OPTIMUM GABOR FILTER DESIGN AND LOCAL BINARY PATTERNS FOR TEXTURE SEGMENTATION

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ABSTRACT

We present a novel approach to multi-texture image segmentation based on the formation of an effective texture feature vector. Texture sub-features are derived from the output of an optimized Gabor filter. The filter's parameters are selected by an immune genetic algorithm, which aims at maximizing the discrimination between the multi-textured regions. Next the texture features are integrated with a local binary pattern, to form an effective texture descriptor with low computational cost, which overcomes the weakness of the single frequency output component of the filter. Finally, a K-nearest neighbor classifier is used to effect the multi-texture segmentation. The integration of the optimum Gabor filter and local binary pattern methods provide a novel solution to the task. Experimental results demonstrate the effectiveness of the proposed approach.

Keywords: Texture segmentation, Gabor filter, Local binary pattern, K-nearest neighbor, Immune genetic algorithm.

1. INTRODUCTION

Gabor filters have been successfully applied to the fields of image processing and image analysis, including edge detection, texture segmentation, and image enhancement (for example, see Tsai et al., 2001; Yang et al., 2003). The goal of texture segmentation is to partition an image into meaningful regions based on the surface textures of objects. Mathematically modeling image textures for the segmentation problem is very difficult as the textures are usually characterized by two-dimensional variations in intensity.

In the past decade, both Gabor filters and local binary patterns (LBP) have been separately recognized as texture detectors with good performance as shown by Ojala et al., (2002) , Topi et al. (2000) and Wu et al., (2001) . The former has optimal join localization both in the spatial and frequency domains, while the latter is widely used as a non-parametric statistical texture indicator. In recent years the filter-design approach to texture segmentation has been introduced in an effort to reduce the computational complexities of the previous filter-bank approaches as shown in Yang et al., (2003). Classifiers utilizing the wavelet and Fourier domains have also been researched that provide good discrimination between textures (see for example, Choi et al., 1999). However the proposed approach is to effectively combine what we will describe below as macro-features detected with the Gabor filter with micro-features from the LBP.

There has been much research into optimum Gabor filter design by genetic algorithm (GA) and by simulated annealing (SA). For example, see Tsai et al. (2001), but both have problems such as premature convergence to local minima, and both require substantive iterations. Recently, biological immune system models have been introduced into the traditional GA to enhance its evolutionary performance as demonstrated by Chen and Zhang (2004). In our approach, we have used the immune genetic algorithm (IGA) to effectively tackle the issue of premature convergence by utilizing its ability to maintain concentration and diversity as demonstrated by Li et al. (2005).

It has been shown that a single optimized Gabor filter can be a highly effective discriminator for separating multi-textured images. However it has also been shown by Tsai et al. (2001), that performance degrades with an increasing number of texture classes within the image. In order to improve the segmentation performance, we have employed the LBP operator described by Topi et al. (2000) as a complementary tool to extract texture features from the Gabor filtered textured images. Finally our proposed approach uses a K-nearest neighbor (K-NN) classification to select and bound the individually textured regions. Our results have shown that the proposed combined classifier enabled a better discrimination between textures than either of the previous classifiers operating individually, and that it has worked well for a larger number of differently textured segments within the image.

The novelty of the proposed method concerns two aspects: (1) we use an IGA with affinity and diversity estimation to search for the optimum Gabor filter. This enabled the filter parameters to not only be found more quickly, but also with a reduced possibility of the selection process being stuck in a local minimum at the conclusion of the analysis, which would result in a sub-optimal filter being designed and (2) we use the combined texture features from a LBP statistical histogram and the averaged intensity output images from the optimized Gabor filter as features for a further K-NN classification. In the proposed method, the IGA based Gabor filter parameter search is implemented as a pre-processing stage that results in strong responses to individual texture patterns. The K-NN classifier as described by Hotta et al. (2004) produces texture partitions and the final feature extraction.

This paper is organized as follows. Section 2 describes the design of the adaptive Gabor filter. Section 3 gives illustrations of how the IGA operates and how it provides parameters for the Gabor filter. The combined feature formation using the outputs of the LBP and the Gabor filter as inputs to the K-NN classifier is discussed in Section 4. Experimental results from the proposed method are discussed in Section 5, and conclusions are provided in the final section.

