time ratios T_p/T_0 for different values of n (where $N = 32$ and $m = 32/n$) are given in Table 1.

Table 1: Area ratio A_p/A_0 and time ratio T_p/T_0

n	1	2	4	8	16
A_p/A_0, %	81	84	89	99	113
T_p/T_0, %	51	54	56	62	75

These results clearly illustrate the advantages of the new structure.

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A.E. Bashagha and M.K. Ibrahim (*Electrical and Electronic Engineering Department, University of Nottingham, Nottingham NG7 2RD, United Kingdom*)

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Fuzzy uncertainty texture spectrum for texture analysis

Yih-Gong Lee, Jia-Hong Lee and Yuang-Cheh Hsueh

Indexing terms: Fuzzy set theory, Texture (image processing)

A new method using fuzzy uncertainty, which measures the uncertainty of the uniform surface in an image, is proposed for texture analysis. A grey-scale image can be transformed into a fuzzy image by the uncertainty definition. The distribution of the membership in a measured fuzzy image, denoted the fuzzy uncertainty texture spectrum (FUTS), is used as the texture feature for texture analysis.

Introduction: Texture analysis is an important technique in image processing. The major problem of texture analysis is the extraction of texture features. The general methods for feature extraction are to estimate local features at each pixel in a texture image and then derive a set of statistics from the distributions of the local features. The surveys and comparisons of different methods for feature extraction can be found in [1, 2].

A new method for texture feature extraction based on fuzzy theory is presented. Fuzzy set theory [3, 4] is a mathematical tool for modelling ambiguity or uncertainty and has been applied to image processing [5]. In texture analysis, we define the 'uniform surface uncertainty', which ranges from 0 to 1, for a point p in the texture as the degree of p belonging to the uniform physical surface (as defined by the neighbourhood average intensity). Therefore, we can transform a grey-scale image into a fuzzy image by using the uncertainty definition. For a rougher texture, the intensity of pixels in its corresponding fuzzy image will cause a smaller value. The fuzzy image membership distribution, denoted the fuzzy uncertainty texture spectrum (FUTS), is then used as a distinguishing feature for texture analysis.

Fuzzy uncertainty texture spectrum: A grey-scale image f can be transformed into a fuzzy image by a fuzzification function ϕ. A variety of fuzzification functions can be used to reflect the degree to which a pixel intensity represents a uniform physical surface. However, textural properties need neighbourhood information about the pixel to adequately define membership functions. A

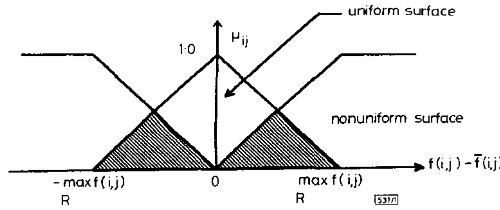

Fig. 1 *Fuzzy membership function for uniform surface*

simplified triangular membership function is used to define a uniform surface, as illustrated in Fig. 1. The uniform surface uncertainty is defined as

$$\mu_{ij} = 1 - \left[\frac{|f(i,j) - \bar{f}(i,j)|}{\max_R f(i,j)}\right] \qquad (1)$$

where $\max_R f(i, j)$ is the maximum intensity within the $(\omega \times \omega)$ surface region R centred at point (i, j), and the average intensity is given by

$$\bar{f}(i,j) = \frac{1}{\omega \times \omega - 1} \sum_{\substack{R \\ m,n \neq i,j}} f(m,n) \qquad (2)$$

Note that if $f(i, j)$ is equal to the average neighbourhood intensity $\bar{f}(i, j)$ then $f(i, j)$ possesses 'full membership' to the surface region R; i.e. $\mu_{ij} = 1$. Alternatively, if $f(i, j)$ is significantly different than the average neighbourhood intensity $\bar{f}(i, j)$, then $\mu_{ij} \to 0$.

To analyse a texture image, we can transform it into its corresponding fuzzy image by using eqn. 1. As the value in the fuzzy image represents the local aspect, the statistics of these values in the fuzzy image should reveal its texture surface information. The occurrence distribution of these values is called the fuzzy uncertainty texture spectrum (FUTS), with the abscissa indicating the belief degree and the ordinate representing its occurrence frequency. To evaluate the performance of the extracted feature by using the proposed method, we calculated and compared the FUTS for two Brodatz textures D77 and D90 [6], respectively. The two textures are shown in Figs. 3*g* and 3*h* and their corresponding FUTS are displayed in Fig. 2. From Fig. 2, we can find that the measured FUTS are distinguishable from each other so they can serve as a good discriminating tool in texture classification. The FUTS of D90 shows a higher frequency than D77 when the measured uncertainty is closed to unity, so that the texture image D90 is smoother than D77.

