Texture and Color Visual Features Based CBIR Using 2D DT-CWT and Histograms

Jitesh Pradhan(✉), Sumit Kumar, Arup Kumar Pal, and Haider Banka

Department of Computer Science and Engineering,
Indian Institute of Technology (ISM), Dhanbad 826004, India
jiteshpradhan@cse.ism.ac.in

Abstract. In content based image retrieval (CBIR) process, every image has been represented in a compact set of local visual features i.e. color, texture, and/or shape of images. This set of local visual features is known as feature vector. In the CBIR process, feature vectors of images have been used to represent or to identify similar images in adequate way. As a result, feature vector construction has always been considered as an important issue since it must reflect proper image semantics using minimal amount of data. The proposed CBIR scheme is based on the combination of color and texture features. In this work initially, we have converted the given RGB image into HSV color image. Subsequently, we have considered H (hue), S (saturation), and V (intensity) components for extraction of visual image features. The texture features have been extracted from the V component of the image using 2D dual-tree complex wavelet transform (2D DT-CWT) where it analyzes the textural patterns in six different directions i.e. $\pm 15°$, $\pm 45°$, and $\pm 75°$. At the same time, we have computed the probability histograms of H and S components of the image respectively and subsequently those are divided into non-uniform bins based on cumulative probability for extraction of color based features. So, in this work both the color and texture features have been extracted simultaneously. Finally, the obtained features have been concatenated to attain the final feature vector and same is considered in image retrieval process. We have tested the novelty and performance of the proposed work in two Corel, two objects, and, a texture image datasets. The experimental results reveal the acceptable retrieval performances for different types of datasets.

Keywords: Content-based image retrieval
Dual-tree complex wavelet transform · Color and texture features
Probability histogram

1 Introduction

1.1 Background

In the present digital era, a radical expansion has been observed in the field of digital and Internet technology. As a result, the uses of digital communication

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and Internet applications have been exponentially increasing steadily. People are exceedingly getting addicted with the Internet applications and spending more time on the web. Consequently, Internet traffic and digital data on web repositories are also escalating exponentially. In these web repositories, a huge chunk of digital data is in form of image. Handling of these gigantic web repositories by human annotation process is considered as an impractical task and at the same time, retrieval of images from these web repositories has become even more difficult. Since, these particular images are not significantly described by human annotation process. Hence, an effective image retrieval scheme is directly associated with construction of salient visual features. In literature, three types of image retrieval schemes have been introduced by contemporary researchers. These three image retrieval schemes are text-based image retrieval (TBIR) [1], content-based image retrieval (CBIR) [2], and semantic-based image retrieval (SBIR) [3]. In TBIR, meta-data (i.e. location name, file name, keywords, tags, etc.) associated with the images are used for the retrieval purpose. Since these meta-data does not represent any actual image information, it is impractical to use them to represent any image. As a result, image retrieval by TBIR systems usually includes lots of junk images. To overcome limitations of TBIR, researchers have introduced a CBIR system [4–6] which works on salient visual contents of the image i.e. shape, texture, and/or color features which are also referred as low-level image features. These actual image features have been represented in a single feature set known as feature vector in image retrieval. Researchers have used shape, texture, and color features alone as well as in different combinations for CBIR applications.

