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AN EFFICIENT APPROACH TO CBIR USING DWT AND QUANTIZED HISTOGRAM

Neelima Nizampatnam[1] and Edara Sreenivasa Reddy[2]

[1]Department of Electronics and Communication
School of Engineering and Technology
Jain University
Kanakapura Road, Jakkasandra Post, Bangalore 562112, India
neelima.niz@gmail.com

[2]Department of Computer Science and Engineering
Acharya Nagarjuna University
Nagarjuna Nagar, Guntur, Andhra Pradesh 522510, India
esreddy67@gmail.com

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Abstract. *CBIR systems retrieve most relevant images for the user defined query image. This paper proposes an efficient image retrieval system using DWT and quantized HSV histogram. The proposed approach has two stages for retrieval. In the first stage the RGB images are converted into HSV space. Features are extracted from the histograms of quantized HSV planes. When the user defines a query image, features are extracted from the corresponding quantized HSV histogram and stored. This feature vector is compared with the feature vectors of database images using Sorensen distance and stored in the ascending order of the distance. In the second stage the images from the first stage are decomposed up to the second level by using DWT. Features are extracted from approximation and detail coefficients and stored. The semantically relevant images are retrieved and displayed with the comparison of similarity distance between the feature vectors with city block distance. Experiments on ALOI and Corel database demonstrate that the proposed approach to image retrieval achieve higher retrieval efficiency compared to the state-of-the-art systems.*
Keywords: Discrete wavelet transforms, Image retrieval, Similarity measure, HSV histogram, Texture features

1. Introduction.

Image retrieval is the new era research as it has different applications involved in medical image systems, scientific databases, art collections, forensics and in the Internet. Content-based image retrieval (CBIR) [1] is the method which is used for browsing, searching and retrieving relevant images from very large databases. The user can search for his favorite vacation place or search for his favorite artist painting. So the retrieval system is to be more efficient when it comes to the user choice. Sometimes the user can give an image as query for which similar images are to be retrieved. These are known as Query by 'X' (where X can be an image or sketch) retrieval systems. These systems focus on retrieving the image by checking similarities with the actual content in the image. Here actual content means features of the image such as shape, texture and color. CBIR is a vigorous and challenging area for research. Any retrieval system is based on two key issues: feature extraction and indexing (or) ranking of the images.

Several frameworks were proposed to address these issues related to the user interested (or) user defined query based retrieval systems. The literature presented in [2-5,7] uses the primary level features for retrieval. These primary level features are color, texture, histogram and orientation [8]. The pixel information is coded as global features in [3,5] and local features with respect to the neighborhood is considered in [4,7]. Both statistical and co-occurrence features are used to encode the texture information in [2]. The similarity matching is performed at each pixel level with respect to the features used. This requires a lot of computational time in both offline and online stages of retrieval. A novel descriptor based on color occurrence is proposed in [4]. RGB color space is quantized to reduce the number of colors and then binary pattern is generated for each pixel with respect to its neighborhood. It offers better results for only Corel database. The major drawback of the above methods in [2-4] is the limitations in the types of features used. The content in the image is described by only one type of feature, which results in not adapting to diverse datasets. With the increase of novelty, Mukhopadhyay [7] proposed a novel approach with fuzzy membership. However, this methodology is evaluated only on texture based datasets. In this neural networks are adapted for indexing the images. The shortcoming is the size of feature vector, which is too large and hence searching time to retrieve these images becomes more. In order to increase the retrieval efficiency multiple features were used as presented in [6,12,16,18]. A rotation and scale invariant approach which uses both color and texture features is proposed in [6]. RGB space is quantized into 64 shades and for each shade six patterns are derived from five structuring elements. Both color and texture features are encoded separately and a combined feature vector is prepared in [15]. Zernike chromaticity distribution contourlet transform is used to encode color and texture features. This approach achieves rotation and scale invariance, but as the features are merged, the dimensionality of the combined feature vector increases. Selected region's wise matching is performed in [12] to reduce the retrieval time at the cost of high computational complexity.