2. SINGLE GABOR FILTERS FOR TEXTURE SEGMENTAION

2.1 The Gabor function and Gabor filter

The Gabor filter has been extended to 2-D operation by Daugman (1985). A 2-D Gabor filter is an oriented complex sinusoidal grating modulated by a 2-D Gaussian function:

$$h(x,y) = g(x,y)\exp[2\pi j(Ux + Vy)] = h_R(x,y) + jh_I(x,y) \qquad (1)$$

where (U,V) is a single spatial frequency, $g(x,y)$ is the Gaussian function with scale parameter σ, and $h_R(x,y)$ and $h_I(x,y)$ are the real and imaginary parts of $h(x,y)$ respectively.

$$g(x,y) = \frac{1}{2\pi\sigma^2}\exp\{-\frac{x^2+y^2}{2\sigma^2}\} \qquad (2)$$

The Gabor filter is a bandpass filter centered on frequency (U,V), with a bandwidth determined by σ. The parameters of the Gabor filter are represented by the spatial frequency U,V and the scale, σ. Usually, a radial frequency $f = \sqrt{U^2+V^2}$, with orientation $\theta = \tan^{-1}(V/U)$, are used in polar coordinates to specify the filter (f, θ, σ). The Gabor filtered output of an image $i(x,y)$ is obtained by the convolution of the image with the specified Gabor function. The local energy measure at a point $(x,y)$is defined as

$$E\ (x,y \mid f,\theta,\sigma) = C_R^2(x,y \mid f,\theta,\sigma) + C_I^2(x,y \mid f,\theta,\sigma) \qquad (3)$$

where

$$C_R(x,y \mid f,\theta,\sigma) = \sum_{l=-w}^{w}\sum_{m=-w}^{w} i(x+l, y+m)h_R(l,m)$$

and $$C_I(x,y \mid f,\theta,\sigma) = \sum_{l=-w}^{w}\sum_{m=-w}^{w} i(x+l, y+m)h_I(l,m) \qquad (4)$$

represent the discrete convolution of the real and imaginary components of $h(x,y)$ with the image over a given neighborhood with a fixed window size of $M = 2w+1$. The resulting feature image, $E(x,y)$, contains a distribution of local energy measures, which depends strongly on the choice of the design parameters (f, θ, σ) of the single Gabor filter.

2.2 Problem statement

Based on the discussion above, the problem of multi-texture segmentation can be stated as follows: Consider the input image *i(x,y)* to be composed of multiple disjointed regions with distinct textures $t_i(x, y), i = 1,2,\cdots, L$. It is assumed that samples of each texture are available in advance, and the number, *L*, of different textures is given. Then the first stage of the proposed approach is to search for an optimal Gabor filter that will provide the greatest discrimination between the energy distributions of the differently textured regions in the feature image defined above. The next stage of the feature extraction concerns combining the output of a LBP texture indicator with the averaged intensities from the Gabor filtered image. In the final stage, a K-NN classification is applied to yield the labeled regions in the segmented images, each of which contain one of the *L* possible textures.

2.3 Design model for the Gabor filter

The optimum Gabor filter is the one with the highest sensitivity to the different patterns in each textured region. Considering the selectivity of the Gabor filters, the texture frequency is not exactly located at the peak of its spectrum with respect to actual textured images， while the energy of the power spectrum from one particular texture is aggregated within a specified small region. So an averaged power spectrum can be taken as an indicator of the texture’s properties instead of using spectral coefficients as demonstrated by Wu et al. (2001). The optimal filter is determined by maximizing the Fisher object function described by Fukunaga (1990):

$$(f^*, \theta^*, \sigma^*) = \arg\left[\underset{(f,\theta,\sigma,M)}{Max}\min\left\{\frac{E_i}{E_j}\bigg|_{i=1,2,\cdots,L-1;\ j=i+1,I+2,\cdots,L}\right\}\right] \tag{5}$$

