Abstract—The Probabilistic Index Map (PIM) model was originally proposed for video processing to extract background of video frames. In this paper, we introduce the PIM model for texture segmentation. We first extract texture features based on Laws and Gabor filters respectively. Then we present a Fuzzy K-Means method to generate the index map and palette, and use the PIM model to improve the segmentation accuracy. Based on the comparison of experimental results produced using different features and different resolutions, we show the proposed method is effective for texture segmentation.

Keywords—PIM model; Fuzzy K-Means; texture segmentation; Laws; Gabor

I. INTRODUCTION

Texture analysis is an important issue in Computer Vision research, as texture plays a major role on natural scene, remote sensing, surface material and medical images. As one of the main research areas in texture analysis, texture segmentation and classification have been extensively studied and a variety of approaches has been proposed based on different techniques, e.g. statistics, structure wavelets and fuzzy clustering[1]. The majority of research focuses on 2D texture which only represents the sample using one still image. However, real-world surface textures normally comprise rough surface geometry and various reflectance properties. Their images can therefore vary dramatically with illumination directions. Thus, it is common to use multiple texture images, which are taken from one texture sample, but having different appearances due to different illumination directions. This series of images have the following characteristic: they have different appearances, but have the same structures in shape. The Probabilistic Index Map (PIM) is suitable for representing this characteristic, as it employs parametric models which can be derived from training data set and further applied for analysis new features of the same sample illuminated from other than the directions in the training data. This is the idea that the PIM can be used for texture segmentation.

A Probabilistic Index Map (PIM) model is a generative model and was originally proposed for video processing to extract background of video frames[2]. The model proposes a posterior probability distribution over a clustering, given the input images. The PIM model supplies a way to calculate the joint probability distribution for the images which have the similar structure. Image segmentation can be obtained by sampling from the probability distribution and prior distributions of the texture features. In this paper, we first use Fuzzy K-Means(FKM) clustering method to generate the index map and palette based on different features and resolutions. Then we apply the PIM to further improve segmentation results. Experimental results based on a number of texture images captured under varied lighting directions prove the effectiveness of the proposed method.

II. THE PROBABILISTIC INDEX MAP MODEL

A. What is the PIM model

A Probabilistic Index Map is an advanced probabilistic model of the index map model. An introduced in [3], an index map model can be depicted by figure 1. A set of images, which have the same structure or shape but different appearance, for instance colors and textures, can be indicated by the index map model. Index maps depict the shape or main structure of the images. In this way, each pixel of images will be indexed, and palettes shows that the images’ appearance. The Probabilistic Index Map model was proposed as an improved model of the index map, which adds a probabilistic model into index map. Thus, the pixel’s index depends on the probabilistic models. When we assume that the index and appearance of each pixel is independent and with a set of Gaussian distributed palettes, we can generate an image by the PIM model. For example, given the probabilistic index map and palette of the kth image, for each pixel, we sample its index from the probabilistic index map first and then obtain its appearance by the Gaussian distribution palettes, the image can be generated.
B. How the PIM model works

In the PIM model, we define that palette parameters, i.e. the mean vector $\mu$ and the covariance matrix $\Phi$, are the model parameters $h$, and the image appearances, such as the measurements, are the observations $v$. Given the observations $v$, if we obtain a proper parameters $h$ to maximize the posterior probability $P(h | v)$, we can compute the clustering index and also can perform image segmentation. This is also the goal of this paper.

We know that the Bayes formula is:

$$P(h | v) = \frac{P(h, v)}{\int_h P(h, v)}$$

(1)

Regarding $\int_h P(h, v)$ as a constant, $P(h | v)$ is proportional to the probability function. Because the palette model can be coupled, Frey and Jojic[2] used minimizing Helmholtzian free energy. By calculating the Kullback-Leibler divergence$^{[4]}$, we have

$$F(Q, P) = \int_h Q(h) \log \frac{Q(h)}{P(h, v)}$$

(2)

where $F(Q, P)$ is Helmholtzian free energy, and $Q(h)$ is a distributions to $h$. By minimizing $F(Q, P)$, we know that $Q(h)$ is approximate to $P(h | v)$.

In the PIM model, EM algorithm is used to calculate $Q$. In the E-step$^{[3]}$, it minimizes $F(Q, P)$ by $Q(h)$, while in the M-step it updates $h$ which is the mean vector $\mu$ and the covariance matrix $\Phi$ and then minimize $F(Q, P)$ by $h$. The algorithm is stopped until convergence or a fixed number of iteration. Figure 2 shows the procedure of PIM parameter estimation.

III. THE FUZZY K-MEANS ALGORITHM

How to generate the index maps and palettes is the key for deriving the PIM models. Initially, we first chose K-Means algorithm to calculate the palette parameters $\mu_s$ and $\Phi_s$, but only produced worse results. Therefore, we introduce an improved method to obtain the index maps and palettes, i.e. Fuzzy K-Means algorithm.

