# Combining Hadamard matrix, discrete wavelet transform and DCT features based on PCA and KNN for image retrieval

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**ABSTRACT:**
Image retrieval is one of the most applicable image processing techniques, which have been used extensively. Feature extraction is one of the most important procedures used for interpretation and indexing images in content-based image retrieval (CBIR) systems. Reducing the dimension of feature vector is one of the challenges in CBIR systems. There are many proposed methods to overcome these challenges. However, the rate of image retrieval and speed of retrieval is still an interesting field of research. In this paper, we propose a new method based on the combination of Hadamard matrix, discrete wavelet transform (HDWT2) and discrete cosine transform (DCT) and we used principal component analysis (PCA) to reduce the dimension of feature vector and K-nearest neighbor (KNN) for similarity measurement. The precision at percent recall and ANR are considered as metrics to evaluate and compare different methods. Obtaining results show that the proposed method provides better performance in comparison with other methods.

**KEYWORDS:** Content-based image retrieval (CBIR), Hadamard matrix and discrete wavelet transform (HDWT2), discrete cosine transform (DCT).

## 1. INTRODUCTION

Content based image retrieval (CBIR) techniques are one of the most applicable and increasingly important topics in multimedia information systems [1]. An important building block in an image retrieval system is image indexing. Image Indexing is known as characterization of images based on some features of images [2]. Feature extraction is one of the most important procedures used for interpretation and indexing images in CBIR systems [3]. There are many proposed methods and approaches for classification, indexing, searching and retrieval of visual information based on analysis of low-level image features, like color, texture, shape, etc. [3].

Effective storage, transmission, indexing and managing a large number of image collections is a serious challenge in computer systems [4]. Recently, these challenges have been studied on different image databases and attempted to solve the problem in computer vision [5], and image processing [6]. The main goal of researchers in this field is to find the procedures to collect a desired image in a large and varied collection of image databases. Traditional problem of image indexing methods has led to the rise of interest in methods for retrieving images based on automatically derived features such as color, texture, and shape, which are known as CBIR [7]. Nowadays, CBIR technology is known as a form of commercial products such as QBIC and Virage [6] in the marketplace. However, because of some practical issues like, absence of hard evidence on the effectiveness of CBIR, this technology has not been used on the significant scale. Many CBIR technology applications have been identified [6]. Medical, industrial, and internet applications are some important examples of the applications. Nowadays, color, texture, or shape features are intensively used in image indexing. The combination of these features also showed more efficient performance in image retrieval [6]. Texture and color features are absolutely easy for computing similarity.

In this paper, we have combined color and texture features, because some CBIR systems have combined texture and color features to get better performance and automatically retrieved relevant images from large image databases [8]. We define the average of red, green, and blue planes as Intensity plane and red, green, and blue planes as RGB planes. Then, we have extracted some texture features from Intensity and RGB planes, separately. There are many different methods that have been proposed to describe image texture. Texture analysis methods are divided into four categories: signal processing, model-based, geometrical, and statistical introduced by Tuceryan and Jain [9]. We have only used signal processing method for extracting the texture feature because signal processing shows better performance than other methods [9]. Texture features are unable to help so much in image discrimination, specially, for too fine or too coarse cases. The size of feature vectors and speed of retrieval are important aspects in performance of image retrieval. In this paper, a novel method for image retrieval is proposed by using Hadamard matrix [10,11], discrete wavelet transform [12] (HDWT2), discrete cosine transform (DCT), and we apply principal component analysis (PCA) [13] to reduce the dimension of feature vector and K-nearest neighbor (KNN) [14,15] for similarity measurement. Then the proposed system is applied in three databases, and the performance of the proposed system is compared with different methods.

This paper has been organized as follows. In section 2, the proposed image retrieval system has been explained step by step. Section 3 details the experimental results. In section 4, the conclusions have been drawn.

## 2. THE PROPOSED CBIR SYSTEM

The most important part in CBIR system is the extraction of image features, which has the task of generating feature vector of each image from the databases, and representing the content of image, accurately [8]. The size of feature vectors must be extremely smaller than the primary image. Therefore, small vector size increases speed of retrieval and reduces storage memory. The proposed CBIR system is conceptually described by the framework depicted in Figure 1.