where E_i and E_j indicate the averaged energy of the ith and the jth filtered sample of the texture image respectively. *L* is the number of texture image samples in the search process for the optimal Gabor filter. Fisher’s object function is a classification method that projects high-dimensional data on to a line and performs classification in one-dimensional space. This criterion is well known in the pattern recognition literature, and has proved effective for supervised texture segmentation tasks. The model mentioned above represents a nonlinear, constrained programming problem with multi-variables. Work has been reported by Tsai et al. (2001), where the GA and SA algorithms have been used to optimize the parameters of the Gabor filter. The SA is well known for its ability to escape from a local minimum, however, it is not efficient with respect to the number of iterations it requires to reach the minimum. The GA also has some unsatisfactory aspects, with either a fast convergence leading to becoming stuck in a local minimum, or a slow convergence finding the minimum at the expense of many iterations. To overcome these limitations we have tried a new approach and applied the IGA to improve the performance and accelerate the parameter search process.

3. IMMUNE GENETIC ALOGRITHM FOR GABOR FILTER DESIGN

3.1 Immune genetic algorithm

The IGA described by Chen and Zhang (2004); Jiao and Wang (2000); and Li et al. (2005) has been proposed in recent years. It works by combining some functions of the biological immune system with a genetic algorithm The IGA has some notable characteristics:- (1) Diversity Maintenance. The feature of antibody diversity is used to provide a higher possibility of finding super-individuals and to ensure fast convergence in the optimum antigen space; (2) Self-adjustment. Its ability to escape from local minima improves the global search capacity. The IGA computational procedure is outlined in the following steps:-

Step1. Generate the initial antibodies
Step2. Evaluate the fitness of the antibodies
Step3. Calculate the concentration of the antibodies
Step4. Based on antibody concentration, perform a promotion /restraint mechanism using fused fitness
Step5. Form a temporary set containing super-individuals
Step6. Produce the next generation by the crossover and mutation operation
Step7. Evaluate the evolutionary criteria. If this is satisfied, the program ends. Otherwise, go to Step 2.

3.2 IGA Based Fitness Evaluation

IGA algorithms that combine some of the mechanisms of a biological immune system with a genetic algorithm have been proposed in recent years. They incorporate a concentration based selection mechanism and memory updating. This can give a superior performance to that of the traditional GA ensuring fast convergence, population diversity, and the avoidance of local minimum solutions. The IGA is described in full by Chen and Zhang (2004); and Jiao and Wang (2000), but as the fitness evaluation of an antibody is central to our argument, we have discussed this further here. Suppose that an immune system consists of N_1 antibodies, each of which is composed of a binary string with length M_1. Let each antibody x (the binary string) be further divided into three sub-segments corresponding to (f, θ, σ) respectively. As with affinity in the immune system, two forms of measurement are involved:- fitness and concentration. Concerning antibody concentration evaluation, the concentration is an indicator of the population's similarity or affinity. As described by Chen and Zhang (2004), the similarity between an antibody x and an antibody y is given by

$$B_{x,y} = 1 / (1 + H_{x,y}) \qquad (6)$$

where $H_{x,y}$ is the information entropy of both antibodies. $H_{x,y}$ is calculated as follows

$$H_{x,y} = \frac{1}{M} \sum_{j=1}^{M} - p_{ij} \log_2 p_{ij} \qquad (7)$$

where p_{ij} is the number of times the antibody i occurs at the gene position j divided by N_1. The concentration of an antibody, i, is given by

$$C_x = \sum_{y=1}^{N} B_{x,y} \big/ N . \qquad (8)$$

Concerning fused fitness in the IGA, one measure for an antibody is composed of fitness *Fit(x)* as discussed in section 3.3, and the concentration of the antibody as given in Li et al. (2005) by,

$$p = \alpha Fit(x) + (1-\alpha) C_x \qquad 0 < \alpha \le 1 \qquad (9)$$

where p is then the fused fitness of an antibody, and is used for a sorting process to determine the priority of the antibody in the population. The C_x and α terms represent the concentration measure and control factor respectively. The control factor is utilized to maintain the antibodies with a high fitness, and to restrain extortionate antibodies that have a high similarity rate. This ensures wide population diversity.

