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Content-based Image Retrieval for Carpet E-commerce Application

Mehdi Reza Shahabi
Department of Communication Engineering, University of Sistan and Baluchestan
Zahedan, Iran
mehdirezashahabi@gmail.com

Mehdi Rezaei
Department of Communication Engineering, University of Sistan and Baluchestan
Zahedan, Iran
mehdi.rezaei@ece.usb.ac.ir

Farahnaz Mohanna
Department of Communication Engineering, University of Sistan and Baluchestan
Zahedan, Iran
f_mohanna@ece.usb.ac.ir

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Abstract—**E-commerce plays an important role in the world economy. A wide variety of websites have been designed to provide the ability of searching different types of products. Carpet is such a product which cannot be addressed easily with a special code in markets due to the huge variety in its specifications such as layout, color, and texture. This paper introduces a content-based image retrieval system for carpet e-commerce application. This system helps development of the carpet e-commerce where an image can be used instead of any tags including codes or models. An image database containing various Persian carpet images is also made for this application. Furthermore, several content-based image retrieval methods are studied and applied on the carpet database and inspiring by the evaluation results, two methods, QCLD and DCDIP are proposed for carpet e-commerce application. Simulation results show 3.1% and 2.3% decrease on the ANMRR value for the proposed QCLD and DCDIP methods respectively. Retrieval running times also are reported 2.84 and 8.15 seconds for the QCLD and DCDIP methods. In overall, these results reflect higher retrieval performance for the proposed methods.**

Keywords—Content-based image retrieval; Tag-based image retrieval; Carpet e-commerce; Image partitioning; Feature extraction

I. INTRODUCTION

E-commerce plays an important role in the world economy. Using World Wide Web, numerous attempts are carried out to acquaint the public with a variety of products. Companies have this opportunity to sell their products through internet. A wide variety of websites have been designed to provide the ability of searching different types of products with a desired price and favourable specifications for the customers. The majority of products such as electronic devices and household equipment are presented in electronic markets by specific models or numbers hence, the customers are able to find their demands using these codes[1-2]. Carpet is such a product which cannot be addressed easily with a special code in markets due to the huge variety in its specifications such as layout, color, and texture. In such cases a sample image that carries more information can be used instead of any tags to find carpet products.

Content based image retrieval (CBIR) focuses on description and retrieves only via visual features. In the CBIR system low level visual features of images, such as color, shape, and texture are used. The color representation is mostly based on the whole image, such as global color histogram, cumulative color histogram, and color moments, which all are invariant according to the image translation and rotation [3]. Also a number of main shape feature extraction methods are, elementary descriptor, Fourier descriptor, template matching, and edge detection [4]. There are also three principle image processing approaches to describe a region texture including statistical, structural, and spectral [5].

The MPEG-7 visual description tools consist of basic structures and descriptors that cover the multimedia contents such as color, texture, shape, localization, and motion [6]. Dominant color descriptor (DCD), color layout descriptor (CLD), region shape descriptor, texture browsing descriptor and edge histogram descriptor are all examples of the MPEG-7 standard descriptors [7]. To retrieve more efficiently images in e-commerce, a number of CBIR systems have also been introduced. However toward better retrieval for different applications in e-commerce, there is still a lot of work that have to be done.

Persian carpets are generally designed of a number of motifs in a simple background as a layout. Different color sets can be used for a design and different designs can also use similar color sets. Hence both color and texture features can be applied in the content-based carpet image retrieval system. Moreover, most of the carpets layout includes two parts: center part and margin part. Considering the facts mentioned above, in this paper a number of relevant CBIR methods are studied and applied to the carpet image database and evaluated in terms of running time and retrieval performance. Inspiring by the evaluation results, the CLD and DCD methods are selected and modified to take advantages of higher retrieval performance and speed.

The rest of the paper is organized as follow. Past work is presented in section2. The CBIR system for carpet e-commerce application is shown in section 3. The proposed CBIR methods are introduced in section 4. Simulation results and their evaluation are shown in section 5 and section 6 concludes the paper.

II. Past Work

Some of the recent papers of CBIR are considered and introduced as follows.