Wang et al. [12] proposed retrieval system based on shape and texture features. To extract the shape features, morphological operations are used with spatially-variant structuring element. Block truncation coding (BTC) is applied over the feature extracted images to construct the feature vectors. It improves the performance of image retrieval system. Huang et al. [13] discussed the system with HSV color model, a method of object-based spatial-color feature (OSCF) for color image retrieval. Firstly, objects are extracted from color, and then image features are represented by objects in it. The authors proposed a novel fuzzy approach to classify the color images based on their content and neural network is used for fast and efficient retrieval [15].

Retrieval using DCT transforms is proposed in [17,20]. Bai et al. [19] proposed that the feature vectors can be obtained from DC and AC coefficients of $8 * 8$ DCT transformation blocks. The DC coefficient is combined with nine AC coefficients to generate the feature vector. However, the disadvantage of the above approaches [18,19] is, DCT transformation removes some of the relevant information which is used to define the texture content. In [17], Moghaddam and Dehaji proposed a new feature scheme called enhanced Gabor wavelet correlogram (EGWC) for image indexing and retrieval. EGWC uses Gabor wavelets to decompose the image into different scales and orientations [17]. The Gabor wavelet coefficients are then quantized using optimized quantization thresholds. In the next step, the autocorrelogram of the quantized wavelet coefficients is computed in each wavelet scale and orientation. In [20], Malik and Baharudin proposed that the DC and the first three AC coefficients are selected, and then histograms are constructed with 32 bin quantizations. These quantized histograms are used as feature vectors. However, considering both time and precision, we proposed an efficient system which can promise better results compared to other systems. In this paper we concentrate on DWT (discrete wavelet transform) rather than DCT. The state-of-the-art method [20] used DCT to construct the feature vectors. The proposed method uses DWT instead of DCT to obtain the coefficients. The approach has two stages of retrieval. The rest of the paper is organized as follows. Section 2 describes the conversion of HSV space and the quantized histogram calculation. Section 3 describes about DWT and texture feature extraction. Section 4 presents the performance evaluation of the proposed method. Section 5 concludes the paper.

2. **Proposed Retrieval Approach.** The block diagram of the proposed image retrieval system is shown in Figure 1. At first, all the images in the database are pre-processed and stored. The remaining process is divided into two stages. In the first stage, all the images in the database are converted from RGB (red-green-blue) to HSV (hue-saturation-value) space. The HSV values are quantized and the corresponding histograms are normalized. The features are extracted from this normalized histogram and stored. When the user enters the query image, these features are calculated for the query image and features are extracted. The features of the query image are compared with the features of the dataset images by using Sorensen distance. According to the increasing order of the distance the images are sorted and stored. In the second stage the images are decomposed up to two levels by using DWT to obtain approximate and detail coefficients. Texture features are extracted from these coefficients and stored in the form of feature vector. These feature vectors are compared with query image feature vector with city block distance as similarity distance to retrieve the most relevant images. The feature extraction is explained in the following sections.