In this method, we divide image databases to train and test parts. Then, all images are resized to 256×256×3 and Intensity plane with size of 256×256 is generated by averaging from red, green, and blue planes and RGB planes with size of 256×256 are constructed by considering red, green, and blue planes, separately.

### 2.1. Feature extraction

We combine Hadamard matrix, discrete wavelet transform (HDWT2) (see section 2.1.1) and DCT (see section 2.1.2) to extract texture features of each plane, and to construct the feature vector.

#### 2.1.1. HDWT2 feature extraction

The flowchart of HDWT2 method is represented in figure 2, and the steps are represented as follows:

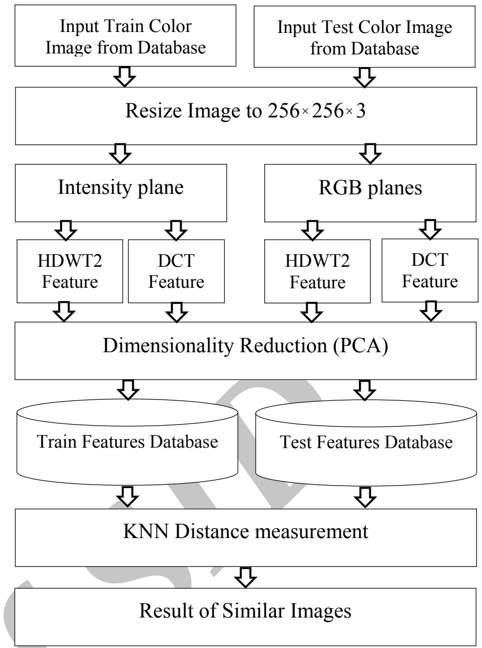


**Fig. 1**. Block diagram of the proposed CBIR system.

Step 1: Applying wavelet transform on the each RGB and Intensity planes separately with size of N×N to generate approximation (Low-Low), horizontal (Low-High), vertical (High-Low), and diagonal (High-High) components. We used approximation and diagonal components for next step because wavelet transform analyses the signal at various frequency bands giving higher frequency resolution and lower time resolution at lower frequencies, lower frequency resolution, and higher time resolution at higher frequencies [16].

Step 2: Construction of modified approximation and diagonal components by multiplying approximation and diagonal components and Hadamard matrix with size of approximation component. Hadamard matrices are square matrix whose entries are either +1 or −1 and whose rows are mutually orthogonal [11]. Furthermore, Hadamard can be reduced to subtraction and addition operations (no division or multiply) [11]. This allows the use of simpler hardware to calculate the transform and increases speed of retrieval due to low complexity.

Step 3: Construction of the modified plane from step 2 by applying inverse wavelet transform with modified approximation and diagonal components, zeroing horizontal, and vertical components. New image is constructed by using inverse wavelet whereas some information is disappeared due to removing horizontal and vertical components. We need a new image in next level to construct the new approximation and diagonal components.