1.2 Literature Review

In past two decades, many CBIR systems have already been introduced based on primitive low-level or combination of low-level image features. In 2008, Chun et al. [4] have proposed a CBIR system in which they have combined the multi-resolution texture and color features together. They have used color autocorrelograms for color features and BDIP and BVLC techniques for texture feature extraction. They have applied wavelet to achieve multi-resolution images and extracted color and texture features form each resolution. Later, they have merged all features for retrieving images. In 2009, Lin et al. [6] have introduced a smart CBIR system which works on three different image features. They have used difference between pixels of scan pattern (DBPSP) and color co-occurrence matrix (CCM) to achieve texture and color features simultaneously. Further, they have also used color histogram for K-mean (CHKM) to extract third image feature based on the distribution of color values. Finally, they have used the different combinations of these three image features for CBIR process. In 2010, Feng et al. [5] have combined the visual attention model with CBIR process to approximate the users perception. They have also used relevance feedback approach to estimate the high-level semantics of the image. They have used visual attention model to extract prominent edges from the image for shape feature extraction. Further, they have used salient region adjacency graphs along with edge histogram descriptors based feature extraction approach for CBIR application. In 2011, Yue et al. [7] have used color and texture image features for image retrieval. They have used texture co-occurrence matrix along with the color histogram to create a feature vector for CBIR application. Yue et al. have shown that the combination of different features works better for image retrieval. In 2012, Youssef [8] have used integrated discrete curvelets for CBIR application. They have proposed a new sub-band clustering technique based on region vector codebook for color feature extraction from color histogram. Subsequently, they have used the most similar highest priority (MSHP) principal based image matching approach for CBIR process. In 2013, Subrahmanyam et al. [9] have introduced modified color motif co-occurrence matrix (MCMCM) for CBIR process. Here, MCMCM extracts the pixel wise inert-correlation of different color components of an RGB image. They have integrated the DBPSP approach with the proposed MCMCM technique for better feature extraction for CBIR process. In 2014, ElAlami [10] has introduced a new image matching technique for CBIR application. He has used DBPSP along with CCM to extract texture and color features simultaneously. Subsequently, he has reduced the feature set by a dimension reduction approach. Later, he has applied artificial neural network for classification and calculated the minimum area between two vectors to compute the distance for CBIR process. In 2015, Guo and Prasetyo [11] have introduced halftoning and truncation coding based CBIR approach. They have used ordered-dither block truncation coding (ODBTC) technique for image compression and extracted bit pattern features (BPF) and color co-occurrence feature (CCF) for CBIR. In 2016, Varish et al. [12] have used color and texture features in hierarchical way to filter out the irrelevant images. They have used different visual features in each level of the hierarchy for image filtration and retrieval from the database. In 2017, Cui et al. [13] have introduced a hybrid learning technique based on textual and visual information. They have used this hybrid learning approach to extract the textual meta-data of the image and combined it with the visual information for CBIR application.

Another image retrieval approach is SBIR which works on high level image information. SBIR does not use the low-level image features as like CBIR, it works on the overall semantic perception of the image. Object detection and recognition, image classification, semantic templates, bag-of-visual-words, image semantic tag assignment [3,14] is some fundamental techniques used in SBIR. SBIR approach needs high pre-processing cost, storage space and CPU time. These are the main limitations of SBIR approaches.

1.3 Major Contribution

In this paper, we have proposed a novel CBIR scheme which works on color and texture visual image features. In this work, we have converted the RGB image into HSV image because in RGB image, color components are highly correlated as a result color chromatic information gets lost. We have used 2D dual-tree complex wavelet transform (2D DT-CWT) for texture analysis in V (intensity) component of the image. Simultaneously, we have created normalized histograms of H (hue) and S (saturation) components of the image. Later, we have computed the probability histograms of the H and S components. Further, we have divided it into 10 non-uniform bins according to the cumulative probability model. Finally, we have combined all visual image features for CBIR process.

1.4 Paper Organization

The Sect. 1 gives the brief introduction about CBIR and current state-of-arts in CBIR. In Sect. 2, we have explained 2D dual-tree complex wavelet transform. The proposed CBIR scheme has been explained in Sect. 3. In Sect. 4, we have presented the retrieval results and furnished the performance comparisons with related CBIR schemes. At last, Sect. 5 shows the conclusions and future works.

