行政院國家科學委員會專題研究計畫　期中進度報告

一個高效率之 MPEG-7 紋理瀏覽描述子的計算法及其於紋理瀏覽和紋理檢索之應用(1/2)

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中文摘要

本計畫係為二年期之計畫， 其主要目的在發展一個MPEG-7紋理瀏覽描述子的計算法， 並將之應用於紋理瀏覽和紋理檢索。一個 MPEG-7 的紋理瀏覽描述子主要包括三部分，即紋理之規律度，方向及紋理在兩個主要方向之大小。在第一年的專案中，我們已提出一個紋理粗分類法，以提供計算紋理之規律度所需之方法。我們將說明此法之中間結果可用於設計一個可應用於紋理檢索之權重法。

我們所提出的紋理粗分類法之主要觀念是基於一個事實，即屬於方向性的紋理，其傅立葉頻譜的反應值會集中在某一個方向，而屬於週期性的紋理，其頻譜的反應值會集中在某幾個方向，而隨機性的紋理，其頻譜的反應值則出現在所有方向。基於上述事實，我們對紋理影像的傅立葉頻譜進行主軸分析以判斷某紋理影像是否屬於方向性的紋理。如果此紋理影像不是方向性的紋理，則我們將紋理影像的頻譜視為一張影像，並再做一次傅立葉轉換，以得到一張加強頻譜，我們接著利用加強頻譜上能量在方向性分佈的變異數來進一步將紋理影像分類為週期性的紋理或隨機性的紋理。

關鍵詞：紋理瀏覽　紋理分類　紋理檢索 MPEG-7

Abstract

The goal of this project is to develop a computation method of MPEG-7 texture browsing descriptor and apply it to texture browsing and texture retrieval. The MPEG-7 texture browsing descriptor primarily consists of three major components: (1) the regularity of the texture, (2) the directionality of the texture, (3) the scales corresponding to the two dominant directions of the texture. To successfully compute these three components, we will develop corresponding computation methods in two years. In the first year, we have provided a coarse classification method for textures to provide the algorithms needed to determine the regularity of textures. It will also be shown that the intermediate results of the proposed method can be used to derive a weighting scheme for texture retrieval.

The proposed coarse classification method is based on the fact that for a directional texture image, the magnitudes of its Fourier spectrum will concentrate on a certain direction; for periodic, on several directions; for random, on all directions. To classify a texture image into directional or non-directional, principal component analysis is conducted on the Fourier spectrum to get the ratio of two eigenvalues, which will be used to measure the directionality of the texture image. If the texture image is not a directional one, based on enhanced Fourier spectrum, a spectral measure consists of the variance of the radial wedge distribution is then calculated to further classify the texture image as a periodic or a random one.

Keywords: Texture Browsing　Texture Classification　Texture Retrieval MPEG-7

Introduction

Texture almost presents everywhere in natural and real world images. Texture, therefore, has long been an important research topic in image processing.

Successful applications of texture analysis methods have been widely found in industrial, biomedical and remote sensing areas. In addition, the recent emerging of multimedia and the availability of large image and video archives have made content-based information retrieval become a very popular research topic. Texture is also deemed as one of the most important features when performing content-based information retrieval. Various textural features have been adopted to fulfill these applications. Since there are a lot of variations among natural textures, to achieve the best performance for texture analysis or retrieval, different features should be chosen according to the characteristics of texture images. Therefore, developing an effective method to preliminarily classify textures based on the textural characteristics will greatly help the design of a texture classification system or a content-based texture retrieval system.

