varying (Li *et al*., 2009), theoretically, any function can be approximated by a linear combination of a set of functions up to arbitrary accuracy, therefore, we propose a novel FCM image segmentation with simultaneous uneven illumination estimation. The uneven illumination is modeled as a linear combination of smooth basis functions; furthermore, introduce it into the objective function in FCM algorithm.

Corresponding Author: Wei Wei-Yi, College of Mathematics and Information Science, Northwest Normal University, Lanzhou, Gansu, China

Uneven illumination field and image segmentation ares simultaneously achieved by Lagrange multiplier method. A salient advantage of our method is that the novel FCM clustering is robust for uneven illumination and simultaneously estimate the field effect.

BACKGROUND

The observed image signal I (x) is model as a product of the true signal S (x) and uneven illumination field effect B (x):

$$I(x) = B(x)S(x) + n(x) \tag{1}$$

The application of a logarithmic transformation to the intensities allows the artifact to be modeled as additive uneven illumination field effect (Wells *et al*., 1996).

$$i(x) = b(x) + s(x) \tag{2}$$

where, s (x) and i (x) are the true and observed log-transformed intensities at pixel x and the b (x) is the uneven illumination field effect.

ROBUST FCM BASED IMAGE SEGMENTATION WITH SIMULTANEOUS UNEVEN ILLUMINATION ESTIMATION

Image segmentation based on FCM clustering: The standard FCM objective function for partitioning

$$\{I(x)\}_{x=1}^{N}$$

into c cluster is given by Pham (2001):

$$J = \sum_{i=1}^{c} \int u_i(x)^m \|I(x) - v_i\|^2 \, dx \tag{3}$$

where $\{v_i\}_{i=1}^{c}$ are the prototypes of the clusters and array $[u_i(x)] = U$ represents a partition matrix, subject to

$$\sum_{i=1}^{c} u_i(x) = 1 \tag{4}$$

$$u_i(x) \geq 0 \tag{5}$$

The parameter m is a weighing exponent on each fuzzy membership and determines the amount of fuzziness of the result classification. $\|I(x)-(v)_i\|$ is the distance of I (x) and the center of class i. the objective function is sensitivity for noise because it omits the structure information. In order to remedy this deficiency, it is a better way that the assignment of a pixel is influenced by its neighboring pixels. This method is known as BCFCM and the modified objective function is:

$$J = \sum_{i=1}^{c} \int u_i(x)^m \|I(x) - v_i\|^2 + \frac{a}{N_R} \sum_{i=1}^{c} \int (u_i(x)^m \sum_{x_r \in N_k} \|I(x_r) - v_i\|^2) \tag{6}$$

where, N_k stands for the set of neighbors that exist in a window around x_k and N_R is the cardinality of N_k The effect of the neighbors term is controlled by the parameter α.

Although, the improved FCM clustering method is more robust for noises than FCM because the structure information was taken into account, it still sensitivity for the spatial intensity variations caused by uneven illumination field effect.

Robust FCM based image segmentation with simultaneous uneven illumination estimation: In general, the intensity inhomogeneity caused by uneven illumination is assumed to be slowly varying. Moreover, any function can be approximated by a linear combination of a set of basis functions up to arbitrary accuracy theoretically. Let $g_1, \ldots, g_M$ be a set of basis functions, we estimate the uneven field effect by a linear combination of the basis functions

$$b(x) = \sum_{t=1}^{M} w(t) g_t(x) \tag{7}$$

In our current implementation, we use orthogonal polynomials as the basis functions. So the true image data is denoted as:

$$s(x) = i(x) - \sum_{t=1}^{M} w(t) g_t(x) \tag{8}$$

Let $W = (w_1, \ldots, w_M)^T$, $G(x) = (g_1(x), \ldots, g_M(x))^T$ and substitute I (x) in Eq. 6 with 8, then the improved objective function which taken into the uneven illumination account is defined as:

$$J_w = \sum_{i=1}^{c} \int u_i(x)^m \|i(x) - W^T G(x) - v_i\|^2 + \frac{a}{N_k} \sum_{i=1}^{c} \int (u_{ik}{}^m \sum_{x_r \hat{I} N_k} \|x_r - v_i\|^2) \tag{9}$$