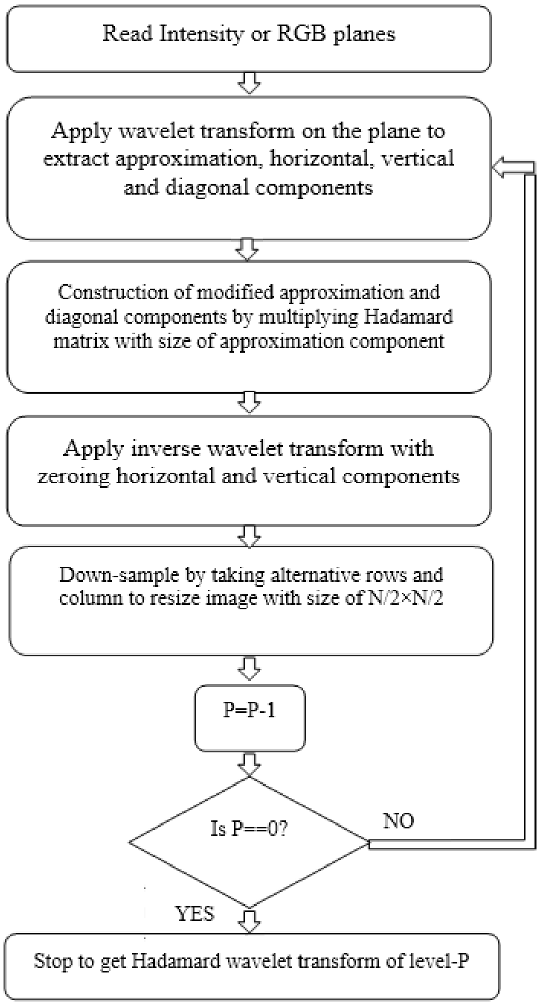


**Fig. 2.** Generating HDWT2 feature level-p.

Step 4: To take alternative rows and columns by down-sampling the output of step 3 with size of N/2×N/2. Down-sampling reduces the size of feature vector, which is very important for increasing speed of retrieval.

Step 5: To construct HDWT2 feature of the level-p by repeating steps 2 to 4, 'P' times on each plane.

Step 6: Using approximation and diagonal components of the level-p of step 2 as HDWT2 feature of the level-p.

Since the level-5 of discrete wavelet transform method has proper size of feature vector, and provides better performance in comparison with other wavelet levels, this level has been considered. Also, in this method, we consider approximation and diagonal components level-5 of step 2 as HDWT2 feature of each plane, and store this feature as the feature vector of planes.

### 2.1.2. Discrete Cosine Transform (DCT) feature extraction

The flowchart of DCT method is shown in Figure 3, and the steps are represented as follows:

Step 1: Resizing each image to size of 36×36.

Step 2: Applying DCT in the output of step 1. DCT is a fast transform. It is a robust method, and it is widely used for image compression. It has excellent compaction for highly correlated data. DCT gives a good compromise between information packing ability and computational complexity [17].

Step 3: Dividing the output of step 2 to 36 blocks.

Step 4: Using the first block as the DCT feature vector.

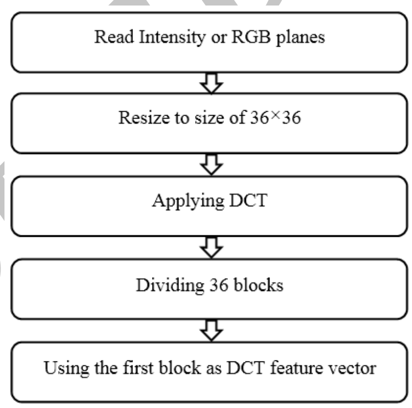


**Fig. 3.** Generating DCT feature.

Feature vectors of each image databases are constructed by using (1) as shown as in below:

$$FV = [\mathit{HDWT2\text{-}Intensity\ level\text{-}5,\ HDWT2\text{-}RGB\ leval\text{-}5,\ DCT\text{-}Intensity,\ DCT\text{-}RGB}] \quad (1)$$

### 2.2. Dimensionality reduction

We reduce the size of feature vector by applying PCA in feature vector and store these features as feature vectors for each image. Because PCA is one of the most applicable techniques for dimension reduction, which utilizes orthogonal transformation to convert a set of correlated variables into set of linearly uncorrelated variables [13]. De-noising and saving the principal component of image for large databases and linear dimension reduction are some of the advantages of PCA [13]. The reduction in the dimension of feature vectors of image results into the reduction of storage memory, and also, increases the speed of retrieval, which we use in the proposed system.

### 2.3. Similarity measurement

Similarity measurement is the other important part of CBIR systems. This part computes distance between the query image and each image of database by using feature vectors of query image and each image of the database to obtain similar images. Train and test feature database are inputs of KNN measurement. General classifiers, which have been widely used are: Bayes, KNN, LLSF, SVM, and so on [14]. KNN is based on eigenvector spatial model and provides better application results with easy realization [14]. Provided that the number of training samples is large enough, this simple rule exhibits good performance [15].