3.3 The Procedure for Optimal Filter Design

In the design procedure, L sub-images, called sample images, are formed. Each has about 6% of the total area of the original image, and each represents one type of texture. These are manually selected to represent different sample textures. The pre-design of the antibody's structure is then carried out to choose the length of each of the three sub-segments for each parameter of the Gabor filter. In the IGA algorithm, given each pair of Gabor filter parameters f, θ, σ with respect to any antibody x, Eq. (3) is used first to calculate the feature images for each of the sample textures. Then the averaged power spectra are computed to form $\{E_1, E_2, \cdots, E_L\}$, which have values of increasing power. The *Fit(x)* in Eq. (9) is similar to the Fisher function:

$$Fit(x) = \left[Max \min \left\{ \frac{E_i}{E_j} \bigg|_{i=1,2,\cdots,L-1;\; j=i+1,I+2,\cdots,L,\; given\;\; f,\theta,\sigma} \right\} \right]$$

This means the maximum discrimination power is reached for a given antibody. Then the concentration of antibodies is computed using Eq. (8), and the promotion/restrain mechanism is performed by a sorting based on Eq. (9). Based on the fused fitness p, the resulting parameters generated by the mutation and crossover operators are applied to yield better parameters for the

Gabor filter. By using the IGA algorithm illustrated in section 3.1, a single optimum Gabor filter with maximum discrimination capacity between different textures has been selected based on a training set of sub-images.

4.FEATURE EXTRACTION USING LBP AND K-NN CLASSIFIER

4.1 Feature extraction with LBP

It has been found experimentally by Tsai et al. (2001), that a single Gabor filter has limited discrimination ability when used with multi-textured images. Specifically, the accuracy of the textured image segmentation gradually decreases as the number of distinct texture regions increases. An optimum Gabor filter can be selected using the Maxmin principle, as described above, to maximize the ratios between the locally averaged energies for the different texture classes. This maximizes the differences in the Gabor filter’s output for the individual texture patterns in the input image. Ideally the distributions of the filter’s output for each individual texture class will be distinct. However, the variance of the filter’s output for each class can be large resulting in an overlapping of the distributions and poor texture discrimination. The averaged intensity can be taken as a good texture indicator in general, but unfortunately, the magnitude of the averaged intensity differences become smaller as the number of texture classes increases. Inaccurate partitions occur, and the probability of individual pixels within an otherwise correctly bounded region being falsely labeled increases resulting in a salt and pepper noise in the segmented image. To overcome these problems, we have incorporated a second texture descriptor to complement the single Gabor filter scheme.

The local binary pattern (LBP) operator, a non-parametric texture indicator, combines statistical and structural approaches to texture analysis by incorporating the occurrence statistics of simple local microstructures as shown by Ojala et al. (2002) and Topi et al. (2000). It is a very efficient methodology with low computational complexity compared to banks of Gabor filters or the wavelet scheme. The multiresolution LBP only requires addition and subtraction operations for texture analysis, classification, and segmentation problems (Ojala et al., 2002). For simplification, the LBP texture operator we report in this paper is derived from a general definition of texture in a 3×3 neighborhood. For each pixel in an image, its neighborhood is thresholded by the value of the central pixel. Next the values of the pixels in the thresholded neighborhood are multiplied by a set of binomial weights given to each of the corresponding pixels. Finally, an LBP code is assigned to the pixel by summing the values of the eight pixels in its neighborhood. A histogram in a small region (size 7×7) is created to collect up the occurrences of the different binary patterns.

4.2. Feature vector and K-NN classifier

The motivation for forming integrated texture features comes from the essential differences between the Gabor filter and LBP measures. The outputs of the Gabor filter can be considered to be macro-features, that is they show general, averaged differences between distinct texture regions. In contrast the LBP codes can be considered as micro-features that indicate small variations on top of the averaged intensity in each texture region. The combination of both can solve the problems of multi-texture segmentation in a low complexity scheme, especially as the optimal Gabor filter is designed beforehand. In essence our approach is to combine these features in a vector, and use a distance measure to provide multi-texture segmentation with a low complexity process.

