A Fast Method for Textural Analysis of DCT-Based Image

YU-LEN HUANG
Department of Computer Science and Information Engineering
Tunghai University
Taichung, 407 Taiwan
E-mail: ylhuang@mail.thu.edu.tw

The multiresolution wavelet transform is an effective procedure in texture analysis. However, many images are still compressed by the methods based on the discrete cosine transform (DCT). Thus, decompression of the inverse DCT is required to yield the textural features based on the wavelet transform for the DCT-coded image. This investigation adopts the multiresolution reordered features in texture analysis. The proposed features are directly generated using the DCT coefficients of the encoded image. Comparisons between the subband-energy features extracted from the wavelet transform and the conventional DCT, using the Brodatz texture database, demonstrate that the proposed method offers the best textural pattern retrieval accuracy and yields a much higher classification rate. The proposed DCT features are expected to be very useful and efficient in retrieving and classifying texture patterns in large DCT-coded image databases.

Keywords: image retrieval, image database, texture analysis, content-based searching, wavelet transform, DCT coefficients

1. INTRODUCTION

Retrieving desired images according to queries from image databases is both challenging and important. With the growth of multimedia applications and the spread of the Internet, access to digital images has become effortless. Hence, image content-based retrieval is essential in digital image libraries and databases. While manual image annotation can offer some help in retrieving images, annotating large collections of digital images remains very time consuming. The accuracy of retrieval of search schemes that require human assistance is always poor because of the extensive involvement required. Thus, computer-automated approaches are being developed for image retrieval. There has been a focus on automated visual content-based approaches towards indexing images. A content-based image retrieval algorithm extracts a feature set for every image based on its pixel values and then provides a rule for comparison. Texture, color, and shape have

Received April 18, 2003; revised July 11 & September 11, 2003; accepted October 3, 2003.
Communicated by Ja-Ling Wu.

*This work was supported in part by National Science Council, Taiwan, R.O.C., under grant NSC 91-2213-E-029-021.
been utilized in many content-based approaches as features for image representation. Other features such as the spatial relationship of objects and adjacent properties of texture patterns also seem promising in image retrieval. This paper focuses on a visual content-based retrieval system. Several methods have been proposed for texture-based image retrieval, including multiresolution techniques such as wavelet transforms [1] and subband analysis [2]. Research has produced algorithms that use the multiresolution wavelet transform and perform very well in texture analysis [3-9]. In [4], the wavelet transform yields much higher classification rate and retrieval accuracy than other types of image decompositions such as discrete cosine transform (DCT) or spatial partitioning. Furthermore, several types of wavelet transform-based textural features for image retrieval are compared in [5]. These Gabor wavelet transform gives the best performance. However, the computational effort required for the Gabor wavelet transform is too high. The orthogonal wavelet transform can be efficiently computed using an FIR filter bank. That is, a lower processing complexity can be achieved by using the orthogonal wavelet transform features. The accuracy of pattern retrieval using the orthogonal wavelet transform-based features is also close to that obtained using the Gabor wavelet transform.

The DCT, which is the most effective and popular technique for image and video compression, has been adopted by most emerging image coding methods, including JPEG (Joint Photographic Experts Group) [10], H.261 [11], H.263 [12], and MPEG (Moving Picture Experts Group) [13-15]. In recent years, JPEG and MPEG have been extensively employed to compress images and thus save on storage space and reduce transmission time. All of the standards employ block-based DCT coding to give a higher compression ratio. Accordingly, DCT encoded images dominate in large image databases. In textural image annotation using wavelet transform features, the first step is to decompress the DCT-coded images into spatial images and then compute the wavelet transform features from the decompressed image data. In practice, image decompression of inverse DCT is a time-consuming task. Therefore, an efficient algorithm for extracting DCT-based textural features is necessary to reduce the computing time required by the content-based retrieval system.