2 Dual-Tree Complex Wavelet Transforms (DT-CWT)

Gabor filters and discrete wavelet transform are the most commonly used techniques for texture analysis but these techniques have some serious disadvantages. Gabor filters takes more time to extract texture features and also these are not orthogonal. Similarly, DWT analyzes textural patterns with less number of directions (i.e. 0°, 45°, and 90°) and also it is not shift invariant. DT-CWT [12] overcomes all the above problems of Gabor filter and DWT. The DT-CWT works in similar way like DWT but it generates two different trees of DWT. Both DWT trees are real with a low-pass and high-pass filters. Both DWT trees analyze the textural patterns parallelly where, first one is considered as real part whereas second one is considered as complex part of DT-CWT. In this manner DT-CWT uses two real DWT with 4 filters to produce real and imaginary parts of the transform. The 2D DT-CWT analyzes the textural patterns on six different directions by producing wavelets in ±15°, ±45°, and ±75° for real and imaginary parts.

Let $I(x,y)$ is an image and 2D DT-CWT decomposes this image by applying six complex wavelets along with a complex scale function. Let, h is high-pass and low-pass filter set of real parts and g is the high-pass and low-pass filter set of imaginary parts of 2D DT-CWT. Here h_1 and g_1 are high-pass filter sets. Similarly, h_2 and g_2 are low-pass filter sets. Based on these assumptions, the complex wavelet function of 2D DT-CWT is defined as:

$$f(x,y) = f(x) \times f(y) \tag{1}$$

$$f(t) = f_h(t) + j \times f_g(t),\ Such\ that\ t = x\ or\ y \tag{2}$$

where, $f_h(t)$ and $f_g(t)$ are real and imaginary parts of 2D DT-CWT. So, the complex wavelet function can be expanded as follows:

$$f(x,y) = \{f_h(x) + j \times f_g(x)\}\{f_h(y) + j \times f_g(y)\} \tag{3}$$

$$f(x,y) = \{f_h(x)f_h(y) - f_g(x)f_g(y)\} + j \times \{f_h(x)f_g(y) + f_g(x)f_h(y)\} \tag{4}$$

where, $\text{Real}(f(x,y)) = \{f_h(x)f_h(y) - f_g(x)f_g(y)\}$ and $\text{Imaginary}(f(x,y)) = \{f_h(x)f_g(y) + f_g(x)f_h(y)\}$.

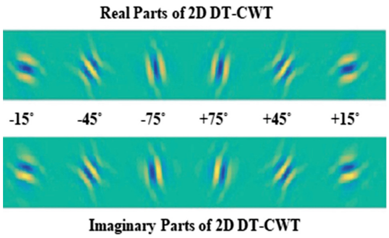

Fig. 1. Six impulse responses of real and imaginary parts of 2D DT-CWT

Figure 1 shows the six directional (i.e. ±15°, ±45°, and ±75°) impulse responses produced by the real and imaginary parts of the dual-tree complex wavelet function. Figure 2 shows the filter arrangement diagram of 2D DT-CWT up to 3 levels of decompositions.

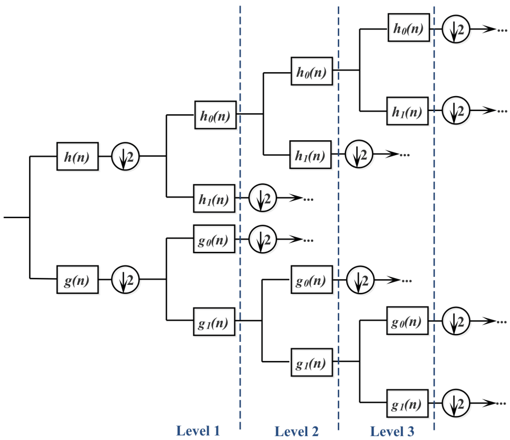

Fig. 2. Filter arrangement in 2D DT-CWT for 3 levels of decompositions

3 Proposed CBIR Scheme

In this section, proposed CBIR scheme has been explained in detail. Our proposed scheme works in two different stages where in first stage we have extracted the texture and color visual image features simultaneously. In second stage, image retrieval has been performed. In feature extraction stage, first we have converted the RGB image into HSV image. Subsequently, we have applied 2D DT-CWT up to n levels of decomposition on value (V) components. Here, we have used $n = 3$ for the retrieval experiments and each level of 2D DT-CWT produces 4 approximated coefficients, 2 form real parts and 2 from imaginary parts.