The proposed method has reduced the size of feature vector and therefore, it has reduced the computation time extremely and gives better precision and recall values. The reasons for reducing the computation time and complexity are using PCA for dimensionality reduction and KNN classifier for distance measurement. KNN has classified train and test. Then, the result of similar images is shown. Then, relevant images are retrieved by comparing feature vectors databases.

## 3. EXPERIMENTAL RESULTS

### 3.1. Evaluation measures

We have compared performance of the proposed method with two evaluation metrics.

a. The normalized rank is a performance measure used to summarize system performance into a scalar value. The normalized rank for a given image ranking $\Omega_{\alpha}^{i}$, denoted as Rank( $\mathrm{H}_{\alpha}$ ), is defined as

$$\mathrm{Rank}(\mathrm{H}_{\alpha})=\frac{1}{\mathrm{NN}_{\alpha}}\left(\sum_{i=1}^{\mathrm{N}_{\alpha}}\Omega_{\alpha}^{i}-\frac{\mathrm{N}_{\alpha}\left(\mathrm{N}_{\alpha}-1\right)}{2}\right) \tag{2}$$

where N is the number of images in the dataset, $\mathrm{N}_{\alpha}$ is the number of relevant images for the query $\mathrm{H}_{\alpha}$, and $\Omega_{\alpha}^{i}$ is the rank in which the i[th] image is retrieved. This measure is 0 for perfect performance and approaches to 1 as performance worsens, where 0.5 is equivalent to a random retrieval [18]. The average normalized rank (ANR) for the full dataset is given by

$$ANR=\frac{1}{N}\sum_{\alpha=1}^{N}Rank(H_{\alpha}) \tag{3}$$

b. Precision and recall are used for evaluating the most CBIR system. Precision is the fraction of the returned images that are relevant to the query. Recall is the fraction of returned relevant images with respect to the total number of relevant images in the dataset according to a priori knowledge. If we denote T the set of returned images and R the set of all images relevant to the query, then the precision and recall criteria are given by using (4) and (5), respectively [18].

$$\mathrm{Precision}=\frac{|T\cap R|}{|T|} \tag{4}$$

$$\mathrm{Recall}=\frac{|T\cap R|}{|R|} \tag{5}$$

Furthermore, we used various methods to evaluate the proposed system. Reference [19] has proposed a method using the combination of precision and recall criteria as performance measures for CBIR systems. According to [19], the following measures have been adopted:

- P (1/3), precision at 33.33% recall (i.e. precision after retrieving 1/3 of the relevant documents)
- P (2/3), precision at 66.66% recall(i.e. precision after retrieving 2/3 of the relevant documents)

We use these values because precision and recall are to be considered in relation to each other, and they are not meaningful if taken separately.

### 3.2. Databases

In order to evaluate the proposed method in image retrieval, we consider three different databases: i) Corel database [20] including 1000 variable size images which images classified in 11 classes of human being, horse, elephant, flower, bus, manmade thing, and natural scenery. ii) The Amsterdam Library of Object Images [21] (ALOI) database, including 72000 variable size images in 1000 classes. iii) MPEG-7 database [22] including 1400 variable size images in 70 classes. The MPEG-7 is a difficult database for color-based image retrieval. Instead of objects, its images composed of photos and sequences of video frames. Also, we are only used photos part of each image. All classes in each dataset are well balanced. We have tried to collect diverse databases to evaluate the proposed method. As described in previous sections, all images' features in every database are extracted using the proposed method and feature vectors of train and test images are constructed. Then, PCA is applied on feature vectors, and KNN classifier is used as similarity measurement.

### 3.3. Indexing results

In this section, we represent the results of the proposed method in three databases and compare the proposed method with different methods. P(1/3) and P(2/3) metrics are obtained for comparing and evaluating the proposed method with different levels of Intensity-Haar wavelet [23], RGB-Haar wavelet [23], Intensity-HDWT2, RGB-HDWT2, Intensity-DCT, RGB-DCT, color layout descriptor (CLD) [24], dominant color descriptor (DCD) [25,26], scalable color descriptor (SCD) [26], and Padua Point (PP) [19]. Size of feature vector and the results of each metrics are shown in Table 1, 2 and 3. The best scores for each metric are highlighted for each table. In each table, it is obvious that leve-5 of Intensity-Haar wavelet, RGB-Haar wavelet, Intensity-HDWT2, RGB-HDWT2 methods have higher performance rates than other levels in comparison with the others wavelet method. Furthermore, RGB methods are better than Intensity methods.