In 1996, Xiong et al. [16] showed that a DCT can be coupled with an embedded zero-tree quantizer. The DCT-based embedded image coder achieved better performance than JPEG. Moreover, Jeong et al. [17] proposed a DCT-based embedded image coder designed for very low bit rate video codec. Motivated by the wavelet structure of the DCT, they rearrange the DCT transformed image into a 2-level wavelet pyramid structure and makes use of improved embedded zero-tree coding. The resulting DCT-based embedded image coder shows better rate-distortion performance than conventional H.263 and MPEG4 as well as embedded zero-tree wavelet-style coders. For the purpose of increasing the efficiency of the content-based retrieval, this paper proposes the use of DCT features for texture analysis. Comparisons with the multiresolution wavelet transform features indicate that the proposed DCT features offer the same accuracy of textural pattern retrieval without the need for decompressing the image data.

The rest of this paper is organized as follows. Section 2 describes the direct extraction of the textural features based on DCT coefficients. Comparisons with other textural features using the Brodatz texture database [18] are given in section 3. Finally, conclusions are drawn in section 4.
2. TEXTURAL FEATURE EXTRACTION IN DCT DOMAIN

In DCT-based image coding, a 2-D DCT is used to map an image into a set of DCT coefficients, which are then quantized and coded. Given an image $F(x, y)$ of size $N \times N$, the corresponding 2-D DCT coefficients are defined as

$$C(u, v) = \alpha(u, v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} F(x, y) \cos \left( \frac{(2x+1)u\pi}{2N} \right) \cos \left( \frac{(2y+1)v\pi}{2N} \right)$$

for $u, v = 0, 1, 2, \ldots, N-1$, where $\alpha$ is given by

$$\alpha(u, v) = \begin{cases} 
\frac{1}{N} & \text{for } u + v = 0 \\
\frac{\sqrt{2}}{N} & \text{for } u \times v = 0 \text{ and } u + v \neq 0 \\
\frac{2}{N} & \text{for } u \times v \neq 0 
\end{cases}$$

For a typical DCT-based coding system, the input image is first subdivided into many equally sized pixel blocks, which are then transformed to generate the blocks of DCT coefficients. Fig. 1 presents the DCT coefficients for a portion of the Lena image that is scaled to 8-bits pixel values. This work examines how to extract textural features directly from the DCT coefficients in the DCT-coded image.

![Fig. 1. (a) A portion of the Lena image and (b) the corresponding DCT coefficients generated by an $8 \times 8$ DCT.](image)

2.1 Wavelet Transform-Based Features and Conventional DCT-Based Features

For wavelet transform based features, image sub-bands can be decomposed by sequentially decomposing the LL sub-band. The LH, HL, and HH sub-bands are not further decomposed. For example, a three level decomposition should yield ten non-uniform
The retrieval of the texture pattern is generally evaluated by calculating the statistical moments of the gray-level histogram of each wavelet sub-band. Accordingly, the textural feature vector consists of the moments from each subband and is used for image classification and retrieval.

However, the image sub-bands are produced uniformly by sorting the DCT coefficients of each image block according to the conventional DCT-based features [4]. The DCT decomposition was used to produce the energy-based feature set. For example, a total of 16 uniform sub-bands are produced from a $4 \times 4$ DCT coded image. As shown in Fig. 2, the DCT coefficients within the block will be stored in 16 uniform sub-bands in a zig-zag order. The energies corresponding to each uniform sub-band are determined by calculating the moments. Although the energy-based feature sets using DCT coefficients give satisfactory retrieval performance, the texture analysis using the multiresolution wavelet transform gives a higher classification and retrieval rate [4]. However, an inverse DCT is required before calculating the textural features. The sets of features presented here are derived in the hope that they can be generated directly in the DCT domain so as to reduce processing time. The method presented yields the same high retrieval performance as that of the wavelet image decomposition.