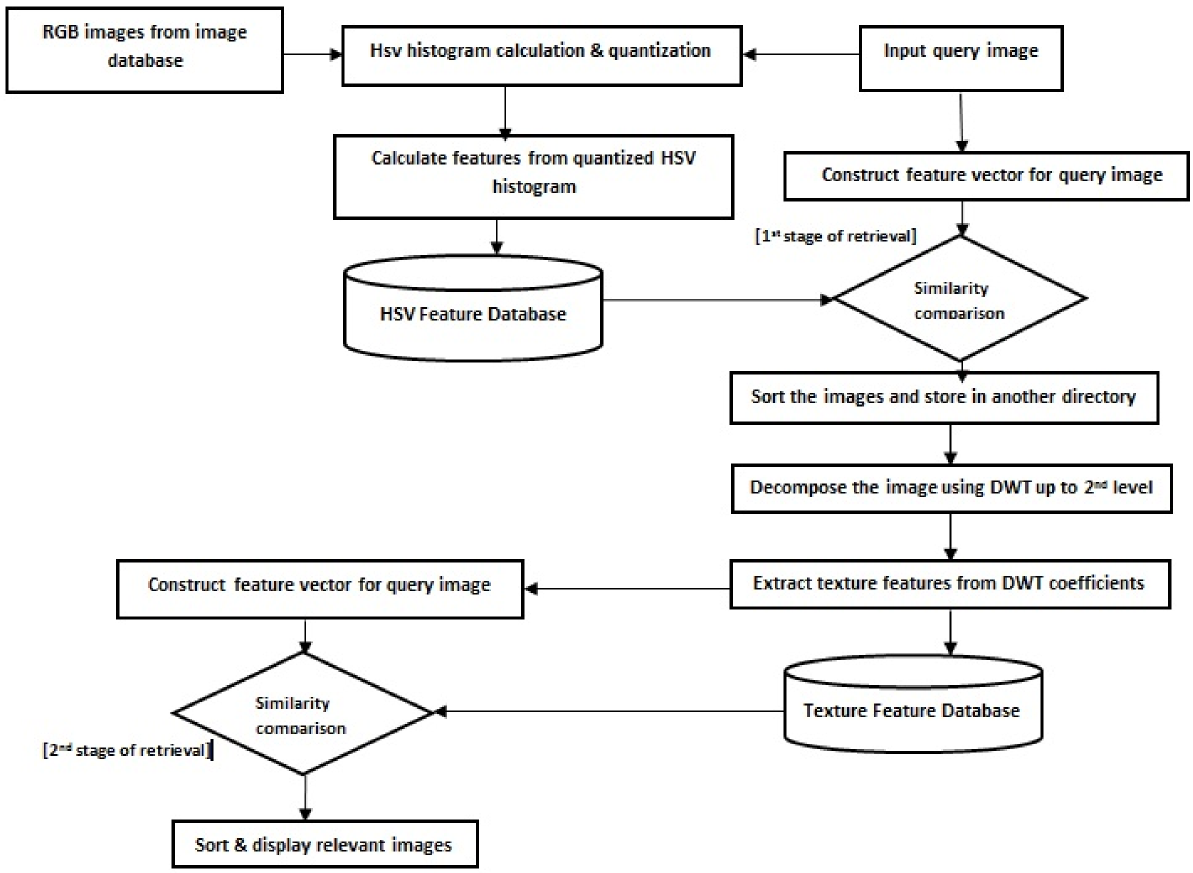

FIGURE 1. Block diagram of the proposed system

2.1. **First stage of retrieval.** The images in the database are RGB color images. All the images in database are converted into HSV space. HSV (hue, saturation and value) domain is widely used in the applications of image description and representation. The RGB coordinates can be easily translated to the HSV space. The color components are differentiated by hue, saturation, and value. Hue (H) describes the actual wave length of the color by representing the color name [10]. The level of purity of a color is measured by saturation (S). The intensity level is given by the value (V). The hue, saturation and values are calculated by using (1), (2) and (3).

$$H = \cos^{-1} \frac{1/2[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \tag{1}$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] \tag{2}$$

$$V = \frac{1}{3}(R+G+B) \tag{3}$$

The angle conversion of hue is given in Equation (4) and value, saturation values are converted into range [0 1] according to (5).

$$H = \left(\left(\frac{H}{255} \right) * 360 \right) \bmod 360 \tag{4}$$

$$V = V/255 \;\text{ and }\; S = S/255 \tag{5}$$

These HSV values are quantized into $8*2*2$ equal bins and the corresponding histograms are calculated. The quantization levels used in this approach are 8 for 'H' space, 2 for 'S' space and 2 for 'V' space. The main differentiation parameter for similarity is hue, so the quantization levels are more. The histograms are calculated from the quantized HSV plane and are normalized. The features extracted from this are stored as feature vectors in feature database. The output is a $1 * 32$ vector of features extracted from the HSV space. When the user defines the query image the corresponding histogram of quantized HSV planes are calculated. This feature vector is compared with the feature vectors of feature database by using Sorensen distance as similarity measure. The Sorensen distance between the two feature vectors of images is given by (6).