The test results on the Corel database have been shown in Table 1. In this experiment, Intensity-HDWT2 and RGB-HDWT2 are better performance than other wavelet methods. The best performance rate that we obtain is 60.44% and ANR = 0.199 from the proposed method, which is a very respectable value for this database regarding the size and complexity. In comparing performance, after the proposed method, CLD with P(1/3)=54.46% and RGB-DCT with P(1/3)=51.15% are better than other methods. However, the size of the feature vector of CLD and the proposed methods are 12 and 40, respectively, but the proposed method has better performance (more than 6%) than CLD method. Obtaining results show that with considering performance rate and size of the feature vectors, the proposed method scores extremely well.

**Table 1.** Size of feature vector, P(1/3) and P(2/3) of different methods on the Corel databases.

| Type | Level | Size of feature vector | ANR | P(1/3) | P(2/3) |
|---|---|---|---|---|---|
| Intensity-Haar wavelet | 1 | 32768 | 0.236 | 36.21% | 29.43% |
| | 3 | 2048 | 0.235 | 39.64% | 32.27% |
| | 5 | 128 | 0.232 | 40.91% | 32.97% |
| | 7 | 8 | 0.240 | 32.73% | 27.52% |
| RGB-Haar wavelet | 1 | 3×32768 | 0.232 | 45.32% | 37.56% |
| | 3 | 3×2048 | 0.229 | 47.03% | 38.39% |
| | 5 | 3×128 | 0.225 | 48.61% | 39.18% |
| | 7 | 3×8 | 0.235 | 42.42% | 34.73% |
| Intensity-HDWT2 | 1 | 32768 | 0.234 | 40.32% | 32.78% |
| | 3 | 2048 | 0.232 | 43.88% | 36.79% |
| | 5 | 128 | 0.230 | 44.94% | 37.76% |
| | 7 | 8 | 0.238 | 34.42% | 29.76% |
| RGB-HDWT2 | 1 | 3×32768 | 0.232 | 43.22% | 35.66% |
| | 3 | 3×2048 | 0.228 | 45.97% | 37.36% |
| | 5 | 3×128 | 0.224 | 47.85% | 38.39% |
| | 7 | 3×8 | 0.234 | 40.03% | 32.42% |
| Intensity-DCT | - | 36 | 0.225 | 49.45% | 40.57% |
| RGB-DCT | - | 3×36 | 0.223 | 51.15% | 41.66% |
| CLD | - | 12 | 0.219 | 54.46% | 39.06% |
| DCD | - | 32 | 0.243 | 47.03% | 37.58% |
| SCD | - | 11×121 | 0.316 | 50.58% | 34.85% |
| Proposed-Method | - | 40 | 0.199 | 60.44% | 52.24% |
| PP-30 | - | 496 | 0.306 | 42.86% | 31.72% |

The test results of the experiment on the ALOI database have been shown in Table 2. Once again, the best performance rate obtained is 92.83% and ANR=0.039 from the proposed method. Intensity-HDWT2 and RGB-HDWT2 are better performance than other wavelet methods. In comparing performance, after the proposed method, SCD with P(1/3) = 91.68%, DCD with P(1/3)=87.71%, and RGB-HDWT2 level-5 with P(1/3)=84.82% are better than other methods. Obtaining results show regarding performance rate and size of feature vectors, the proposed approach provided better scores in comparison with other methods.