![Uniform DCT coefficient sub-bands](image)

**Fig. 2.** Sorted coefficients of each $4 \times 4$ DCT block in zig-zag order to produce 16 uniform sub-bands.

### 2.2 Multiresolution Reordering Algorithm

Multiresolution decomposition is shown to provide information that is useful in classifying texture patterns. Thus, the DCT coefficients of each image block are reor-
dered to give image sub-bands in a multiresolution decomposition-like form. First, the
coefficients within each DCT image block must be denormalized. For example, the JPEG
denormalization for the coefficients \( T(u, v) \) within an \( N \times N \) DCT block is given by

\[
C(u, v) = [T(u, v)Z(u, v)],
\]

where \( C(u, v) \) is a denormalized coefficient and \( Z \) is an \( N \times N \) normalization array, which
is in JPEG standard. The experiments reveal that the most important information for tex-
ture classification is frequently that of the AC coefficients. In this paper, all of the AC
coefficients are reserved to yield the feature vector in the following approach. The DC
coefficient always include the lowest frequency information in each DCT block. The
mean of each block in the spatial domain can be reconstructed using the DC coefficient.
The reconstructed mean is determined by dividing the DC coefficient of each DCT block
by a constant, \( 1/N (\alpha(0, 0) = 1/N) \) and adjusting each divided coefficient by \(+128\).

The coefficients are reordered into \((3\log_2 N + 1)\) multiresolution sub-bands for the
DCT-based image with block size \( N \times N \) in order to represent the denormalized transform
coefficients in a multiresolution form. For a coefficient \( C(u, v) \), let \( 2^{a-1} \leq u < 2^{a} \) and \( 2^{b-1} \leq v < 2^{b} \), where \( a \) and \( b \) are integers. Then, the coefficient is reordered and stored in
sub-band, \( S_i \), and \( i \) is determined by

\[
i = \begin{cases} 0 & \text{for } m = 0 \\ (m-1)\times3 + \left\lfloor a/m \right\rfloor \times 2 + \left\lfloor b/m \right\rfloor & \text{otherwise,} \end{cases}
\]

where \( m = \max(a, b) \). If the coefficient, \( C(u, v) \) from the DCT block, \( B(z, w) \), belongs to
\( S_i \), then the reordered location of \( C(u, v) \) is \((z \times 2^{m-1} + u - 2^{m-1}, w \times 2^{m-1} + v - 2^{m-1})\).
For example, in the case of a DCT block of size \( 8 \times 8 \), the DCT coefficients produce ten
multiresolution sub-bands. The coefficients \( C(0, 0), C(0, 1), C(1, 0), \) and \( C(1, 1) \) of each
DCT block are stored in sub-bands \( S_0, S_1, S_2, \) and \( S_3 \), respectively, according to the reor-
dering procedure. The coefficients, \( C(0, 2), C(0, 3), C(1, 2), \) and \( C(1, 3) \) belong to \( S_i \) and
the location can be determined by the reordering location function. Similarly, sub-bands
\( S_4, S_5, S_6, S_7, \) and \( S_8 \) can be constructed from the corresponding DCT coefficients. Fig. 3
shows the construction of multiresolution sub-bands for the coefficients in a DCT block.

2.3 Textural Feature Representation

In the multiresolution wavelet transform decomposition, the mean value and the sta-
tistical moments of the gray-level histogram corresponding to each of the DCT coeffi-
cient sub-bands are used as components in the feature vector. Let \( z \) denotes a discrete
random variable representing gray-level in the range \([0, L - 1]\), and let \( p(z) \) be the nor-
malized histogram component corresponding to the \( j \)th value of \( z \), where \( j \) represent
the specific sub-band. The \( n \)th moment of \( z \) about its mean value for sub-band \( j \) is
The reordered DCT coefficient sub-bands

\[ S_0 \quad S_1 \quad S_3 \quad S_2 \quad S_4 \quad S_5 \quad S_6 \quad S_7 \]

The coefficients in a DCT Block of size 8 × 8

Fig. 3. A reordering example of an 8 × 8 DCT block.

