ILLUMINATION INVARIANT FUZZY IMAGE SEGMENTATION

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ABSTRACT

In this work we present an image segmentation method that utilizes the fuzzy c-planes algorithm [1, 2] in an effort to make the segmentation process more robust to local illumination variations in the scene. The presented method includes a local regularization scheme for the updating of the membership functions that makes the membership of an image pixel sensitive to the memberships of its neighbors. Pixel coordinates are also included as a feature in the classification to make the segmented regions spatially connected. The effectiveness of the method is verified on synthetic and real images.

1. INTRODUCTION

Local illumination variations may exist in images causing a handicap in the segmentation process. For example, MR images [3] may have different intensities in their different parts. Strong illumination variations and shading effects also occur in natural scenes. We present an algorithm to segment images in the presence of local illumination variations. For this purpose, we introduce first a method based on fuzzy c-planes (FCP) method [1, 2, 4] where the mean finding step of the fuzzy c-means algorithm [5, 6] is replaced with a plane fitting approach. The method we present may be extended to the more general "fuzzy c-surfaces" scheme by fitting surfaces of higher order instead of planes. Secondly, the method includes a local regularization scheme for the updating of the membership functions. The main motivation behind the local regularization is to make the membership of an image pixel closer to the mean of the memberships of its neighbors, but avoiding smoothing over large differences between the neigbours, which may be due to genuine segments. As expected, the local regularization also helps to eliminate the effects of noise. Thirdly, in order to constrain the segmented regions to be spatially connected, we incorporate in the feature vector the weighted location information of the pixels along with the intensity values.

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Previous work that addresses the problem of illumination variations in segmentation of MR images can be found in [7, 8, 9, 10]. A recent study [3] proposes an adaptive fuzzy c-means algorithm for image segmentation in the presence of intensity inhomogeneities. It uses a multiplier field to model the intensity inhomogeneities which need to be solved for iteratively. The plane (or surface) fitting approach we present does not need any time consuming iterations and if prior information is available, it can be altered according to characteristics of the illumination variation throughout the image.

2. IMAGE SEGMENTATION USING FUZZY C-PLANES

The objective function to be minimized in the fuzzy c-planes image segmentation is:

$$J_{FCM} = \sum_{i=1}^{C} \sum_{(x,y)} u_i^q(x,y) D_i^2(x,y), \tag{1}$$

where

$$D_i(x,y) = \left\| \begin{bmatrix} I(x,y) \\ \alpha x \\ \alpha y \end{bmatrix} - \begin{bmatrix} a_i x + b_i y + d_i \\ \alpha m_i \\ \alpha n_i \end{bmatrix} \right\|, \tag{2}$$

and C denotes the total number of classes, $u_i(x,y)$ denotes the membership value at pixel location (x,y) for class i such that $\sum_{i=1}^{C} u_i(x,y) = 1$; $I(x,y)$ denotes the intensity value of the pixel at location (x,y); a_i, b_i, d_i are the parameters of the plane fit to class i, q is an exponent parameter controlling the fuzziness of the classification and α denotes the relative importance attached to the spatial coordinate information. The larger q is, the fuzzier the classification becomes. The operator $\|.\|$ denotes any distance function which in this study is chosen as the Euclidean distance. The steps of the algorithm proposed for the minimization of the above objective function are:

1. Choose C initial cluster centroids as:

$$\underline{v}_i = \begin{bmatrix} d_i \\ \alpha m_i \\ \alpha n_i \end{bmatrix}, i = 1, \ldots, C. \tag{3}$$

where d_i denotes the average gray level of the i^{th}cluster, (m_i, n_i) denote the location of the cluster centroid, and a_i, b_i, which are the plane parameters, are chosen as zero. The initial average gray levels are chosen as the local peaks of the histogram of the image.

Set the iteration counter to 1 ($z = 1$).

2. Compute the membership of pixel (x, y) to class i as:

$$u_i(x,y) = \frac{\|D_i(x,y)\|^{-2/(q-1)}}{\sum_{k=1}^{C} \|D_k(x,y)\|^{-2/(q-1)}}, \qquad i = 1, \ldots, C. \tag{4}$$

Increment iteration counter (z) by 1.

3. Smooth the membership values using the following local regularization:

$$\hat{u}_i(x,y) = u_i(x,y) + \mu(u_{i,av} - u_i(x,y)) \exp\left(-\frac{(u_{i,av} - u_i(x,y))^2}{\sigma^2}\right)$$

where

$$u_{i,av} = \frac{1}{N_W} \sum_{(x,y) \epsilon W} u_i(x,y) \tag{5}$$

and W denotes a neighborhood (usually the eight neighbors) of pixel at location (x, y), N_W denotes the number of pixels in the neighborhood. The parameters σ and μ adjust the sensitivity of the current pixel to its neighbors. Then let,

$$\tilde{u}_i(x,y) = \frac{\hat{u}_i(x,y)}{\sum_{k=1}^{C} \hat{u}_i(x,y)} \tag{6}$$

for normalization of the membership values so that they still add up to 1, and assign $u_i(x, y)$ to $\tilde{u}_i(x, y)$.