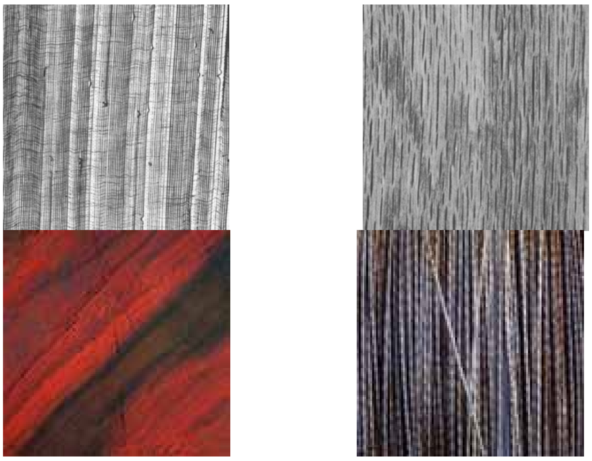
Rao and Lohse [1] had conducted a texture study based on human perception, the conclusion of their work indicates that the three most important dimensions of natural texture discrimination are periodicity, directionality, granularity and complexity. On the other hand, texture modeling based on Wold decomposition has been proposed by Francos et al. [2-3]. Wold decomposition is to decompose a 2D homogeneous random field into three mutually orthogonal components: periodicity, directionality and randomness which are consistent with the three most important dimensions of human texture perception. If texture images can be coarsely classified into these three categories, texture features can then be chosen or designed specifically for each category. To be more specific, for periodic textures, the periodic features can be extracted using methods specifically designed for periodic textures [5-6]; for random textures, MRSAR model [7] is reported to have the best performance and can be used for texture discrimination applications. The texture retrieval method proposed by Liu and Picard [4] used this idea and got a better performance. It provides a pre-classification step giving weights to the two classes of a texture image: periodic and non-periodic, the weight of each class stands for the probability that the texture image belongs to the class. Our proposed method also provides a weighting scheme for three classes: directional, periodic and random to which a texture image belongs. Thus, the proposed method provides a finer pre-classification than [4].

The properties of the Fourier spectrum of textures have been well studied [9-11], they can be summarized as follows: (1) for periodic textures, the Fourier spectrum consists of significant peaks scattering out regularly on some directions; (2) for textures with strong directionality, the directionality will be preserved in the Fourier spectrum; (3) for random textures, the distribution of the responses of spectrum are not restricted to certain directions. The proposed method is developed based on these properties, it consists of two phases: (1) directionality classification; (2) periodicity and randomness classification. In directionality classification phase, Fourier transform is first performed on the texture image to obtain its Fourier spectrum. Principal component analysis is then conducted to get two eigenvalues. If the texture image contains strong directionality, then the larger eigenvalue will be much greater than the smaller eigenvalue. Based on this phenomenon, the ratio of the larger eigenvalue to the smaller eigenvalue is used to measure the directionality of the texture image. If the texture image is not classified as a directional one, the periodicity and randomness classification phase is entered. Fourier transform is applied to the Fourier spectrum to obtain an enhanced Fourier spectrum. The enhanced Fourier spectrum has more discriminative properties in separating periodic textures from random ones than Fourier spectrum. For periodic textures, those points with high magnitude appear in some directions more clearly than those in the Fourier spectrum. Based on these properties, a discriminative measure is then provided to classify the texture image as a periodic or a random texture. Texture images from Brodatz album [8] and Corel image database are used to demonstrate the effectiveness of the proposed method. It is also shown that the intermediate results of the proposed method can be used to derive the weights used for texture retrieval.

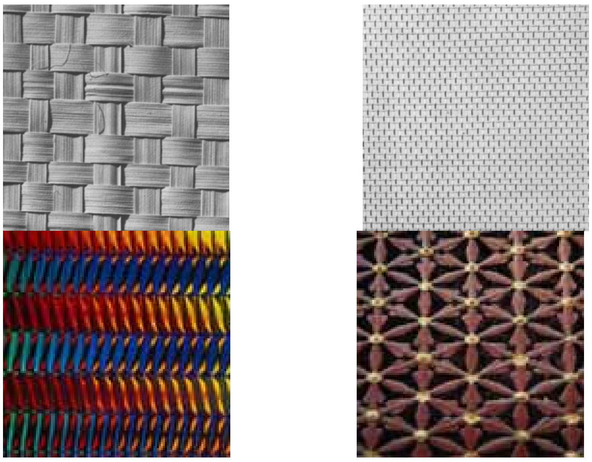
Experimental Results and Discussion

Texture images of Brodatz album and Corel Gallery image database are used to test the proposed method. To build up the Brodatz album database, eight patches for each of the 112 textures in Brodatz album are scanned and 896 texture images are obtained for experiments. 4 out of the 8 patches of each texture are used as training set to obtain the empirical values for parameters used, while the remaining images are used as testing set. To further validate the performance of the proposed method, 1896 natural color texture images from Corel Gallery image database are selected and used as testing set as well, including abstract textures, bark textures, creative textures, food textures, light textures, and other textures etc. We will report the experimental results of Brodatz database and Corel database, respectively.