The CBIR system using an optimized neural network named PSO-ANN was presented in [8] for medical application. The features of images such as shape, texture, mean and standard deviation were extracted and clustered by using k-means algorithm. From the clustered features, similar images of query were retrieved applying the PSO-ANN classifier. The CBIR method for feature fusion in visual and textual images was proposed in [9]. If any text appeared within the query then it was classified as textual, and its text was detected and formed as a bag of textual words. If the query was classified as non-textual, the visual salient features were extracted and formed as a bag of visual words. Next, the visual and textual features were combined, and top similar images were retrieved based on the combined feature vector. A non-dominated sorting based on the multi-objective whale optimization algorithm was reported in [10] for CBIR. The method avoided the drawbacks in other non-dominated sorting multi-objective methods that had been used for CBIR. A CBIR method using image quality assessment (IQA) was presented in [11]. The method combined two images IQA model namely mean-structural-similarity-index measure (MSSIM) and feature-similarity-index measure (FSIM) to take the relative advantage of each other. The MSSIM algorithm recognized the structural information from an image, and the FSIM extracted its color information. Finally, a combination of four image features including luminance, contract, structure, and color were used for similarity matching. A variant of multi-trend structure descriptor (MSTD) was shown in [12] for CBIR. The variant of MSTD encoded color/edge orientation/texture quantized values versus orientation of equal, small and large trends. To reduce the time cost of the variant of MTSD with the preservation of its accuracy, the image was decomposed into fine level using the discrete Haar wavelet transform and the fine level for decomposition of an image was determined empirically. Euclidean similarity was applied to compute the similarity information between query and images in database.

A supervised deep hash method that constructed binary hash codes from labeled data for large-scale image search was presented in [13]. They assumed that the semantic labels were governed by several latent attributes with each attribute on or off, and classification relied on these attributes. According to this assumption, their method, dubbed supervised semantics-preserving deep hashing (SSDH), constructed hash functions as a latent layer in a deep network and the binary codes were learned by minimizing an objective function defined over classification error and other desirable hash codes properties. Some of the important contributions associated with image retrieval based on support vector machine (SVM) in the last two decades were revisited in [14].

A number of the key challenges of SVM involved in the adaptation of existing CBIR approaches were also discussed so as to explore more powerful strategies and develop more efficient systems to handle the large scale real-world image collections. An image texture and hue statistical projection based retrieval were introduced in [15]. First the image was converted to HIS color model, the gray value of the image was also extracted, and in addition, its texture was extracted by the Robert algorithm, then the image was divided into blocks and the main color block was extracted and blocks of the main coloring were respectively projected in the horizontal and vertical direction, and finally the projections histograms were got as the features of image similarity calculation. A scheme supporting CBIR from encrypted images was presented in [16]. The features were identified from the outsourced images and by using locality-sensitive hashing, pre-filter tables were generated for increasing the efficiency of retrieving. A machine learning algorithm retrieved most similar images from cloud. The cloud server also embedded a unique watermark to the encrypted images by using a watermark based protocol. A combination of features in multiresolution analysis framework for image retrieval was proposed in [17]. The concept of multiresolution analysis was exploited through the use of wavelet transform. The local binary pattern was combined with moments at multiple resolutions of wavelet decomposition of image. These feature vectors were used to search and retrieve visually similar images. A texture-color descriptor was introduced integrating the multi-channel features. A fixed sized local intensity based descriptor, and maximal multi-channel local binary pattern, were integrated as the multi-channel local binary information. The histogram of the obtained pattern was used for representing the image texture. Its color information was also captured by quantizing the RGB color space and was presented with histogram. These feature vectors were used to retrieve visually similar images from large database.

III. CBIR System for Carpet E-Commerce

Block Diagram

The block diagram of CBIR system for carpet e-commerce application is shown in Figure 1. Initially a database is made by distributer from various carpet images taken from producer, and then the feature vector of database is created and stored. A user chooses a query carpet image through carpet websites and also the desired retrieval method from a list and runs the system. Next, feature vector of a query image is formed and compared with the extracted feature vector of images in the database. Finally, similarity comparison is done and retrieved images are indexed according to their matching score. The customer is now able to have details of desired carpets as a text file attached to each carpet image hence a close relationship can be established between producer and carpet enthusiasts through this system.

Carpet Image Database

Our database contains 1126 carpet images mostly photted by the authors. The layout and color of different parts of a carpet are important from the user point of view.