Along with approximated images, it also generates six directional wavelets (i.e. $\pm 15°$, $\pm 45°$, and $\pm 75°$) from real parts and six directional wavelets (i.e. $\pm 15°$, $\pm 45°$, and $\pm 75°$) from imaginary parts. Further, we have calculated statistical parameters from all wavelet coefficients of each level of decomposition and approximated coefficients of final level of decomposition. Simultaneously, we have calculated normalized histograms of hue (H) and saturation (S) components of the image. Further, we have calculated probability histograms and divided it into m non-uniform bins and in experiments we have used $m = 10$. Later, we have extracted statistical parameters from each bin of the histogram. Finally, all features have been combined together for CBIR process. Figure 3 shows the schematic block diagram of the proposed CBIR scheme. Further, Algorithms 1, 2, and 3 explains the detailed steps of CBIR process.

Algorithm 1 takes an RGB image and converts it into HSV image. Further, 2D DT-CWT has been employed on the V component of the image since it contains most of the textural visual features. The 2D DT-CWT will extract the

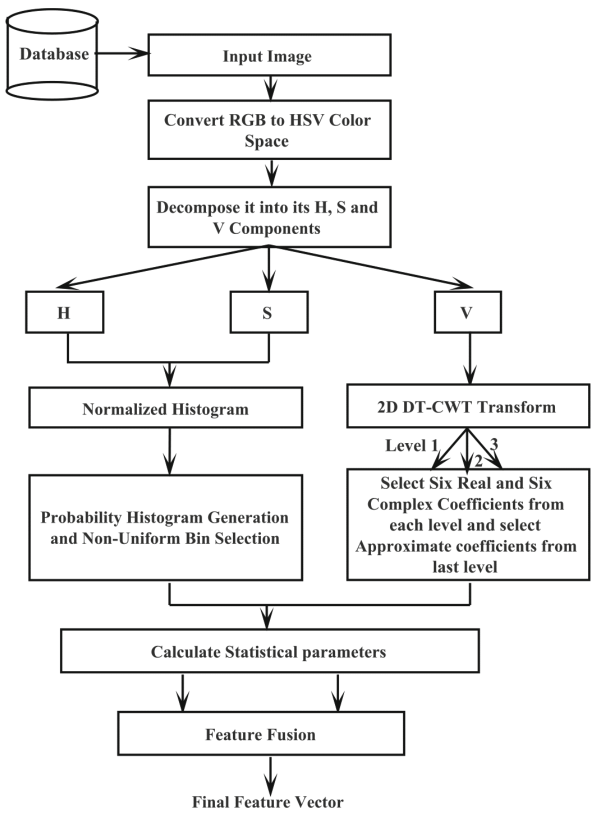

Fig. 3. Schematic block diagram of the proposed CBIR scheme

Algorithm 1. Texture Feature Extraction Algorithm (TFEA).

Input: An RGB color image.
Output: Final set of texture visual image features.

1: Take an RGB colored image as an input from user.
2: Convert RGB image to HSV color image.
3: Select value (V) components from the HSV color image.
4: Apply 2D DT-CWT on V component for 3 levels of decomposition.
5: Calculate mean and standard deviation statistical parameters of all detailed coefficients of all decomposition levels and approximate coefficients from last decomposition level.
6: Store all calculated statistical features in a form of texture feature vector.

Algorithm 2. Color Feature Extraction Algorithm (CFEA).

Input: An RGB colored image.
Output: Final set of color visual image features.