The K-NN is one of the most popular algorithms for data classification. Given the training data $D = \{x_m^1, x_m^2, \cdots, x_m^n\}$ as a set of *n* labeled model vectors, the nearest neighbor classifier assigns a test vector $x_s \in R^d$ which is a label associated with its closest neighbors in *D*, as described by Zhang and Zhou (2005). In our case, a feature vector x_s consisting of two parts is formed from the probability distributions with *B* bins calculated from the LBP codes, and the averaged intensities within a small region of a Gabor filtered texture-image. To calculate $L(x_s, x_m^k)$, the similarity measures between the test vector x_s and the *k*th model vector x_m^k in a training set, a weighted Euclidean distance is defined as follows:

$$L(x_s, x_m^k) = \left(\sum_{i=1}^{B} | x_{si} - x_{mi}^k |^2 + \beta(x_{s(B+1)} - x_{m(B+1)}^k)\right)^{1/2} \qquad (10)$$

where x_{mi}^k and x_{si} are the *i*th component of the *k*th model vector in *D* and the *i*th component of the test vector, respectively. The vector dimension $d = B + 1$, where *B* is the number of bins in the histogram distribution derived from the LBP codes. The first *B* components of the vector therefore concern the LBP measures and the last the Gabor filter measure.

The parameter $0 < \beta < 1$ is the weighting factor for the last component of the vector. It is related to the averaged intensity in a small window of optimal Gabor filtered images and is therefore image feature or texture type dependant. It effectively controls the ratio between the influences of the two types of feature corresponding to the LBP based micro-features and the averaged intensity related macro-feature. Because of the dependence of β on the actual texture types within the image it is best determined experimentally. For any given testing vector *k*, the most similar neighbors are selected based on the Euclidean distance between the test vector and the model ones. Then the testing vector is assigned to a label *j* when more model vectors within its closest *k* neighbors belong to the *j*th class than any other.

5. EXPERIMENTAL RESULTS

5.1 IGA performance

In this section we present the experimental results of the IGA's performance with respect to its evolutionary process and its robustness as the control parameters are varied. Fig. 1(a) shows the averaged fitness in population against the number of generations for both the IGA and a GA. The GA based search is slow in the early generations, whereas the fitness of the IGA increases rapidly to almost one within just a few generations. The fast convergence of the IGA is contributed to by the memory updating based on the balanced considerations of the higher fitness and diversity of antibodies in certain generations. There is no memory unit in the GA resulting in some outstanding individuals being dropped from consideration during the evolution. Fig.1 (b) shows fitness using the best and averaged individuals for the IGA. It shows that the population in the IGA keeps its variety since the fitness between the best and averaged individuals are quite different.

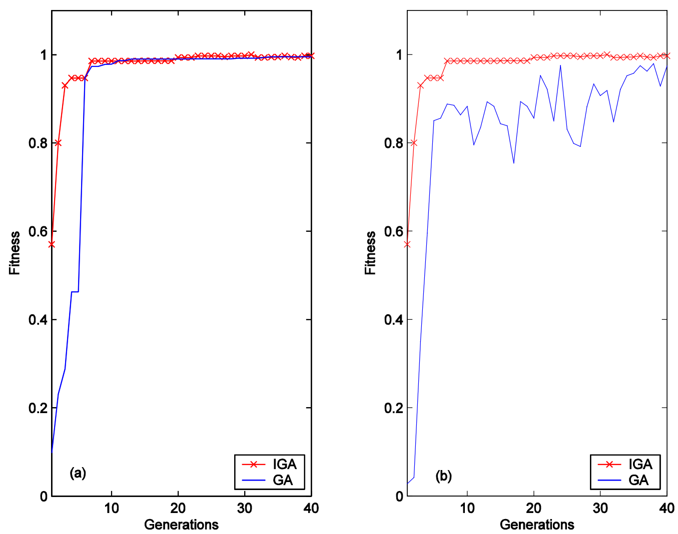

Fig.1. (a) Comparison between the evolutionary processes of the IGA and GA, (b) Fitness using the best and average individuals for the IGA

Fig.2 shows the effectiveness of crossover rate variation on the evolutionary processes in both the IGA and GA where four rates have been used in the experiments. Fig.2 (a) indicates that the GA is sensitive to the crossover rate chosen. That is, a rate of 0.3 or 0.57 results in the process becoming trapped in different local maximum, while the same rates used in the IGA demonstrated that the correct global maximum was reached as shown in Fig.2 (b). This implies that the promotion-restraint scheme in the IGA can effectively choose outstanding individuals while being robust to the rate variation.