Our aim in performing the local regularization given in equation (5) is to adjust the membership value of the current pixel towards the average membership value of its neighbors if the difference between them is not large.

In equation (5), the variance of the Gaussian function can be adjusted in a decreasing manner as the iterations proceed. For example we may set:

$$\sigma = \frac{1}{z^n}, \tag{7}$$

where n is a positive integer and z is the iteration counter. As the variance of the Gaussian function decreases, the neighbors have less and finally almost no effect on the membership values of the current pixel. By this way, we do not disturb the convergence properties of the original fuzzy c-means algorithm, which still holds in our case.

4. Find the plane parameters and the position of class centroids by minimizing:

$$\sum_{(x,y)} u_i^q(x,y)[(I(x,y) - (a_i x + b_i y + c_i))^2 + (\alpha x - \alpha m_i)^2 + (\alpha y - \alpha n_i)^2] \tag{8}$$

We can do this separation since for each i in equation (1) the corresponding summation over all the pixels have a positive value. So, it is enough to minimize each individual term to minimize the overall expression. We can further split equation (8), to find plane parameters that minimizes:

$$\sum_{(x,y)} u_i^q(x,y)[I(x,y) - (a_i x + b_i y + c_i)]^2 \tag{9}$$

We take the partial derivatives of the above expression with respect to a_i, b_i and d_i and equate them to zero, which results in the following system of equations:

$$\begin{bmatrix} \sum x^2 u_i^q(x,y) & \sum xy u_i^q(x,y) & \sum x u_i^q(x,y) \\ \sum xy u_i^q(x,y) & \sum y^2 u_i^q(x,y) & \sum y u_i^q(x,y) \\ \sum x u_i^q(x,y) & \sum y u_i^q(x,y) & \sum u_i^q(x,y) \end{bmatrix} \begin{bmatrix} a_i \\ b_i \\ c_i \end{bmatrix} = \begin{bmatrix} \sum x I(x,y) u_i^q(x,y) \\ \sum y I(x,y) u_i^q(x,y) \\ \sum I(x,y) u_i^q(x,y) \end{bmatrix}.$$

Find the location of the cluster centroids that minimizes the following expression:

$$\sum_{(x,y)} u_i^q(x,y)[(\alpha x - \alpha m_i)^2 + (\alpha y - \alpha n_i)^2]. \tag{10}$$

After equating the partial derivatives to zero,

$$m_i = \frac{\sum_{(x,y)} u_i^q(x,y) x}{\sum_{(x,y)} u_i^q(x,y)} \tag{11}$$

$$n_i = \frac{\sum_{(x,y)} u_i^q(x,y) y}{\sum_{(x,y)} u_i^q(x,y)} \tag{12}$$

5. Repeat Steps 2-4 until the sum of the error between two successive values a_i, b_i and d_i is less than a threshold value T.

Instead of fitting a plane, we can also fit higher order surfaces to the data, to make the algorithm robust to other nonlinear intensity inhomogeneities.

The parameter α in Step 1 is chosen in our experiments such that the relative weight of d_i to the x and y coordinates is around 4. The parameters μ and σ in Step 3 are chosen around the values 1 and 0.5, respectively. The threshold for the stopping criterion in Step 5 is chosen around 0.001.

If we start with a small number of classes and wish to increase the number of classes as necessary, an efficient cluster center selection scheme would be choosing a new class near an existing class with the largest fit error. The fit error for class i is defined as:

$$E_i = \sum_{(x,y)} u_i^q(x,y) \left\| \begin{bmatrix} I(x,y) \\ \alpha x \\ \alpha y \end{bmatrix} - \begin{bmatrix} a_i x + b_i y + d_i \\ \alpha m_i \\ \alpha n_i \end{bmatrix} \right\| \tag{13}$$

The fit error can also be used as a cluster validity criterion for the FCP algorithm. Other cluster validity criteria using the membership function [11, 12, 13] can also be used.

3. EXPERIMENTAL RESULTS

In order to test the presented image segmentation approach we first used a 30×30 image that has two rectangles of uniform intensity (gray levels 50 and 255), and two stripes with linear intensity variations (from 65 to 210), which is shown in Fig.1(a). There is also additive white Gaussian noise so that the peak signal to noise ratio (PSNR) is 10dB. In Fig.1(b) and Fig.1(c) we give the segmentation results obtained using the standard fuzzy c-means algorithm (FCM) and the proposed fuzzy c-planes (FCP) algorithm, respectively. The gray levels in the segmented images are not necessarily correlated with the intensities of the classes that they represent.

We can see that the standard FCM results in an incorrect segmentation regarding the region boundaries, whereas the FCP algorithm can correctly identify the four regions of the original image. The results when we decrease the PSNR of the original image to 4dB are given in Fig.2.