1: Take an RGB colored image as an input from user.
2: Convert RGB image to HSV color-space image.
3: Select hue (H) and saturation (S) components from the HSV color-space image.
4: Create normalized histograms of H and S components.
5: Calculated probability histograms of both H ans S histograms as follows:

$$Ph_k(i) = \frac{Hg_k(i)}{\sum_{j=1}^{n} Hg_k(j)} \tag{5}$$

where, i represents the i^{th} component of a histogram, Ph_k represents the probability histogram of k^{th} image, Hg_k represents the histogram of k^{th} image and n is the total count of coefficients.
6: Divide the probability histograms into m non-uniform groups where the cumulative probability of each group must be $\leq \frac{1}{m}$.
7: Calculate standard deviation, skewness, and kurtosis statistical parameters from all bins.
8: Store all calculated statistical features in a form of color feature vector.

textural features from six different directions. Simultaneously, in Algorithm 2 H and S components have been used to generated color histograms. Further, both these color histograms have been converted into probability histogram to reduce the feature dimension. Statistical color features have been extracted from the m non-uniform beans of the probability histograms. Final feature vector combines both the texture ans color features for CBIR process. Finally, Algorithm 3, have been used to extract the similar images from the image dataset.

Algorithm 3. Content-Based Image Retrieval Algorithm (CBIRA).

Input: An RGB color image.
Output: Retrieved set of similar images.

1: Take an RGB color image as an input from user.
2: Extract texture and color visual features using algorithms TFEA and CFEA.
3: Combine the normalized texture and color features in a form of single feature vector.
4: Select an image dataset with n numbers of images and extract texture and color features for all images using algorithms TFEA and CFEA.
5: Combine the normalized texture and color features of each dataset image in a form of single feature vector.
6: Create a feature space which congregate the feature vectors of all dataset images with same index value as in dataset.
7: Compute the Euclidean distance in between query feature vector and feature space feature vectors.
8: Retrieve first k (where $k \leq n$) images from dataset having minimum distance values.

4 Results and Performance Analysis

In this section, we have presented the retrieval results of the proposed CBIR scheme in terms of precision, recall, and f-score which are defined as follows:

$$\mu_P(\%) = \frac{RI}{RI + NI} \times 100 \tag{6}$$

$$\mu_R(\%) = \frac{RI}{RI + DI} \times 100 \tag{7}$$

$$\mu_{Fs}(\%) = \frac{2 \times \mu_P \times \mu_R}{\mu_P + \mu_R} \times 100 \tag{8}$$

Here, μ_P is the precision, μ_R is the recall, and μ_{Fs} is the f-score. RI is similar image in retrieved image set and NI is the dissimilar image in the retrieved image set. DI is the similar image present in dataset other than RI. Later, we have used five different image datasets to check the retrieval performance of the proposed CBIR scheme. In these five datasets, first two are natural image datasets i.e. Corel-1000 [12] and GHIM-10K [12]. The next two image datasets are object image datasets i.e. COIL-100 [15] and Produce-1400 [16]. The fifth dataset is a texture image dataset which is Outex [17]. Table 1 gives the brief description about all five datasets. Later, sub-section explains the feature vector length calculation. Sub-section shows the time performance of the proposed CBIR. Sub-section shows the retrieval performance. Finally, sub-section shows the performance comparisons.

Table 1. Brief description of all five image datasets used in retrieval experiment

Image dataset	Nature of dataset	No. of classes	Total no. of images	No. of images in each class
Corel-1000	Corel	10	1000	100
GHIM-10K	Corel	20	10000	500
COIL-100	Object	100	7200	72
Produce-1400	Object	14	1400	100
Outex	Texture	24	4320	180