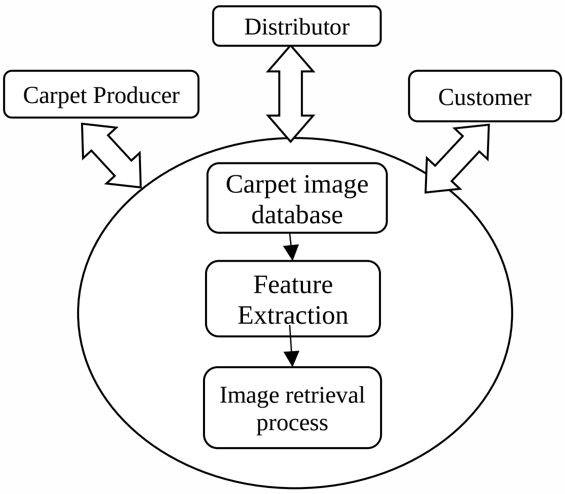

Figure 1. Block diagram of CBIR system for carpet e-commerce

So, full images were captured from various view angles relatively to the carpet center, with different sizes, colors and textures. Different sets of color images for each layout and different layouts for each color sets were also collected.
All the database images are stored in the JPEG format and 70 percentages of them are classified in 110 sets and the rest of them remained unclassified. These images are used to estimate the retrieval results. Layout of the most carpets usually include many details therefore, carpet images with higher resolution should be used in application. Due to this, carpet images in the database are resized into 496×368 pixels in the pre-processing step.

IV. Proposed Methods

Quantized Color Layout Descriptor Method

The proposed quantized color layout descriptor (QCLD) method is the modified CLD in order to take advantages of higher retrieval performance and speed. Therefore, first the original CLD method is presented in part A.1., and followed by introducing of the proposed QCLD method in part A.2. of this section.

Color Layout Descriptor Method (CLD)

The CLD represents the spatial distribution of colors which is resolution-invariant. The flowchart of CLD method is illustrated in Figure 2 which includes 4 steps including, image partitioning to 8×8 blocks, block representative color detection, the discrete cosine transform (DCT) of the blocks representative colors, and a zigzag scanning of the DCT coefficients to make a feature vector [19]. An YC_bC_r color space conversion stage is used for original CLD method as in the MPEG-7 standard [20].

In the partitioning stage, the RGB input image is divided into 64 blocks to guarantee the scale and resolution invariance. Then, a single representative color is selected from each block. The color average of the block pixels is used as the corresponding representative color to make a tiny 8×8 image icon. A sample of this tiny image is shown in Figure 3.

If color space conversion between RGB and YC_bC_r is needed, it can be applied to the tiny image in order to reduce computation. Next, the luminance, Y and blue and red chrominance, C_b and C_r components of the tiny image pixels are transformed by the 8×8 DCT, so 3 sets of the 64 DCT coefficients are obtained.

A zigzag scanning is also performed on these 3 sets of coefficients. The scan schema is presented in Figure 4. Finally, the CLD descriptor is formed by reading in zigzag order 6 coefficients from the Y-DCT matrix and 3 coefficients from the each DCT matrix of the two chrominance components. The descriptor can be saved as an array of 12 values [20].