Fig. 4. The decomposition of (a) the multiresolution wavelet transform and (b) the multiresolution reordered DCT.

\[ \mu_0(z) = \sum_{j=0}^{L-1} (z_j - m') p^j(z_j) \]  \hspace{1cm} (5)

where \( m' \) is the mean value of \( z \) for sub-band \( j \)

\[ m' = \sum_{j=0}^{L-1} z_j p^j(z_j). \] \hspace{1cm} (6)

Note from Eq. (5) that \( \mu_0 = 1 \) and \( \mu_1 = 0 \) for all subbands. The second moment \( \mu_2(z) \) is of particular importance in texture analysis. Hence, the textural feature vector is constructed...
from \( m' \) and \( \mu_j'(z) \) as feature components for sub-band \( j \). The dimension of the feature vector for the DCT-based images of block size \( N \times N \), is \( K = 2 \times (3\log_2 N + 1) \). Thus, the feature vector \( \tilde{f} \) is formed as

\[
\tilde{f} = \left[ m'^0, \mu_j^0(z), m'^1, \mu_j^1(z), m'^2, \mu_j^2(z), ..., m'^{K-1}, \mu_j^{K-1}(z) \right].
\]  

(7)

### 2.4 Measuring the Distance of Feature in Texture Classification and Pattern Retrieval

The distance measure used to compare two image texture patterns, \( p_1 \) and \( p_2 \), is defined as

\[
d(p_1, p_2) = \sum_{k=0}^{K-1} \frac{f_k^p - f_k^{p_n}}{\alpha(f_k)}.
\]

(8)

where \( \tilde{f}^p \) and \( \tilde{f}^{p_n} \) are the feature vectors of \( p_1 \) and \( p_2 \), respectively. The term, \( \alpha(\tilde{f}_k) \), is the standard deviation of the respective features in the image database and is employed to normalize the feature components. Fig. 5 presents a diagram of the texture pattern retrieval scheme using the proposed multiresolution reordered DCT features.

![Fig. 5. Textural pattern retrieval using the proposed multiresolution reordered DCT features.](image)

### 3. SIMULATION RESULTS

The image database used here includes 112 texture images from the Brodatz Album [18]. Both the texture classification and results of pattern retrieval are obtained using the
same image database. The orthogonal wavelet transform uses 16-tap Daubechies wavelets [1] as the filter to complete the three level wavelet decomposition and then produce ten wavelet sub-bands. The size of the DCT image blocks in the simulations is $8 \times 8$. Thus, the proposed multiresolution reordered DCT generates ten DCT coefficient sub-bands. We first compare the computation time of textural analysis using a traditional procedure (apply the $8 \times 8$ inverse DCT first and then use the wavelet decomposition) and the proposed method. All simulations are made on a single-CPU Intel Pentium III 1GHz personal computer running Windows XP. Table 1 shows the average computation time for texture analysis of a $512 \times 512$ gray-scale image. The computation time of the traditional procedure is 170 times longer than that of the proposed method.

<table>
<thead>
<tr>
<th>Phase of inverse DCT</th>
<th>Phase of Wavelet analysis</th>
<th>Phase of Multiresolution reordering</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional procedure</td>
<td>2.814</td>
<td>1.632</td>
<td>-</td>
</tr>
<tr>
<td>The proposed method</td>
<td>-</td>
<td>-</td>
<td>0.025</td>
</tr>
</tbody>
</table>

### 3.1 Texture Classification

The 112 texture classes in the Brodatz collection are employed in the texture classification experiments. Each of the $512 \times 512$ images is divided into 20 randomly positioned textures. A total of 2240 texture sub-images are used. Ten training sets of different sizes are used for comparison. For the training set $T_i$ ($i = 1, 2, 3, \ldots, 10$), ten texture sub-images are arbitrarily selected from each textual class. The remaining ten texture sub-images from each class are used as a test set. For the orthogonal wavelet transform (OWT) and the multiresolution reordered DCT subband (MRDCT) decompositions, the 20-term feature vectors for each textural class are generated by averaging the feature vectors that belong to that textural class. The classification performance of three feature components with different dimensions (8, 14, and 20) is compared for the OWT and MRDCT. Both the OWT-8 and MRDCT-8 features use the lowest four frequency sub-bands ($S_0, S_1, S_2$, and $S_3$) to give feature vectors of length 8 ($4 \times 2$). Likewise, the OWT-14 and MRDCT-14 generated the 14 ($7 \times 2$) term feature vectors using sub-bands $S_0, S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}$, and $S_{13}$. The OWT-20 and MRDCT-20 use all the sub-bands to generate feature vectors. Fig. 6 and Table 2 present the classification performance of the energy-based feature sets. In these experiments, the best classification was obtained using the proposed DCT feature sets.