The Sorensen distance between the feature vectors of query image (Q_i) and database images (Db_i) is given by (6)

$$sorensen(Q_i, Db_i) = \frac{\sum_{i=1}^{n} |Q_i - Db_i|}{\sum_{i=1}^{n} (Q_i + Db_i)} \tag{6}$$

where Q_i is the feature vector of the query image and Db_i is the feature vector of the images from the database; $i = 1, 2, 3, \ldots, n$.

3. **Second Stage of Retrieval.** In the second stage the texture features are extracted by using discrete wavelet transforms. Texture features represent the repetitive patterns of surfaces within the image [20]. The wavelet transform which is used in this work is described in the following section.

3.1. **Discrete wavelet transform.** Discrete wavelet transform provides sufficient information for both analysis and synthesis of the signal. It reduces the computational time. It is most widely used in the analysis of multi-scale images. Wavelet transform represents an image as a sum of wavelet functions with different locations and scales (or) resolutions [1]. When any image is decomposed by using wavelets it is divided into two categories.

One represents detailed parts of an image given by high frequencies and the other represents smooth parts of the image given by low frequencies. In [12] the image, denoted by $f(t)$ is represented in terms of scaling and wavelet functions which is given in (7).

$$f(t) = \sum_n c_j(n)\Phi(t-n) + \sum_n \sum_{j=0}^{j=1} d_j(n)2^{\frac{1}{2}}\psi\left(2^j t - n\right) \tag{7}$$

where c_j is j level scaling coefficient and d_j is j level wavelet coefficient, $\psi(t)$ is the wavelet function, and t is the time. The scaling and wavelet functions are represented in Figure 2 and Figure 3. Each level is created by scaling and translation operations. Discrete wavelet transform decomposes the image into four sub bands LL (low-low), LH (low-high), HL (high-low) and HH (high-high) which represents approximation coefficients [12] and detail coefficients. As the LL band consists of 95% of the total energy we select only LL band coefficients for further level of decomposition.

Selection of proper wavelet transform is one of the major factors in retrieval. Discrete Meyer wavelet is used in this work, which is an FIR (finite impulse response) based approximation of the Meyer wavelet. It allows fast and wavelet coefficients calculation using DWT. The discrete approximation of this wavelet is symmetric and continuous. It is used to solve a two scale equation. The Meyer wavelet has rapid decay and infinite differentiability. For a given basis Meyer employed Fourier techniques to compute DTFT (discrete time Fourier transform) for the coefficients. It is orthogonal and is given by (8)

$$G_0\left(e^{j\omega}\right) = \sqrt{2}\sum_k \psi(2\omega + 4k\Phi) \tag{8}$$

where $\psi(x)$ is the wavelet function and $\Phi(x)$ is the scaling function of Meyer wavelet, given in (9) and (10).

$$\psi(\omega) = \begin{cases} \dfrac{1}{\sqrt{2\pi}}\sin\left(\dfrac{\pi}{2}v\left(\dfrac{3|\omega|}{2\pi}-1\right)\right)e^{\frac{j\omega}{2}} & \text{if } 2\pi/3 < |\omega| < 4\pi/3 \\ \dfrac{1}{\sqrt{2\pi}}\cos\left(\dfrac{\pi}{2}v\left(\dfrac{3|\omega|}{4\pi}-1\right)\right)e^{\frac{j\omega}{2}} & \text{if } 4\pi/3 < |\omega| < 8\pi/3 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where $v(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } 0 < x < 1 \\ 1 & \text{if } x > 1 \end{cases}$.