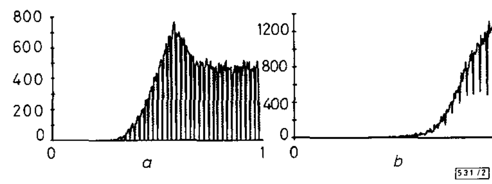

Fig. 2 *Fuzzy image and FUTS of textures D77 and D90*

a D77
b D90

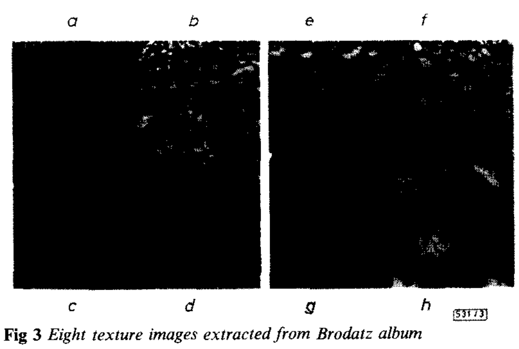

Fig 3 *Eight texture images extracted from Brodatz album*

a D4, *b* D5, *c* D9, *d* D15, *e* D18, *f* D54, *g* D77, *h* D90

Texture classification and results: To demonstrate the discrimination performance of the FUTS, we use a supervised classification with a minimum distance rule to classic nature images, extracted from the Brodatz album. Eight 256 × 256 natural images with 256 grey-levels are used for the texture classification (see Fig. 3). Each texture image is divided into 16 nonoverlapping 64 × 64 subimages. The subimages are further divided into two sets: a training set and a test set. The evaluation is performed using a supervised classification over these test subimages. In the process of classification, the uniform surface uncertainty values (0 – 1) in a fuzzy image are uniformly quantised into 256 levels to reduce the calculation time for the pursuit statistics. The procedure used in our experiment is described as follows:

Step 1: Randomly select one subimage as the training set from each texture image.

Step 2: For each texture type k, calculate the FUTS of the corresponding training samples, denoted $S_k(j)$, $k = 1, ..., 8$ and $j = 0, ..., 255$.

Step 3: Calculate the FUTS for each considered test subimage, denoted $T(j)$.

Step 4: Calculate the distance of the FUTS between the considered test subimage and the training result $S_k(j)$ as

$$D(k) = \sum_{j=0}^{255} |S_k(j) - T(j)| \tag{3}$$

Step 5: The test subimage will be assigned to class l such that $D(l)$ is the minimum among all the $D(k)$s.

The experimental results listed in Table 1 show an average accuracy rate of 97.5%.

Table 1: Result of test set classified by using FUTS method (average accuracy rate = 97%) Average surface intensity $\bar{f}(i, j)$ given over (7 × 7) region

	Classification result							
ID	D4	D5	D9	D15	D18	D54	D77	D90
D4	15							
D5		15						
D9			15					
D15				14			1*	
D18					15			
D54		2*				13		
D77							15	
D90								15

*: misclassification

Conclusions: A new method using FUTS has been proposed for texture analysis. The classification method is simple, and the number of mathematical operations applied to the FUTS is small. Promising results have been obtained with an accuracy rate of 97.5% by using only one training sample for each texture type. From the experimental results, we conclude that the FUTS is an excellent discriminating tool for texture analysis and classification.

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Yih-Gong Lee, Jia-Hong Lee and Yuang-Cheh Hsueh (*Department of Computer and Information Science, National Chiao Tung University, Hsinchu, Taiwan 30050, Republic of China*)

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Pose estimation for known arbitrary and noisy planar curves

G.M.T. Man, J.C.H. Poon and W.C. Siu

Indexing term: Computer vision

A new algorithm for pose determination of known arbitrary planar curves is presented. The method directly computes the pose by using Fourier descriptors and the paraperspective projection models. The method is shown to be accurate, efficient and robust to high frequency noises.

Introduction: One of the important issues in computer vision is to determine the pose of an object in a picture. This pose represents the orientation of the object with respect to a known camera co-ordinate system. Recent work [1, 2] has shown that it is possible to estimate the pose of an arbitrary planar curve by using the single perspective image. Generally, these methods require heavy computation, such as complex conic fitting procedures [1] and solving a large set of simultaneous equations [2]. Nevertheless, none of these methods produce satisfactory results on the estimation of the tilt angles. Furthermore, their performances rapidly degenerate in the presence of noise. We present a Fourier-descriptor based algorithm which is highly accurate and computationally efficient for pose recovery.

Algorithm: Consider a shape lying on an object plane with a gradient (p, q) in the world co-ordinate system $OX'Y'Z'$, we can express it by a periodic sequence of co-ordinates, x_{wn} and y_{wn}. When this shape is projected onto the image plane, we obtain a 2-D contour which is represented by another periodic sequence of co-ordinates x_n and y_n. These co-ordinate sequences can be expressed by two series of Fourier descriptors (FDs). In the following derivations, we show that the FDs of the object image (denoted by X_{wk} and Y_{wk}) can be related to the FDs of the projected image (denoted by X_k and Y_k) [3].

According to the paraperspective inverse transformation [4], we have

$$x_{wn} = \frac{c(1-Bq)}{(1-pA-qB)^2}x_n + \frac{Aqc}{(1-pA-qB)^2}y_n - \frac{Ac(pA+qB)}{(1-pA-qB)^2}$$

hence

$$X_{wk} = \frac{c(1-Bq)}{(1-pA-qB)^2}X_k + \frac{Aqc}{(1-pA-qB)^2}Y_k \tag{1}$$

where (A, B) is the centre mass of the projected contour and c is the z-intercept of the object plane. Similarly,

$$y_{wn} = \frac{cpB}{(1-pA-qB)^2}x_n + \frac{c(1-pA)}{(1-pA-qB)^2}y_n - \frac{cB(pA+qB)}{(1-pA-qB)^2}$$

and we have

$$Y_{wk} = \frac{cpB}{(1-pA-qB)^2}X_k + \frac{c(1-pA)}{(1-pA-qB)^2}Y_k \tag{2}$$