### 3.2 Pattern Retrieval

Each of the $512 \times 512$ images is further divided into 16 non-overlapping $128 \times 128$ sub-images for pattern retrieval simulations. Thus, 1792 texture images are generated. The test texture patterns in the following simulations are arbitrarily selected from the
Fig. 6. Classification performance according to training texture cuts per class.

Table 2. Correct classification percentage according to training class size for 112 Brodatz textural classes.

<table>
<thead>
<tr>
<th>Training texture cuts per class</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRDCT-20</td>
<td>72.59%</td>
<td>78.13%</td>
<td>80.45%</td>
<td>82.50%</td>
<td>83.13%</td>
<td>84.11%</td>
<td>84.55%</td>
<td>84.38%</td>
<td>84.02%</td>
<td>84.02%</td>
</tr>
<tr>
<td>MRDCT-14</td>
<td>67.14%</td>
<td>74.29%</td>
<td>75.09%</td>
<td>77.41%</td>
<td>77.95%</td>
<td>78.66%</td>
<td>78.93%</td>
<td>79.55%</td>
<td>79.29%</td>
<td>79.73%</td>
</tr>
<tr>
<td>MRDCT-8</td>
<td>54.29%</td>
<td>59.11%</td>
<td>60.98%</td>
<td>62.95%</td>
<td>63.21%</td>
<td>64.91%</td>
<td>64.11%</td>
<td>65.45%</td>
<td>65.45%</td>
<td>65.63%</td>
</tr>
<tr>
<td>OWT-20</td>
<td>55.63%</td>
<td>67.05%</td>
<td>71.61%</td>
<td>74.64%</td>
<td>76.52%</td>
<td>79.20%</td>
<td>80.27%</td>
<td>80.09%</td>
<td>81.43%</td>
<td>80.54%</td>
</tr>
<tr>
<td>OWT-14</td>
<td>48.48%</td>
<td>58.57%</td>
<td>64.64%</td>
<td>69.46%</td>
<td>70.63%</td>
<td>73.21%</td>
<td>73.57%</td>
<td>73.11%</td>
<td>75.63%</td>
<td>75.63%</td>
</tr>
<tr>
<td>OWT-8</td>
<td>44.02%</td>
<td>52.23%</td>
<td>55.98%</td>
<td>60.54%</td>
<td>62.77%</td>
<td>65.45%</td>
<td>65.54%</td>
<td>65.98%</td>
<td>67.68%</td>
<td>68.57%</td>
</tr>
</tbody>
</table>

1792 texture images. The three image decompositions that are used to produce the feature vectors are compared. They are the OWT sub-band, the conventional DCT sub-band (CDCT), and the proposed MRDCT sub-band. Notably the coefficients of the conventional DCT are sorted in zig-zag order to give 64 sub-bands and thus generate feature vectors. The feature vectors of the test query patterns, $p_q$, are produced by following the three methods. The distance measure, $d(p_q, p_i)$ is determined for each texture image in the database, where $p_i$ is a query texture from the database. The retrieved texture images are ordered by increasing distance from the test pattern. The ideal situation for retrieval is that the top 15 matches are from a single large texture image. The performance is evaluated in terms of the average correct retrieval rate, which is defined as the average percentage of patterns that belong to the same Brodatz image (not including the query pattern) as the query pattern. The query pattern is always the top one because its distance is zero.

In order to show that the proposed MRDCT can produce a good texture feature set. The comparison of the energy-based feature sets was made by using feature vectors of identical length. In the simulations, the five texture images from each texture class were
randomly selected and utilized as the test patterns. Fig. 7 (a) presents the retrieval performance as a function of the number of patterns retrieved at a fixed feature vector length 20 ($10 \times 2$), for the various textural features. In conventional DCT features, only the first ten sub-bands of the 64 conventional DCT sub-bands are used to generate a $10 \times 2$ component feature vector (denoted CDCT-20) for comparison. For example, for the MRDCT features, retrieving the top 50 patterns retrieves, on average, 87.2% (that is, over 13 out

![Graph](image1)