To classify the texture images in the testing set into directional, periodic or random, we first classify the textures into directional or non-directional ones (step 1). Those classified as non-directional are then further classified into periodic or random (step 2). By inspecting the images in the testing set, the classification rate of each step as well as the estimated and actual classification rates are reported. The estimated classification rate is obtained by multiplying the classification rates of both steps. The actual classification rate is the total number of correctly classified images via both steps divided by the total number of images in the testing set. The classification result of Brodatz database and Corel database are summarized in Tables 1 and 2, respectively. Fig. 1 shows some examples of correctly classified directional, periodic and random texture images. Four images are shown for each category, the first two images are from Brodatz database and the latter two images are from Corel database.



(a) Some correctly classified directional textures.



(b) Some correctly classified periodic textures.

(c) Some correctly classified random textures.

Fig. 1. Some correctly classified texture images from Brodatz database and Corel database.

Table 1: The performance for the classification of Brodatz database.

	Step 1	Step 2
Step Classification Rate	99.3%	96.1%
Estimated Classification Rate	95.4%	
Actual Classification Rate	95.5%	

Table 2: The performance for the classification of Corel database.

	Step 1	Step 2
Step Classification Rate	99.8%	98.8%
Estimated Classification Rate	98.6%	
Actual Classification Rate	98.8%	

Tables 1 and 2 both show that the classification rates of step 1 (99.3% and 99.8%) are quite high, this demonstrates the effectiveness of the proposed method in discriminating directional textures from non-directional textures. Some of the misclassified textures in step 1 are shown in Fig. 2. Fig. 2(a) is a periodic texture image classified as directional. It can be noticed that although there are both vertical lines and horizontal lines present in the image, the horizontal lines are not significant enough. Thus, the high spectral pixels of its Fourier spectrum (Fig. 2(b)) form a horizontal line-like region, making it misclassified. Fig. 2(c) shows a directional texture classified as non-directional. Since there are only three classes used, we consider Fig. 2(c) as a directional texture. However, there are actually groups of straws arranged in four different directions. Therefore, its Fourier spectrum shown in Fig. 2(d) also presents four lines distributed in different directions. This makes Fig. 2(c) classified as non-directional in step 1, and in step 2, Fig. 2(c) will be further classified as periodic. This classification error is due to that too few classes are used. In fact, Fig. 2 (c) is neither directional nor periodic, it is multi-directional. Thus, to be more accurate in classifying textures, we can add additional classes named multi-directional to accommodate the diversity of natural textures. Some examples of multi-directional textures from Corel database are shown in Fig. 3.

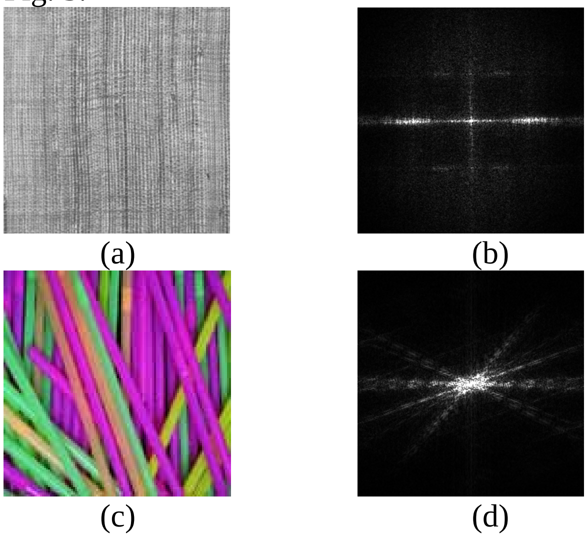


Fig. 2. Some misclassified textures and their Fourier spectra of step 1.