The Meyer scaling function is given by

$$\Phi(\omega) = \begin{cases} \dfrac{1}{\sqrt{2\pi}} & \text{if } |\omega| < 2\pi/3 \\ \dfrac{1}{\sqrt{2\pi}}\cos\left(\dfrac{\pi}{2}v\left(\dfrac{3|\omega|}{2\pi}-1\right)\right) & \text{if } 2\pi/3 < |\omega| < 4\pi/3 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

The process of extracting features from DWT is summarized as below.

1) Decompose the image into four sub-bands for the first level (LL1, LH1, HL1 and HH1).

2) Select LL1 sub band and further decompose it into four sub bands which results LL2, LH2, HL2, and HH2.

3) Calculate energy and weighted average entropy of these coefficients.

The approximation and detail coefficients are calculated and arranged into blocks. The entropy is calculated for both low and high frequencies. The final entropy is the weighted average entropy of all the blocks which is given in equation. The energy and entropy of these coefficients are calculated and used as features. These features are calculated by using (11) and (12). The entropy of any 8-bit gray image is given by (11), where $P(i)$ is the probability of pixel i in the image. Based on this the entropy of a wavelet coefficient block is given by (12). In this $l_{\min}$, $l_{\max}$ represent the minimum and maximum values of wavelet coefficients in the corresponding block; x represents the detail coefficients in both low and high frequencies, and j represents the level of decomposition.

$$H(z) = -\sum_{i=0}^{255} P(i) \log_2 P(i) \tag{11}$$

$$H_x^j(z) = -\sum_{i=l_{\min}}^{i=l_{\max}} P(i) \log_2 P(i) \tag{12}$$

The weighted average entropy is given by (13)

$$H^b(z) = \sum_{j=1}^{b} \left[\left(\frac{1}{4}\right)^j \left(H_h^j(z) + H_v^j(z) + H_d^j(z)\right) \right] + \left(\frac{1}{4}\right)^b H_\varphi^b(z) \tag{13}$$

where b is the level of decomposition which is $1, 2, \ldots, n$.

The energy which is another feature is calculated by using (14) and (15)

$$E_{detail} = \sqrt{\left(d_j^H\right)^2 + \left(d_j^V\right)^2 + \left(d_j^D\right)^2} \tag{14}$$

The energy of approximation coefficients is given by $E_{approx} = \sqrt{(a_j)^2}$.

The correlation between these two energies is given by

$$E_{ratio} = E_{detail}/E_{approx} \tag{15}$$

The energy and weighted average entropy are calculated and stored in feature vector. These feature vectors are compared with the feature vector of the query image with city block distance.

3.2. **Similarity metric.** The distance between the two feature vectors decides the nearest matching for the query image. The similarity metric measures the similarity between the two vectors of images, and the maximally similar the most relevant. The distance metric measures the dissimilarity between the images and a small difference means the two images are mostly similar [14].

City Block distance. The Cityblock distance [14] between the feature vectors of query image (Q_i) and database images (Db_i) is given by (16)

$$\text{Cityblock}(Q_i, Db_i) = \sum_{i=1}^{n} |Q_i - Db_i| \tag{16}$$

where $Q_i = [Q_1, Q_2, Q_3, \ldots, Q_n]$, and $Db_i = [Db_1, Db_2, \ldots, Db_n]$.

Euclidean distance. The Euclidean distance [14] between the feature vectors of query image (Q_i) and database images (Db_i) is given by (17)

$$\text{Euclidean}(Q_i, Db_i) = \sqrt{\sum_{i=1}^{n} (Q_i - Db_i)^2} \tag{17}$$

where $Q_i = [Q_1, Q_2, Q_3, \ldots, Q_n]$, and $Db_i = [Db_1, Db_2, \ldots, Db_n]$.