(a)

![Graph](image2)

(b)

![Graph](image3)

(c)

Fig. 7. Retrieval performance according to the number of top matches considered, (a) length of feature vector is 20, (b) CDCT feature vectors with different lengths, and (c) OWT and MRDCT feature vectors with different lengths.
of 15) of the correct textures. Using of the proposed features can be observed to yield a higher accuracy of retrieval than the orthogonal wavelet transform in most cases. Moreover, the accuracy of retrieval is compared using the MRDCT features and the CDCT feature vector of lengths 20, 32, 64, and 128. Fig. 7 (b) indicates that the MRDCT features also offer better retrieval performance than those of the CDCT using a higher dimension feature vector. Fig. 7 (c) shows the retrieval results using the OWT and the proposed method for the three different dimensions of the feature vector. Table 3 presents complete simulation results of pattern retrieval. The results indicate that the proposed method performs very well in retrieving texture patterns. Fig. 8 (a) offers an example of a texture-based image retrieval application, using the MRDCT features. Figs. 8 (b) and (c) show examples of the retrieval of OWT-20 and RMDCT-20, respectively.

Fig. 8. (a) An example of a texture-based retrieval application. Examples of pattern retrieval using (b) the OWT features (retrieval rate is 80%, i.e., 12 out of 15) and (c) the MRDCT features (retrieval rate is 87%, i.e., 13 out of 15). The query image is D3: Reptile skin, and the top 15 matches are shown in the order with increasing distance.
Fig. 8. (Cont’d) (a) An example of a texture-based retrieval application. Examples of pattern retrieval using (b) the OWT features (retrieval rate is 80%, i.e., 12 out of 15) and (c) the MRDCT features (retrieval rate is 87%, i.e., 13 out of 15). The query image is D3: Reptile skin, and the top 15 matches are shown in the order with increasing distance.

<table>
<thead>
<tr>
<th>Query pattern</th>
<th>D3_1</th>
<th>D3_7</th>
<th>D3_5</th>
<th>D3_15</th>
<th>D3_3</th>
<th>D3_13</th>
<th>D3_0</th>
</tr>
</thead>
<tbody>
<tr>
<td>distance=3.28</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance=3.73</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=4.26</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=4.40</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=4.73</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=5.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=5.33</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=5.38</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=5.56</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D3_9</td>
<td>D3_6</td>
<td>D3_2</td>
<td>D3_12</td>
<td>D3_11</td>
<td>D3_14</td>
<td>D80_2</td>
<td>D97_13</td>
</tr>
<tr>
<td>distance=5.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D3_6</td>
<td>D3_2</td>
<td>D3_12</td>
<td>D3_11</td>
<td>D3_14</td>
<td>D80_2</td>
<td>D97_13</td>
<td></td>
</tr>
<tr>
<td>distance=6.31</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D3_12</td>
<td>D3_11</td>
<td>D3_14</td>
<td>D80_2</td>
<td>D97_13</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=6.58</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D3_11</td>
<td>D3_14</td>
<td>D80_2</td>
<td>D97_13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=6.61</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D3_14</td>
<td>D80_2</td>
<td>D97_13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=6.88</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D80_2</td>
<td>D97_13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance=6.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D97_13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Retrieval performance of various feature sets.