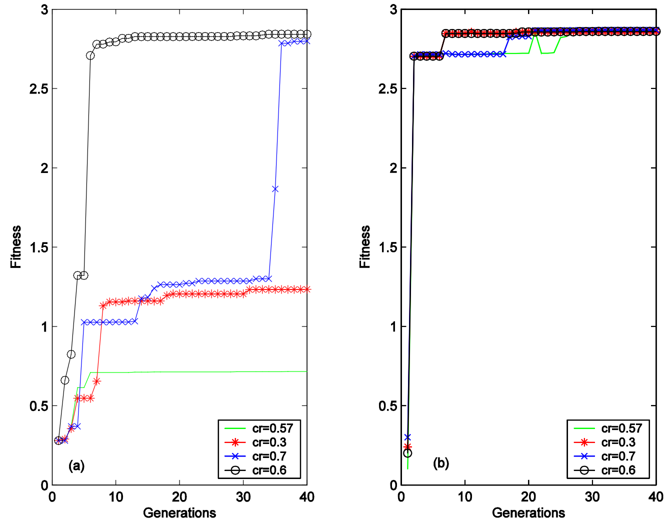

Fig. 2. Comparison of variations in crossover rate. (a) GA, (b) IGA.

5.2 Segmentation results

The experimental results for an evaluation of the proposed approach are given in Fig. 3. An original image with five distinct textures is shown in Fig. 3(a). The segmentation involved finding a single optimum Gabor filter using the IGA. This was used to filter the image. The LBP histogram (10 bins) was calculated and texture feature vectors were composed from this and the averaged intensity in a small region of the Gabor-filtered image with a window size w = 5x5 pixels. The training set for the K-NN classifier consisted of five sub-image texture samples taken from the original image shown in Fig. 3(a). Each covered 20% of the area occupied by the texture. The K-NN classification results are given in Fig.3 (b) for parameter k = 1, and Fig.3(c) for parameter k = 5. The weighting factor: β = 0.765 in eqn. (10) was chosen experimentally to give the largest distance possible between the individuals in the range of textures considered. The larger value of k has resulted in a smoother segmentation, but at the expense of a heavier computation burden. In order to further improving the performance, when k = 5, a relaxation iteration as described by Kittler and Illingworth (1985); and Raghu and Yegnanarayana (1996) was performed after the K-NN based segmentation. The result is given in Fig. 3(d).

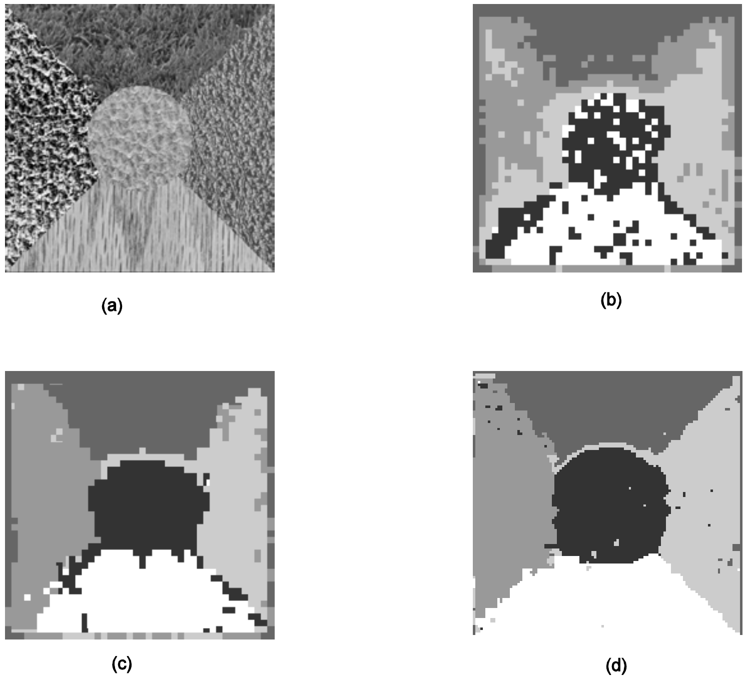

Fig. 3 Segmentation results for a five-texture image.