4. **Results.** In this work experiments were conducted with two different types of datasets. The relevance between the color features is measured with Sorensen distance and the texture features are measured with different distance metrics proposed in (16) and (17). As per the results city block distance gives maximum retrieval efficiency, the performance of the proposed system is evaluated in terms of precision which is defined in Equation (18). The average precision rate is calculated as per (19).

$$precision = \frac{a}{a+b} \quad \text{and} \quad recall = \frac{a}{a+c} \tag{18}$$

where a is the number of relevant retrieved images, and $a+b$ is the total number of images in database.

The average precision rate (APR) is given by

$$APR = \sum_{i=1}^{n} RR_i \tag{19}$$

where n is the number of different categories (or) classes in the dataset.

4.1. **ALOI database.** The first dataset used for the evaluation of the proposed approach is ALOI (Amsterdam library of object images), which is a collection of 1000 classes. The precision of the system is evaluated in terms of three levels P(1/3), P(2/3) and P(1). The precision after retrieving 1/3 of the relevant images is denoted by P(1/3). The precision after retrieving 2/3 of relevant documents is denoted by P(2/3) and P(1) is the precision after retrieving all the relevant images. Table 1 provides the detailed analysis of retrieval efficiency of the proposed approach with different wavelets. Table 2 provides the precision with respect to different similarity metrics. The detail comparison of the proposed approach with the state-of-the-art method is given in Table 3. The performance comparison with respect to state-of-the-art system [6] with different levels of precision P(1/3), P(2/3), P(1) are plotted in Figure 3. X-axis represents the level of decomposition and Y-axis represents the average precision rate.

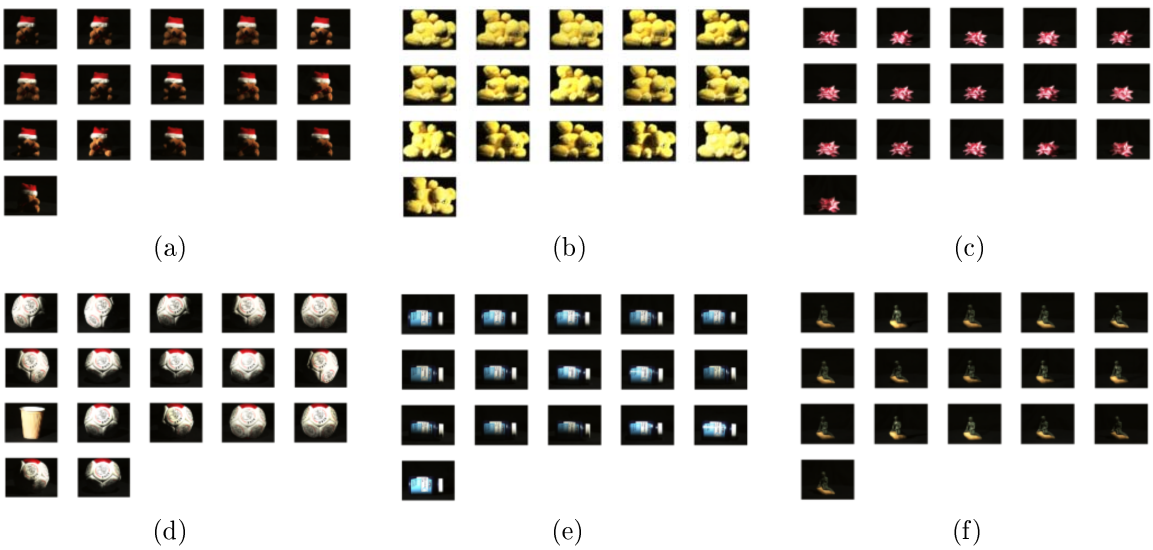

FIGURE 2. The retrieval results at precision P(2/3) in ALOI database for some of sample query images

TABLE 1. Average retrieval rate of different wavelets with different levels of decomposition in ALOI dataset