<table>
<thead>
<tr>
<th>Number of top matches considered</th>
<th>15</th>
<th>20</th>
<th>30</th>
<th>40</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>80</th>
<th>90</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>OWT-8</td>
<td>43.45%</td>
<td>50.48%</td>
<td>61.01%</td>
<td>66.25%</td>
<td>70.30%</td>
<td>73.51%</td>
<td>76.31%</td>
<td>78.93%</td>
<td>80.65%</td>
<td>82.02%</td>
</tr>
<tr>
<td>OWT-14</td>
<td>53.93%</td>
<td>61.49%</td>
<td>71.19%</td>
<td>76.67%</td>
<td>79.94%</td>
<td>82.62%</td>
<td>84.94%</td>
<td>86.55%</td>
<td>88.27%</td>
<td>89.64%</td>
</tr>
<tr>
<td>OWT-20</td>
<td>63.57%</td>
<td>68.45%</td>
<td>78.69%</td>
<td>83.10%</td>
<td>85.89%</td>
<td>87.62%</td>
<td>89.82%</td>
<td>90.95%</td>
<td>92.20%</td>
<td>92.92%</td>
</tr>
<tr>
<td>MRDCT-8</td>
<td>48.39%</td>
<td>53.93%</td>
<td>63.39%</td>
<td>69.64%</td>
<td>73.57%</td>
<td>76.79%</td>
<td>78.81%</td>
<td>80.65%</td>
<td>82.20%</td>
<td>83.51%</td>
</tr>
<tr>
<td>MRDCT-14</td>
<td>62.74%</td>
<td>68.39%</td>
<td>77.32%</td>
<td>80.95%</td>
<td>84.29%</td>
<td>87.08%</td>
<td>88.69%</td>
<td>89.70%</td>
<td>90.71%</td>
<td>91.67%</td>
</tr>
<tr>
<td>MRDCT-20</td>
<td>70.60%</td>
<td>75.42%</td>
<td>79.82%</td>
<td>83.81%</td>
<td>86.37%</td>
<td>88.93%</td>
<td>90.48%</td>
<td>91.55%</td>
<td>92.20%</td>
<td>92.68%</td>
</tr>
<tr>
<td>DCT-20</td>
<td>61.07%</td>
<td>67.20%</td>
<td>74.64%</td>
<td>78.39%</td>
<td>81.67%</td>
<td>83.45%</td>
<td>84.88%</td>
<td>86.85%</td>
<td>88.10%</td>
<td>89.05%</td>
</tr>
<tr>
<td>DCT-32</td>
<td>65.24%</td>
<td>70.42%</td>
<td>77.74%</td>
<td>81.31%</td>
<td>83.51%</td>
<td>84.94%</td>
<td>86.01%</td>
<td>87.32%</td>
<td>88.27%</td>
<td>89.17%</td>
</tr>
<tr>
<td>DCT-64</td>
<td>68.87%</td>
<td>73.27%</td>
<td>80.30%</td>
<td>83.51%</td>
<td>85.06%</td>
<td>87.02%</td>
<td>88.15%</td>
<td>89.23%</td>
<td>90.30%</td>
<td>90.83%</td>
</tr>
<tr>
<td>DCT-128</td>
<td>69.65%</td>
<td>74.10%</td>
<td>81.01%</td>
<td>83.62%</td>
<td>85.63%</td>
<td>87.81%</td>
<td>89.52%</td>
<td>90.65%</td>
<td>91.13%</td>
<td>91.84%</td>
</tr>
</tbody>
</table>

4. CONCLUSIONS

This paper examines texture-based classification and image retrieval for DCT compressed images using energy-based features derived from wavelet transforms and DCT decompositions. The multiresolution wavelet transforms have been shown to yield a high retrieval rate with a lower feature dimensionality. However, the textural features are produced following DCT decompression and wavelet decomposition. Hence, a texture-based analysis was proposed for extracting textural features directly from the DCT coefficients. The classification and retrieval performances of the presented method are very close to those of the conventional wavelet transform for a specified feature dimen-
sion. The MRDCT features were also shown to give better retrieval performance than the conventional DCT method when larger feature dimensions were used. The experimental results reveal that the proposed MRDCT features should be very useful and efficient in textural pattern retrieval in a large DCT coded image database. Future work will extend the proposed method to real image and video database applications.

REFERENCES

Yu-Len Huang (黃育仁) was born in Chiayi, Taiwan, on May 22, 1970. He received the B.S. degree in Computer Science from Tunghai University, Taiwan, R.O.C., in 1990, and the M.S. and Ph.D. degrees in Computer Science and Information Engineering from National Chung Cheng University, Taiwan, R.O.C., in 1994 and 1999. He is currently an Assistant Professor in the Department of Computer Science and Information Engineering, Tunghai University, Taiwan, R.O.C. His research interests include digital image/video coding, neural networking, computer networking, and medical imaging. Dr. Huang is a member of IEEE and Phi Tau Phi.