4.1 Feature Vector Analysis

In this work, we have used 2D DT-CWT with 3 levels of decompositions for texture analysis where we have used it in value (V) components. In 2D DT-CWT, each level produces two approximate images with real and imaginary coefficients for further decomposition. So, in total it generates four approximate coefficients in each level of decomposition. Along with approximate coefficients, it also produces six real and six imaginary wavelet coefficients. Here, we have selected all wavelets coefficients of all 3 levels with 4 approximated coefficients of third level. Further, we have calculated mean and standard deviation from each coefficient. Hence, texture feature vector is having 80 feature elements (i.e. 3 levels $\times$ 12 wavelet coefficients $\times$ 2 parameters + 4 approximated coefficients $\times$ 2 parameters = 80 elements). At the same time, we have calculated 3 statistical parameters from each bin of hue and saturation probability histograms. Hence, number of elements in color feature vector is 60 (i.e. 2 histograms $\times$ 10 bins $\times$ 3 parameters = 60 elements). As a result, final feature is having 140 feature elements (i.e. 80 texture elements + 60 color elements = 140 elements).

4.2 Time Performance Analysis

Here, we have presented the time performance analysis in terms of CPU time required by any process. In this proposed CBIR scheme, there are 4 different types of processes which are texture feature extraction, color feature extraction,

Table 2. CPU time (in seconds) analysis for different process of proposed CBIR scheme

Image dataset	Texture feature extraction	Color feature extraction	Feature fusion	Image retrieval
Corel-1000	0.099 s	0.035 s	0.010 s	0.092 s
GHIM-10K	0.106 s	0.037 s	0.010 s	0.412 s
COIL-100	0.065 s	0.026 s	0.010 s	0.305 s
Produce-1400	0.512 s	0.157 s	0.010 s	0.104 s
Outex	0.064 s	0.025 s	0.010 s	0.215 s

feature fusion, and image retrieval. Table 2 shows the average CPU time taken by each process of CBIR while performing image retrieval from all 5 datasets.

4.3 Retrieval Performance Analysis

In this sub-section, we have presented the retrieval performance of the proposed CBIR scheme for top 10 and top 20 retrieved images in terms of precision (μ_P), recall (μ_R), and f-score (μ_{Fs}). We have retrieved these images from five different image datasets. Table 3 gives the retrieval performance in terms of average precision, recall and f-score for all five datasets for top 10 and top 20 retrieved images. In this table, we can see that all retrieval precisions are above 75%. This shows that, the proposed method is performing well for different types of images. Later, Fig. 4(i) to (iv) shows the precision graph of all five image datasets for top

Table 3. Overall average performance of proposed CBIR for top 10 and top 20 retrieved images from all five image datasets

Image dataset	$\mu_P(\%)$		$\mu_R(\%)$		$\mu_{Fs}(\%)$	
	Top 10	Top 20	Top 10	Top 20	Top 10	Top 20
Corel-1000	87.67	81.50	8.77	16.30	15.94	27.17
GHIM-10K	87.00	76.10	1.74	3.05	3.41	5.85
COIL-100	93.18	81.08	12.94	22.52	22.73	35.25
Produce-1400	91.19	78.69	9.12	15.74	16.58	26.23
Outex	95.94	87.79	5.33	9.75	10.10	17.56

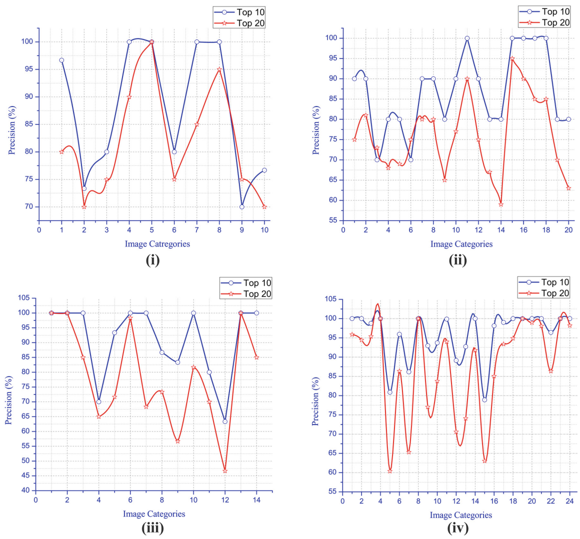

Fig. 4. Precision graph of (i) Corel-1000 (ii) GHIM-10K (iii) Produce-1400 (iv) Outex datasets for top 10 and top 20 retrieved images