In Fig.4, the different feature extraction schemes have been compared to show the effectiveness of the proposed one. In each case the K-NN was used with k = 3. Fig. 4(a) shows the results when only the LBP based histogram patterns were taken as texture features. The segmentation is very poor with only part of the lower segment separated. Fig. 4(b) shows the result when only the averaged intensity from the Gabor filter output was used as the feature vector. The central segment has not been separated from the bottom segment. There are two reasons for these poor individual results:- (1) The LBP code, calculated in only a small 3x3 neighborhood, was not able to distinguish the different texture patterns. This may be improved if a larger scale LBP was used to evaluate the patterns. (2) The discrimination capacity of the averaged intensities modulated by the Gabor filter is limited for a single optimised filter. A better performance of the proposed feature formation scheme has been reached in Fig. 4(c) where both features have been integrated.

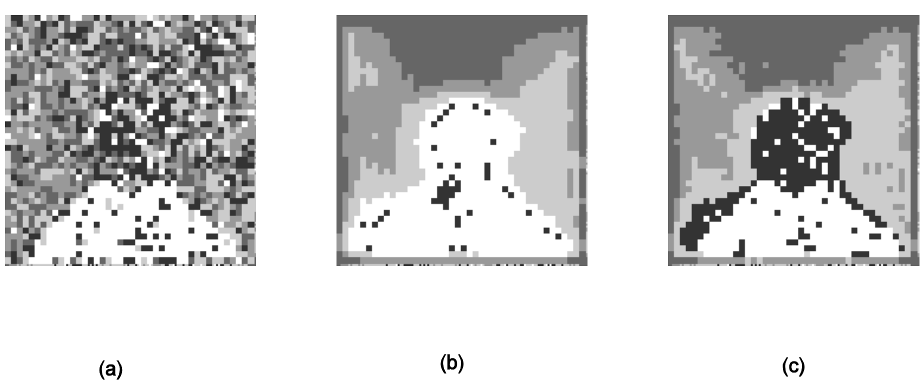

Fig.4 Segmentation comparisons using the K-NN with:- (a) LBP only, (b) Gabor filter only, (c) LBP and Gabor filter.

A further experiment was performed using our approach on a bi-textured image taken from Brodatz's book of textures (D17 and D77). This image is shown in Fig. 5(a) and the segmented image in Fig. 5(b). The two textures have been correctly identified, but one texture has dominated the central meeting point and the boundaries are not perfectly straight. A four-textured image formed by a combination of textures D11, D21, D22 and D17 is shown in Fig. 5(c). The segmentation results are given in Fig.5 (d). Again there has been some pattern leakage at the central point and some of the boundaries are not straight.

Experiments based on the proposed approach have shown that the IGA based search can be effectively applied for optimum Gabor filter design. Furthermore, integrating the LBP histograms with an optimised Gabor filter provided a novel way of extracting promising features from textured images, and improved the quality of the segmentation.

Table 1 Comparison of segmentation accuracy (%) for single and combined feature extraction algorithms

No. of texture classes	Single Gabor	LBP	Single Gabor and LBP
2	96.23	94.72	97.42
3	82.45	82.32	93.80
4	75.56	70.20	91.62
5	70.34	43.24	89.63