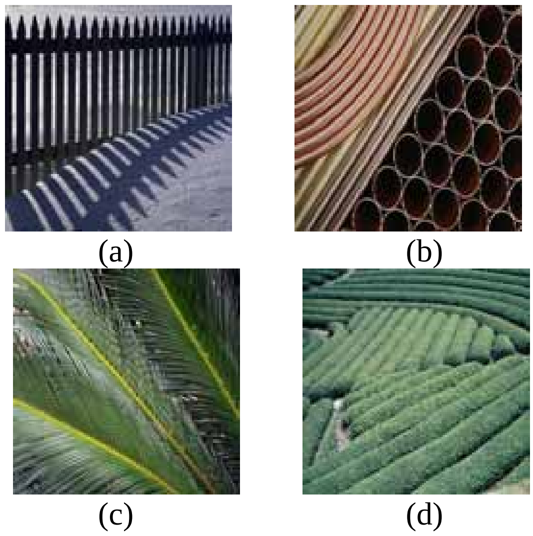
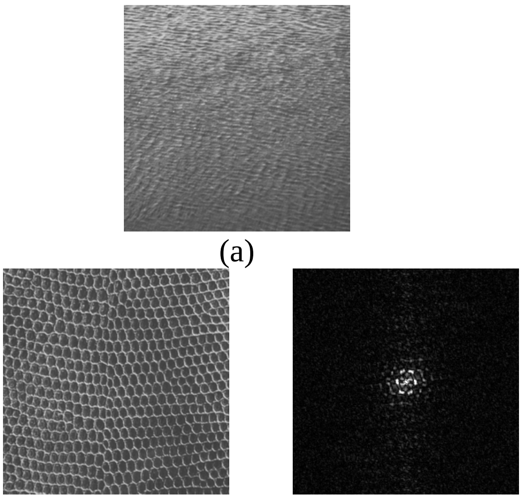


Fig. 3. Some examples of multi-directional textures from Corel database.

Similarly, some of the misclassified textures of step 2 are shown in Fig. 4. Fig. 4(a) shows a wave texture and is classified as periodic, however we consider it as a random texture. It is observed that in addition to most of the homogeneous areas, there are directional wave-like patterns present in the image. The classification error is due to that although Fig. 4(a) is not close to any class, it has to be classified to one of the three classes used. Fortunately, the class probabilities of Fig. 4(a) for periodic and random are 0.53 and 0.47, respectively. As these two probabilities are quite close, Fig. 4(a) can be considered as an ambiguous texture. In practice, all images of this kind can be considered as ambiguous. Fig. 4(b) shows a periodic texture misclassified as random. Although Fig. 4(b) is perceived to have clear directionality and some periodicity, however some local variations present and distort the directionality and periodicity. Thus, the high spectral pixels of its enhanced Fourier spectrum (Fig. 4(c)) do not concentrate at certain directions. This makes Fig. 4(b) classified as random.

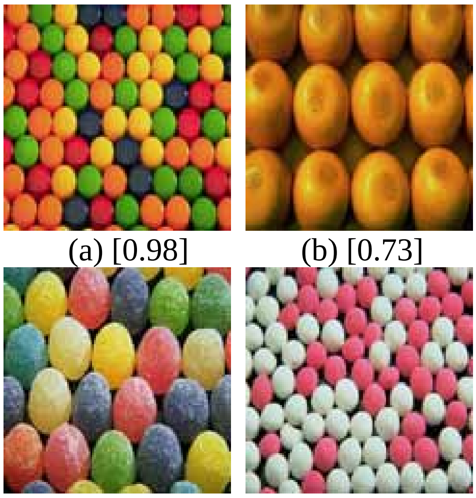


(a)

(b) (c)

Fig. 4. Some misclassified textures and their enhanced Fourier spectra of step 2.

Fig. 5 shows four textures from Corel database. They are all textures with clearly defined texture primitives but different in the regularity of displacement. The regularity of their displacements is in decreasing order from Figs. 5(a) to 5(d). The corresponding class probability for periodic is listed under each figure. These values are also in decreasing order. This reveals that the class weights calculation scheme proposed is consistent with human perception. In addition, a descriptor to measure the regularity of textures has been specified in the texture browsing descriptor of MPEG-7 [12]. The calculated periodic weight can also be used to implement this regularity descriptor.



(a) [0.98] (b) [0.73]

(c) [0.15] (d) [0.11]

Fig. 5. Four textures with clear primitives but different displacements.

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