We can achieve the U, V and W by Lagrange multiplier. Let

$$F_w = \sum_{i=1}^{c} \int u_i(x)^m \|i(x) - W^T G(x) - v_i\|^2 + \frac{a}{N_k} \sum_{i=1}^{c} \int (u_{ik}{}^m \sum_{x_r \hat{I} N_k} \|i(x_r) - v_i\|^2) + \lambda(1 - \sum_{i=1}^{c} u_i(x)) \tag{10}$$

Let

$$\frac{\partial F_w}{\partial u_i(x)}=0,\ \frac{\partial F_w}{\partial v_i}=0, \text{we can obtain :}$$

$$u_i(x)^* = \frac{(1/\|i(x)-W^TG(x)-v_i\|^2)^{1/(m-1)}}{\sum_{j=1}^{c}(1/\|i(x)-W^TG(x)-v_j\|^2)^{1/(m-1)}} \quad (11)$$

$$v_i^* = \frac{\sum_{k=1}^{N} u_i(x)^m x_k}{\sum_{k=1}^{N} u_i(x)^m} \quad (12)$$

As for W, fix the u and v, solve $\frac{\partial F_w}{\partial W}$ and let it is 0, we can obtain

$$W = A^{-1}Z \quad (13)$$

where

$$A = \sum_{i=1}^{c}\int u_i(x)^m G(x)G(x)^T dx$$

$$A = \sum_{i=1}^{c}\int u_i(x)^m G(x)G(x)^T dx \quad (14)$$

and

$$Z = \sum_{i=1}^{c}\int u_i(x)^m (i(x)-v_i)G(x)dx \quad (15)$$

The improved image segmentation algorithm with simultaneous uneven illumination estimation:

Step 1: Transform image data to logarithmic field
Step 2: Initialization of u, m and g
Step 3: Update u, v and w by Eq. 9-13
Step 4: Check convergence criterion. if convergence has been reached, stop the iteration. otherwise, go to step 3

RESULTS

We investigate the very applicability of the above-modified FCM in image segmentation. Present experimental results here demonstrate that when the segmentation for intensity inhomogeneity and noisy images is required, the above-modified FCM has obvious advantage over FCM.

Figure 1a shows an original rat's bladder tissue image. The image is corrupted as its artificial noisy image