		P(1/3)	P(2/3)	P(1)
Meyer	Level 1	100	92.76	84.89
	Level 2	**100**	**96.75**	**89.75**
	Level 3	95.24	95.98	80
Haar	Level 1	100	90.62	84.32
	Level 2	100	92.35	81.25
	Level 3	92.65	89.88	79.55
db1	Level 1	88.23	76.45	72.13
	Level 2	84.24	78.14	68.24
	Level 3	79.15	72.13	66.67

TABLE 2. Retrieval performance of discrete Meyer wavelet level 2 with different similarity measures in ALOI dataset

	P(1/3)	P(2/3)	P(1)
Euclidean	100	94.25	82.34
Cityblock	**100**	**96.75**	**89.75**

TABLE 3. Performance analysis of the proposed system with the state-of-the-art system [6]

State-of-the-art system [6] method using HMMD-HDWT				Proposed system method using HSV-DMWT			
	P(1/3) %	P(2/3) %	P(1) %		P(1/3) %	P(2/3) %	P(1) %
Level 1	99.95	79.88	77.54	Level 1	100	92.76	83.89
Level 3	100	92.59	80.32	Level 2	**100**	**96.75**	**89.75**
Level 5	**100**	**94.66**	**83.14**	Level 3	100	95.98	80

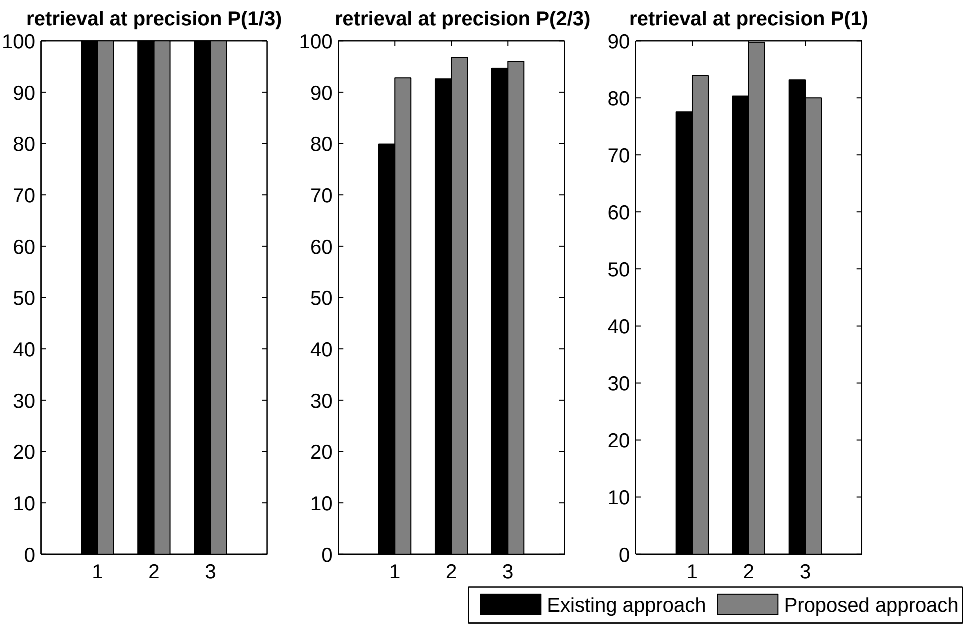

FIGURE 3. Performance comparison of the proposed and the state-of-the-art approach [6] with different levels of wavelets in ALOI dataset

4.2. **Corel database.** Corel database consists of 10 different classes of images with 100 similar images in each class. Figure 4 plots the performance comparison of the proposed system and state-of-the-art system [6] with respect to different levels of precision P(1/3), P(2/3), P(1). The maximum precision achieved is only 62.73% for the approach used in [6]. The maximum efficiency for the proposed approach is 92.23%. From Table 4 it is evident that better retrieval rate is achieved compared to the existing system. Another state-of-the-art framework is proposed in [20] that has the maximum retrieval efficiency of 82%, but this small difference is acceptable in terms of complexity.