10 and top 20 retrieved images. These all precision graphs show the group wise average precisions values. In all these graphs, we can see that most of the nodes are showing above 75% precision value so these are acceptable results. Since Coil-100 has 100 different image groups so we have not presented the precision graph for Coil-100.

4.4 Performance Comparison

In this paper, we have used 3 standard state-of-arts CBIR scheme to compare with our proposed CBIR scheme. These schemes have been introduced by ElAlami [10], Guo and Prasetyo [11], and Zeng et al. [18]. In Table 4, we have demonstrated the comparison of our anticipated CBIR scheme with these three other standard schemes. Table 4 shows the comparison for top 20 retrieved images in terms of average precision, recall, and f-score from Corel-1000 dataset. In this table we can see that, our anticipated CBIR scheme has shown better performance with respect to other three schemes. Later, Fig. 5 shows the category

Table 4. Comparison in terms of average precision, recall, and f-score for top 20 retrieved images from Corel-1000 dataset

Image retrieval methods	Corel-1000		
	$\mu_P(\%)$	$\mu_R(\%)$	$\mu_{Fs}(\%)$
ElAlami	76.10	16.10	25.90
Guo and Prasetyo	77.90	15.58	26.85
Zeng et al.	80.57	16.11	25.96
Proposed method	81.50	16.30	27.17

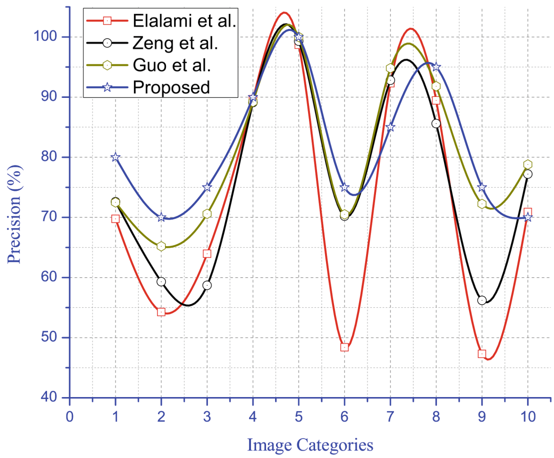

Fig. 5. Performance comparison in terms of precision for top 20 retrieved images from Corel-1000 dataset (Color figure online)

wise comparisons for top 20 retrieved images from Corel-1000 dataset. In Fig. 5, we can see that the blue line represents the proposed CBIR scheme and it has shown maximum high peaks. From Fig. 5, it has been clear that our proposed CBIR scheme is performing better for most of the cases as compare to other three schemes.

5 Conclusions

In RGB color space all color components shows high inter-correlations and due to which chromatic information of the image gets distorted. Hence, HSV color-space is better option for feature visual extraction. So in this work, the authors have presented a novel CBIR scheme which extracts texture and color visual image features simultaneously from HSV color image rather than considering RGB color-space. Here, we have applied 2D DT-CWT on value (V) components with 3 levels of decompositions because, it is shift invariant and it analyzes textures in six directions. Further, we have picked all six directional wavelet coefficients from real and imaginary part from each level of decomposition. We have also picked 4 approximated coefficients from third level of decompositions. Later, statistical parameters have been computed to preserve the texture features. Simultaneously, we have computed the probability histograms of hue (H) and saturation (S) components and we have divided these histograms into m non-uniform bins. Here, the bin division is based on the cumulative probability approach such that each bin will have approximately same number of pixel. As a result, color property of the image will get evenly distributed among all bins. Finally, the resultant feature vector contains better low-level visual color and texture features. We have also performed comparisons between our anticipated CBIR and other schemes in which our scheme has shown better performance. We have tested the robustness of our anticipated CBIR scheme by performing image retrieval form 5 different image datasets. The retrieval results validate the novelty and robustness of the proposed CBIR scheme with respect to different standard image datasets.