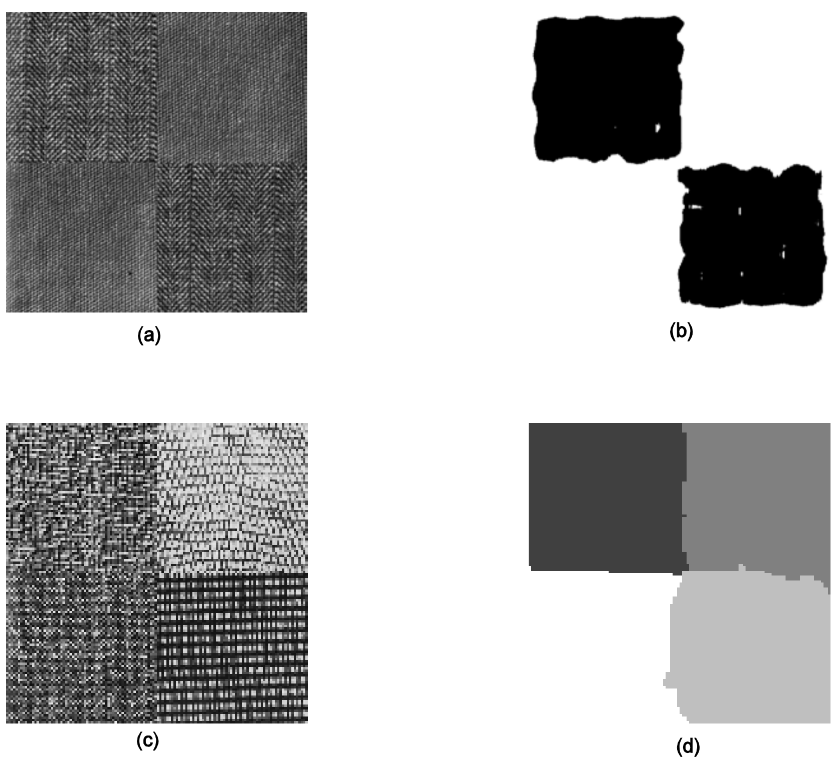

Fig.5 Segmentation results for multi-textured images constructed from Brodatz patterns

The analysis of the results in Table 1 shows the Single Gabor filter to be efficient for a small number of textured classes, but with a moderate increase to three or more, it could not discriminate texture differences reliably. A slightly poorer performance was noted for the LBP for two and three texture class images, but its performance reduced considerably for five classes. The LBP pattern-encoding scheme had a limited size of 3x3 pixels, but computed very efficiently. As with the Single Gabor filter, the LBP has poor performance in cases with many textured patterns. However by using the combination of a Single Gabor filter and the LBP, good results were obtained for images containing up to five textures.

Our combination of these two simple and easily computed classifiers has resulted in efficient, accurate segmentation. The optimised Gabor filter measures averaged intensity differences between texture regions, whereas in contrast, the LBP extracted texture pattern distributions for a small local area surrounding each pixel. We conclude the combination of these two diverse measures has resulted in a reliable classification scheme.

6. CONCLUSIONS

In this paper, a supervised approach to texture segmentation has been presented. The K-NN driven segmentation task focuses on the combination of the outputs from two texture measures. A texture sensitive indicator: a single Gabor filter, was optimized for the particular textures within an image by an IGA, which used a selection objective based on the Maxmin principle. It maximized the local Energy ratio between any two distinct texture classes. The first measure, a texture-feature component, was the intensity output from the Gabor filter averaged over a small region. The second measure was an LBP code-based probability distribution with B bins that acted on complementary texture features to that of the first measure. The measures were combined to form a fused feature vector. A procedure was applied to weight the contributions from each measure. Compared to other supervised schemes for texture segmentation, the novelty and advantages of the proposed method are as follows:- (1) The approach uses only a single Gabor filter instead of a bank of Gabor filters to reduce the computational load. The single filter can be realized because an IGA is used to select coefficients, which enable it to optimally distinguish between the taught patterns. The IGA has a higher convergence rate and is more robust to the control parameters used in the evolutionary process than the traditional GA; (2) By combining an LBP based histogram with an optimized Gabor filter, the segmentation accuracy was improved especially for cases with an increasing number of texture classes in the image.

Experiments on bi-textured, four-textured and five-textured images demonstrated the effectiveness of the methods proposed. It was verified by experiment that the fused texture-indicator that combined the optimum Gabor filtered image output and the probability distribution based on the LBP, was highly discriminating between textures. It was evident from the experiments that post-processing was still needed after the K-NN classification. In order to improve the K-NN's performance, future work will be performed to study multiscale LBP statistics, and the addition of spatial information to the similarity measure used.

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