**Table 2.** Size of feature vector, P(1/3) and P(2/3) of different methods on the ALOI database

| Type | Level | Size of feature vector | ANR | P(1/3) | P(2/3) |
|---|---|---|---|---|---|
| Intensity-Haar wavelet | 1 | 32768 | 0.121 | 70.66% | 56.77% |
| | 3 | 2048 | 0.095 | 76.38% | 62.80% |
| | 5 | 128 | 0.095 | 76.39% | 63.67% |
| | 7 | 8 | 0.243 | 61.83% | 49.86% |
| RGB-Haar wavelet | 1 | 3×32768 | 0.095 | 76.86% | 62.87% |
| | 3 | 3×2048 | 0.091 | 80.64% | 67.75% |
| | 5 | 3×128 | 0.086 | 81.28% | 69.21% |
| | 7 | 3×8 | 0.095 | 73.56% | 60.25% |
| Intensity-HDWT2 | 1 | 32768 | 0.221 | 65.34% | 59.76% |
| | 3 | 2048 | 0.095 | 77.77% | 64.10% |
| | 5 | 128 | 0.095 | 77.59% | 67.23% |
| | 7 | 8 | 0.243 | 62.55% | 53.75% |
| RGB-HDWT2 | 1 | 3×32768 | 0.091 | 78.54% | 65.66% |
| | 3 | 3×2048 | 0.089 | 81.81% | 68.95% |
| | 5 | 3×128 | 0.081 | 84.82% | 73.03% |
| | 7 | 3×8 | 0.095 | 75.17% | 62.26% |
| Intensity-DCT | - | 36 | 0.089 | 80.71% | 66.65% |
| RGB-DCT | - | 3×36 | 0.091 | 82.67% | 69.98% |
| CLD | - | 12 | 0.065 | 84.68% | 72.03% |
| DCD | - | 32 | 0.047 | 87.71% | 78.98% |
| SCD | - | 11×121 | 0.042 | 91.68% | 80.70% |
| Proposed-Method | - | 40 | 0.039 | 92.83% | 83.84% |
| PP-30 | - | 496 | 0.764 | 47.86% | 27.72% |

**Table 3.** Size of feature vector, P(1/3) and P(2/3) of different methods on the MPEG-7 database

| Type | Level | Size of feature vector | ANR | P(1/3) | P(2/3) |
|---|---|---|---|---|---|
| Haar wavelet | 1 | 32768 | 0.124 | 70.55% | 61.43% |
| | 3 | 2048 | 0.099 | 76.48% | 65.38% |
| | 5 | 128 | 0.099 | 76.85% | 65.45% |
| | 7 | 8 | 0.211 | 66.28% | 55.57% |
| HDWT2 | 1 | 32768 | 0.211 | 65.64% | 53.45% |
| | 3 | 2048 | 0.099 | 76.48% | 65.50% |
| | 5 | 128 | 0.099 | 76.50% | 65.61% |
| | 7 | 8 | 0.246 | 58.14% | 48.92% |
| DCT | - | 36 | 0.099 | 75.85% | 63.76% |
| Proposed-Method | - | 40 | 0.086 | 82.65% | 74.50% |
| PP-30 | - | 496 | 0.091 | 82.24% | 62.08% |

The test results of the experiment on the MPEG-7 database have been shown in Table 3. In this case, the best performance rate provided by using the proposed method is 82.65% and ANR=0.086. Intensity-HDWT2 and RGB-HDWT2 are better performance than other methods. The performance of PP-30 with size of 496 is very near to the proposed method, but the size of the feature vector is more than the proposed method with size of 40 (more than 12 times). Obtaining results show that considering performance rate and size of feature vectors, the proposed method provides the higher score in comparison with the other methods.

Furthermore, as observed in Table 1, 2 and 3 the proposed method has even better performance than other wavelet transform methods, CLD, DCD, SCD, and PP-30. Therefore, the proposed technique can be considered as a more powerful method than other methods. Moreover, the proposed system not only reduces the size of feature vector and storage space, but also the performance of image retrieval has been improved.

## 4. CONCLUSIONS

Image retrieval is an applicable technique used to find relevant images in a large image database. By increasing the size of databases the challenge of average reduction in precision, recall, and speed of retrieval become more serious. In this paper, we proposed a new method based on HDWT2 and DCT features and PCA and KNN classifier to improve the performance of image retrieval. We used an average of three planes of red, green, and blue to generate intensity plane and considering red, green, and blue planes separately to generate RGB planes to test the proposed method. Obtaining results show using the proposed method can improve the performance of image retrieval in databases. Moreover, the proposed system reduces the size of feature vector and storage space and improves the performance of image retrieval.

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