References

1. Gudivada, V.N., Raghavan, V.V.: Design and evaluation of algorithms for image retrieval by spatial similarity. ACM Trans. Inf. Syst. (TOIS) **13**(2), 115–144 (1995)
2. Liapis, S., Tziritas, G.: Color and texture image retrieval using chromaticity histograms and wavelet frames. IEEE Trans. Multimed. **6**(5), 676–686 (2004)
3. Guérin, C., Rigaud, C., Bertet, K., Revel, A.: An ontology-based framework for the automated analysis and interpretation of comic books images. Inf. Sci. **378**, 109–130 (2017)
4. Chun, Y.D., Kim, N.C., Jang, I.H.: Content-based image retrieval using multiresolution color and texture features. IEEE Trans. Multimed. **10**(6), 1073–1084 (2008)
5. Feng, S., Xu, D., Yang, X.: Attention-driven salient edge(s) and region(s) extraction with application to CBIR. Signal Process. **90**(1), 1–15 (2010)

6. Lin, C.-H., Chen, R.-T., Chan, Y.-K.: A smart content-based image retrieval system based on color and texture feature. Image Vis. Comput. **27**(6), 658–665 (2009)
7. Yue, J., Li, Z., Liu, L., Fu, Z.: Content-based image retrieval using color and texture fused features. Math. Comput. Model. **54**(3), 1121–1127 (2011)
8. Youssef, S.M.: ICTEDCT-CBIR: integrating curvelet transform with enhanced dominant colors extraction and texture analysis for efficient content-based image retrieval. Comput. Electr. Eng. **38**(5), 1358–1376 (2012)
9. Subrahmanyam, M., Wu, Q.M.J., Maheshwari, R.P., Balasubramanian, R.: Modified color motif co-occurrence matrix for image indexing and retrieval. Comput. Electr. Eng. **39**(3), 762–774 (2013)
10. ElAlami, M.E.: A new matching strategy for content based image retrieval system. Appl. Soft Comput. **14**, 407–418 (2014)
11. Guo, J.-M., Prasetyo, H.: Content-based image retrieval using features extracted from halftoning-based block truncation coding. IEEE Trans. Image Process. **24**(3), 1010–1024 (2015)
12. Varish, N., Pradhan, J., Pal, A.K.: Image retrieval based on non-uniform bins of color histogram and dual tree complex wavelet transform. Multimed. Tools Appl. **76**(14), 15885–15921 (2017)
13. Cui, C., Lin, P., Nie, X., Yin, Y., Zhu, Q.: Hybrid textual-visual relevance learning for content-based image retrieval. J. Vis. Commun. Image Represent. **48**, 367–374 (2017)
14. Pradhan, J., Pal, A.K., Banka, H.: A prominent object region detection based approach for CBIR application. In: 2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC), pp. 447–452. IEEE (2016)
15. Nene, S.A., Nayar, S.K., Murase, H., et al.: Columbia object image library (COIL-20) (1996)
16. tropical-fruits-db-1024x768.tar.gz. http://www.ic.unicamp.br/~rocha/pub/downloads/tropical-fruits-DB-1024x768.tar.gz/. Accessed 18 Aug 2017
17. site www, vision & image: lagis-vi.univ-lille1.fr (2017). http://lagis-vi.univlille1.fr/datasets/outex.html. Accessed 18 Aug 2017
18. Zeng, S., Huang, R., Wang, H., Kang, Z.: Image retrieval using spatiograms of colors quantized by Gaussian mixture models. Neurocomputing **171**, 673–684 (2016)