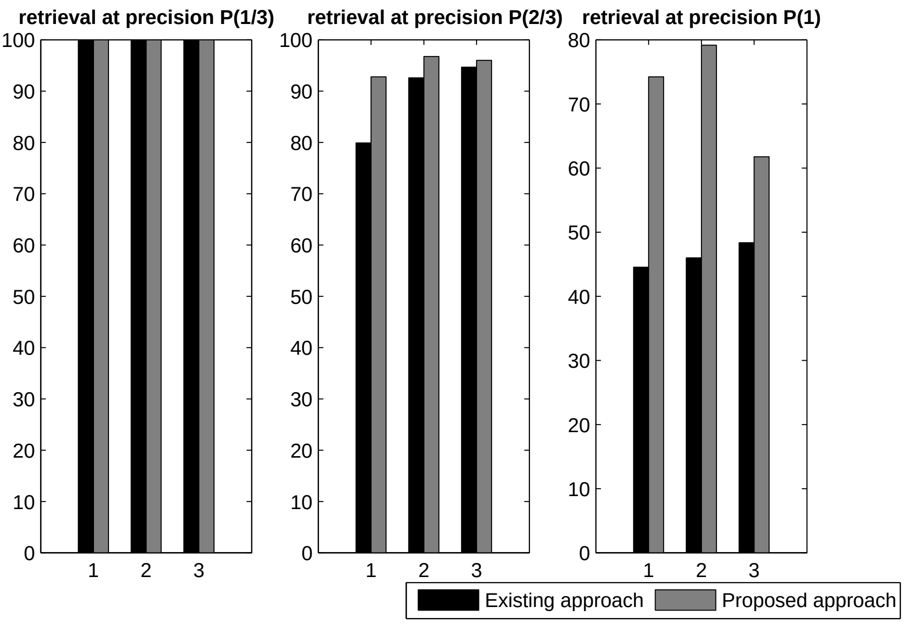

FIGURE 4. Performance comparison of the proposed and existing approach [6] with different levels of wavelets in Corel dataset

TABLE 4. Performance analysis of the proposed system with the state-of-the-art system [6,20]

State-of-the-art system [6] method using HMMD-HDWT				Proposed system method using HSV-DMWT				State-of-the-art system [20]
	P(1/3) %	P(2/3) %	P(1) %		P(1/3) %	P(2/3) %	P(1) %	
Level 1	57.21	50.24	44.54	Level 1	90.35	87.27	74.23	**82%**
Level 3	59.21	52.27	45.98	Level 2	**92.23**	**84.25**	**79.15**	
Level 5	**62.73**	**55.52**	**48.34**	Level 3	79.27	67.56	61.76	

5. **Conclusion.** The performances are recorded and evaluated with respect to average precision rate (APR). Different data sets such as ALOI and Corel are used for performance evaluation. The proposed system is compared with the state-of-the-art systems [6,20]. The proposed system extracts color features from quantized HSV histogram and texture features from DWT coefficients. This vigilant choice of features gives high performance in terms of precision in retrieval. By using DWT accurate texture features are calculated there by increasing the efficiency of the system compared to the one which uses DCT in [20]. With the help of quantization, maximum retrieval efficiency of 89.75% is achieved with respect to 83.14% in ALOI database and 79.15% with respect to 48.34% in Corel database as proposed in [6]. With respect to Tables 3 and 4, we proved that

very strong retrieval efficiency is achieved with the databases used for evaluation. As we considered three different datasets and we tried to find the common solution for retrieval, we may not achieve maximum efficiency in all the cases. However, considerable increase in precision is observed in the evaluation with respect to all the databases. We found that the proposed method can adapt to different categories of images especially in visual content based retrieval. We conclude that the proposed approach which uses color features from quantized HSV histogram and texture features extracted from DWT achieves the maximum precision and fast retrieval.

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