Another example is given in Fig.3. The original image consists of two balls illuminated with two different light sources at the top and at the bottom. The background consists of two parts (top and bottom) that have an intensity gradient as shown in Fig.3(a). The PSNR is chosen as 10dB. The standard FCM algorithm is not able to segment the background correctly in two parts as shown in Fig.3(b). This is both due to the noise and the intensity gradient of the background. The FCP algoritm segments the background and the ball on the left better than the FCM algorithm. FCP is more robust to noise and the intensity variations.

Finally, the algorithm is tested with a color image which is shown in Fig.4. The segmentation result of the FCM algorithm is given in Fig.4(b) and the result of the FCP algorithm is given in Fig.4(c). The FCP algorithm is carried out in the HSV (hue, saturation, value) color space and planes are fit to the V component. As seen in Fig.4, the left part of the cola can is segmented better than the FCM using the FCP algorithm.

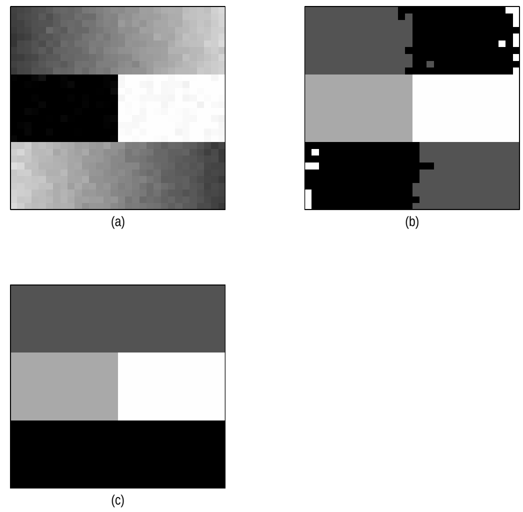

Figure 1: (a) The original test image with PSNR = 10dB. (b)The segmentation result using the standard fuzzy c-means algorithm for four classes. (c) The segmentation result using the proposed fuzzy c-planes algorithm.

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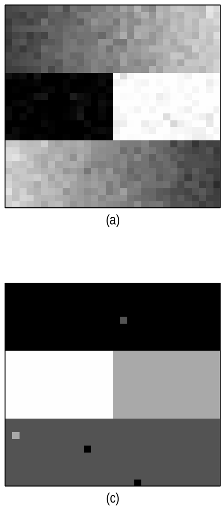

Figure 2: (a) The original test image with PSNR = 4dB. (b)The segmentation result using the standard fuzzy c-means algorithm for four classes. (c) The segmentation result using the proposed fuzzy c-planes algorithm.

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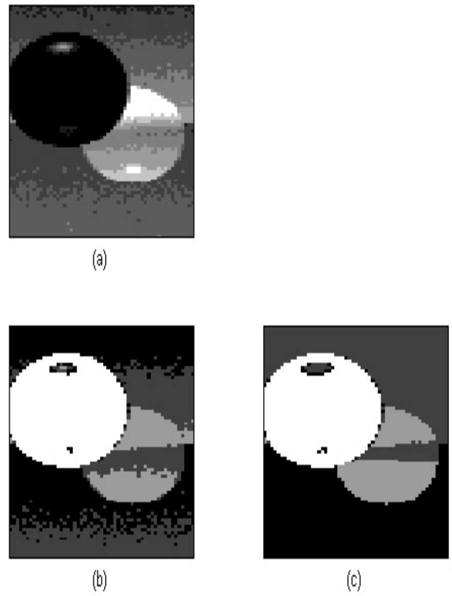

Figure 3: (a) The original test image with PSNR = 10dB. (b)The segmentation result using the standard fuzzy c-means algorithm for four classes. (c) The segmentation result using the proposed fuzzy c-planes algorithm.

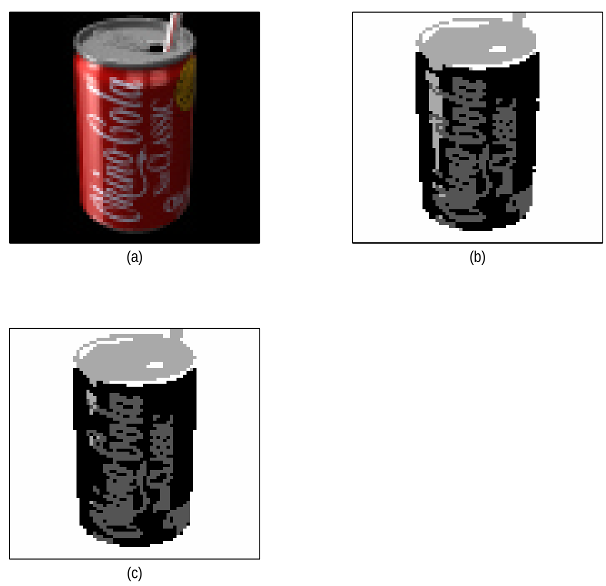

Figure 4: (a) The original test image. (b)The segmentation result using the standard fuzzy c-means algorithm for four classes. (c) The segmentation result using the proposed fuzzy c-planes algorithm.