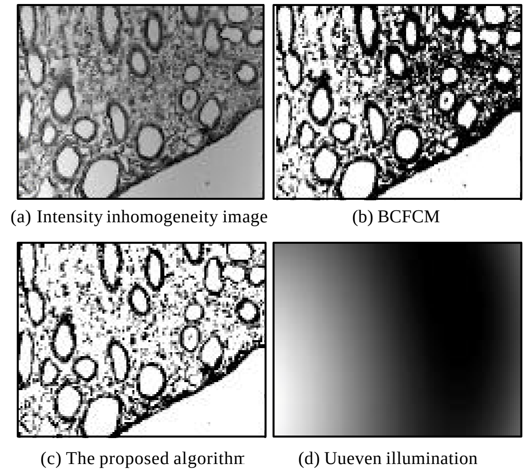

Fig. 1: (a-d) segmentation results for rat's bladder tissue image

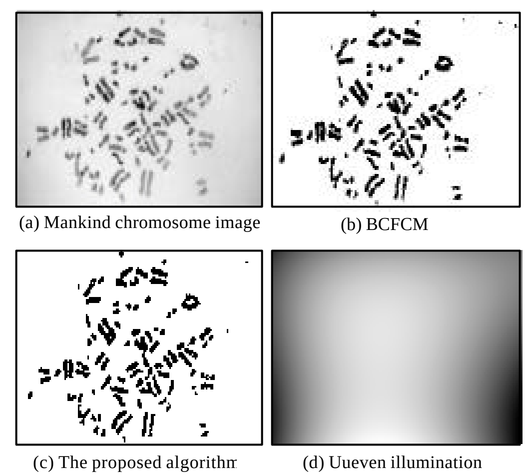

Fig. 2: (a-d) segmentation results for mankind chromosome image

and intensity inhomogeneity caused by uneven illumination. Figure 2a shows a mankind chromosome image acquired under the circumstance of uneven illumination. Both in Fig. 1 and 2b and c demonstrate the segmentation results using BCFCM and the proposed modified FCM, Obviously, the proposed modified FCM outperforms BCFCM for this test image and get uneven illumination field effect estimation as Fig. 1d.

CONCLUSION

In this correspondence, we propose a robust fuzzy clustering based segmentation method for noisy and intensity inhomogeneity caused by uneven illumination.

This method is rooted at the proposed modified FCM which originates from a novel objective function and uneven illumination presentation. It is robust for noises and intensity inhomogeneity; meanwhile, it can estimate the uneven illumination simultaneously.

Future research may be focused on more mathematical analysis about the fitting of uneven illumination field effect and the time efficiency.

ACKNOWLEDGMENT

The study is supported by the Gansu Natural Science Foundation of China under Grant (No. 1010RJZA011).

REFERENCES

Ahmed, M.N., S.M. Yamany, N. Mohamed, A.A. Farag and T. Moriarty, 2002. A modified fuzzy C-means algorithm for Bias field estimation and segmentation of MRI data. IEEE Trans. Med. Imaging, 21: 193-199.

Brinkmann, B.H., A. Manduca and R.A. Robb, 1998. Optimized homomorphic unsharp masking for MR grayscale inhomogeneity correction. IEEE Trans. Med. Imaging, 17: 161-171.

Chaira, T. and A.K. Ray, 2003. Segmentation using fuzzy divergence. Pattern Recognition Lett., 24: 1837-1844.

Dawant, B.M., A.P. Zijdenbos and R.A. Margolin, 1993. Correction of intensity variations in MR images for computer-aided tissue classification. IEEE Trans. Med. Imaging, 12: 770-780.

Hoppner, F. and F. Klawonn, 2003. Improved fuzzy partitions for fuzzy regression models. Int. J. Approx. Reason., 32: 85-102.

Li, C., C. Gatenby, L. Wang and J.C. Gore, 2009. A roubst parametric method for Bias field estimation and segmentation of MR Images. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, June 20-25, Miami, USA., pp: 218-223.

Liew, A.W.C., H. Yan and N.F. Law, 2005. Image segmentation based on adaptive cluster prototype estimation. IEEE Trans. Fuzzy Syst., 13: 444-453.

Mohamed, N.A., M.N. Ahmed and A. Farag, 1999. Modified fuzzy C-mean in medical image segmentation. IEEE Int. Conf. Acoustics SSP, 6: 3429-3432.

Pham, D.L. and J.L. Prince, 1999. Adaptive fuzzy segmentation of magnetic resonance images. IEEE. Trans. Med. Imag., 18: 737-752.

Pham, D.L., 2001. Spatial models for fuzzy clustering. Comput. Vision Image Understanding, 84: 285-297.

Wei-Yi, W., L. Zhan-Ming, Z. Gui-Cang and Z. Guo-Quan, 2010. Novel color microscopic image segmentation with simultaneous uneven illumination estimation based on PCA. Inform. Technol. J., 9: 1682-1685.

Wells, W.M., W.E.L. Grimson, R. Kikinis and F.A. Jolesz, 1996. Adaptive segmentation of MRI data. IEEE Trans. Med. Imag., 15: 429-442.

Xu, C., D.L. Pham and J.L. Prince, 1997. Finding the brain cortex using fuzzy segmentation, isosurfaces and deformable surfaces models. Inform. Process. Med. Imaging, 1230: 399-404.