Fuzzy K-Means algorithm (FKM)$^{[5]}$ was developed based on K-Means(KM) algorithm. Both FKM and KM are based on the similar idea; the only difference is that for FKM a fuzzy membership is used in the cluster assignment matrix. In KM, the clustering result is kept by the clustering matrix $U(r, c)$, whose elements are binary values i.e. either 0 or 1,

![Figure 1. Index map model containing index map and palettes][3]

![Figure 2. Iterative EM algorithm to update PIM model][4]
\[
\sum_{r=1}^{k} u_{rc} = 1, c=1,..., n .
\]  

(3)

Where \( r \) is the number of clustering; \( c \) is the number of measurements. However in FKM, instead of using a binary value, continuous variables are employed for grading. Therefore, we have

\[
u_{rc} \in (0,1).
\]

The whole FKM algorithm consists of following steps:
[a] Initialize the clustering matrix \( U(r,c) \) and the threshold value \( \epsilon \) which is set to the minimum.
[b] Calculate the fuzzy cluster centers by

\[
\mu_r = \frac{\sum_{c=1}^{n} u_{rc}^m x_c}{\sum_{c=1}^{n} u_{rc}^m}
\]

Where \( \mu_r \) is the center of group \( r \).
[c] Calculate the cost using

\[
Cost(U, \mu_1, \mu_2, ..., \mu_k) = \sum_{r=1}^{k} \sum_{c=1}^{n} u_{rc}^m d_{rc}^2
\]

(d) Calculate new \( U(r,c) \) by

\[
u_{rc} = \frac{1}{\sum_{j=1}^{k} \left( \frac{d_{rc}^2}{d_{jc}^2} \right)^{(m-1)}} .
\]

[e] if the cost > \( \epsilon \), turn to step[c].

Figure 3 shows the workflow for FKM

IV. EXPERIMENT AND RESULT

A. Experiment instruction

Texture images we used for experiments are chosen from the database of the Texture Lab affiliated with Heriot-Watt University. \( \text{ftp.macs.hw.ac.uk/pub/imaging/Photex SCOPE} \). Nine sets of textures are labeled by acc, acf, acg, ach, aci, ack, acl, acm, adf. Each set comprises 12 images captured under different illumination angles, so they have same structure but have different appearances. Four sets from the nine textures are montage to form one group for the experiment. In this experiment, we get 4 groups of samples: (1) acc-acf-acg-ach (2) acl-acm-adf-aci. (3) acc-acf-aci. (4) acf-acf-aci. Figure 2 and Figure 3 show that how the program flow works.

B. Texture features in the experiment

A number of texture features have been studied for texture analysis, but not all of them are capable for segmenting the texture montage which has similar structure. In this paper, we employ Laws mask\(^6\) and Gabor filters\(^7\) which are commonly used in texture analysis.

1) Laws masks

Laws masks can depict statistical energy characteristics of the sample texture. Texture description uses five characters: level, edges, spots, ripples, waves which are indicated by five vectors in Eq(4):

\[
\begin{align*}
L5 &= (1,4,6,4,1) \\
E5 &= (-1,-2,0,2,1) \\
S5 &= (1,0,2,0,-1) \\
R5 &= (-1,4,6,-4,1) \\
W5 &= (-1,2,0,-2,-1)
\end{align*}
\]  

(4)
Laws masks are generated by mutual multiplying these 5 vectors in Eq(4).

2) Gabor filters

Gabor functions have multi-scale and multi-orientation characteristics and can take attention to both spatial and frequency domains. The Gabor filters have well reflect texture energy response and structural property. In this paper, We define the Gabor function by Eq(5)

$$G(x,y) = \frac{1}{2\pi|s^2_y}} \exp \left[ -\frac{1}{2} \left( \frac{x}{s_x} + \frac{y}{s_y} \right)^2 \right] + 2pi(U_x + V_y)$$ (5)

where U,V represent frequency domain variables due to Fourier transform.

In our experiments, we choose four scales (γ=1.4, 1.8, 2.4, 2.8) and four orientations (θ =30°, 60°, 90°, 120°). Thus, we obtain 16 Gabor filters to extract features.

C. experimental results and analysis

We test four groups of samples, and list two of them in Table 1 and 2. Example segmentation results in the experiment are shown in Figure 4 and 5. From the tables, we can see that the accuracy of the two groups of texture in different resolutions and different features is around 90% in average, except for the montage image acl-acm-adf-aci under illumination tilt angle 60° based on Gabor features with the resolution of 512*512. Images with high resolution(512*512) are better than in low resolution (256*256). As we compare the results with and without PIM models in Figure 4 and 5, we can see that blurring effect and edges are improved. Blurs become less obvious or even disappear, while the edges become thinner and smooth. This means segmentation with PIM produces better results than purely using Fuzzy K-Means clustering.

![Figure 4. Montage acc-acg-acg-ach and segmentation under 60° illumination directions (a): original image acc-acg-acg-ach (b): initial segmentation based on Gabor features and without using PIM (c) final segmentation based on Gabor filters followed by PIM (d) initial segmentation based on Laws features and without using PIM (e) final segmentation based on Laws followed by PIM.](image)

![Figure 5. Montage acl-acm-adf-aci and segmentation under 270° illumination directions (a): original image acl-acm-adf-aci (b): initial segmentation based on Gabor features and without PIM (c) final segmentation based on Gabor filters followed by PIM (d) initial segmentation based on Laws features and without using PIM (e) final segmentation based on Laws followed by PIM.](image)

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Table 1. ACC-ACF-ACG-ACH accuracy of result in PIM model.

Initial: the result of segmentation before PIM; final: the result of segmentation after PIM.
V. CONCLUSION AND FUTURE WORK

In this paper, we introduced a new method for texture segmentation based on the combination of Fuzzy K-Means clustering method and Probabilistic Index Maps. If we directly apply original PIM for texture segmentation, the algorithm fails to produce good performance because of the poor index maps and palettes produced by traditional K-Means clustering algorithms. Thus, we introduced a Fuzzy K-Means algorithm to generate better index maps and palettes. The experimental results produced by the new scheme show that the PIM model performs better for segmenting texture images which have similar structure frames.

There are still several aspects that can further improve the current algorithm. The current PIM model considers simple probabilistic models such as Gaussian distribution. Introducing more sophisticated models, such as MRF model or other texture features might produce better performance in segmentation. We would also like to investigate the analysis of 3D surface texture using Probabilistic Index Maps.

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REFERENCE