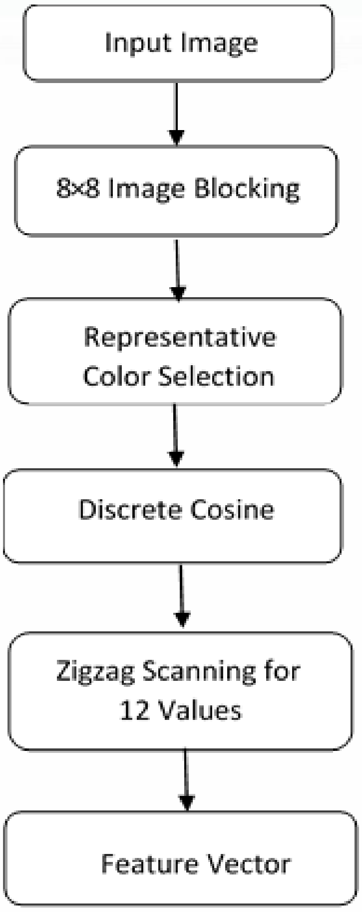

Figure 2. CLD extraction process

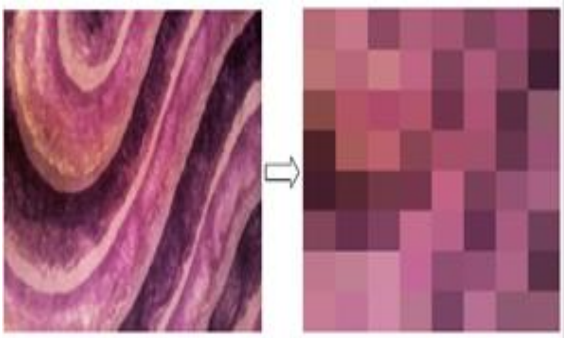

Figure 3. Representative color selection

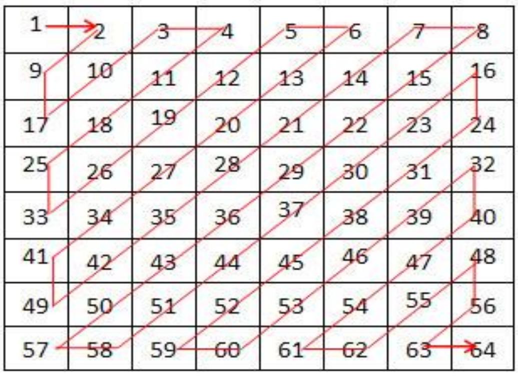

Figure 4. Zigzag scanning

Proposed QCLD Method

Block diagram of the proposed QCLD method is shown in Figure 5 which includes following steps.

I. Color Quantization

Textiles used in a carpet have typically 3 to 8 colors so we can expect only few dominant colors in the carpet images. However, depending on the imaging system and light conditions many colors are appeared in the carpet image histogram. Therefore, in QCLD method, a color quantization step precedes CLD algorithm. The quantized colors illustrated in Table I are used for the color quantization step.

II. Image Partitioning

The RGB input image is divided into 8× 8 blocks. Each block contains 62 × 46 pixels.

III. Representative Color Selection

The average of color of pixels in each block is used as the corresponding representative color. An image of 64 blocks is created as shown in Figure 3.

IV. Discrete Cosine Transform

The 2D 8×8 DCT is applied on each Y, C_b and Cr components of the tiny image pixels.

V. Zigzag Scanning

The QCLD descriptor or feature vector is an array of 22 values that is formed by the 10 DCT coefficients of the luminance component and the 6 DCT coefficients from each of the chrominance components in zigzag scan order.

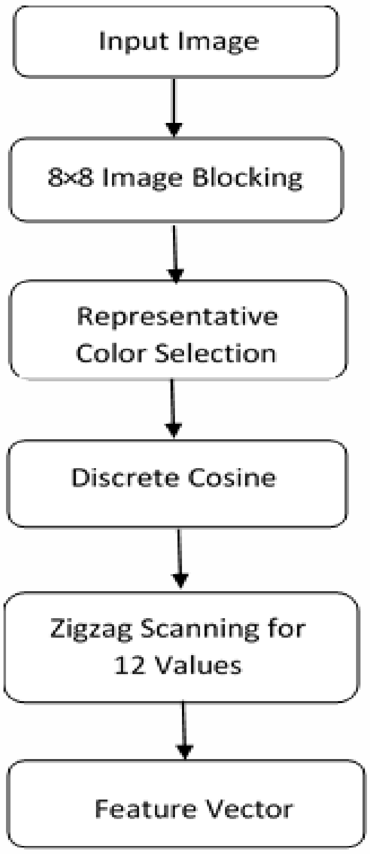

Figure 5. QCLD extraction process

TABLE I. PERCEPTUAL COLORS USED IN THE QCLD METHOD

S/No	Red	Green	Blue	S/No.	Red	Green	Blue
1	255	0	0	**20**	0	204	255
2	255	102	0	**21**	200	200	200
3	255	255	153	**22**	210	210	175
4	255	255	0	**23**	255	0	255
5	128	0	0	**24**	255	153	204
6	255	153	0	**25**	0	255	255
7	255	153	51	**26**	153	51	0
8	0	51	0	**27**	153	102	51
9	51	153	51	**28**	102	128	51
10	51	51	0	**29**	204	102	0
11	128	128	51	**30**	0	0	0
12	51	153	102	**31**	255	255	255
13	153	204	0	**32**	51	102	153
14	0	255	0	**33**	0	51	102
15	0	128	0	**34**	0	128	128
16	51	102	255	**35**	51	51	153
17	153	204	255	**36**	153	51	102
18	0	0	255	**37**	204	153	255
19	0	0	128	**38**	85	75	60

Dominant Color Descriptor on Independent Partitions Method

The proposed dominant color descriptor on independent partitions (DCDIP) method is the modified DCD in order to take advantages of higher retrieval performance and speed. Therefore, first the original DCD method is presented in part B.1. and followed by introducing of the proposed DCDIP method in part B.2. of this section.

Dominant Color Descriptor Method (DCD)

In the DCD method, image feature is formed by a small number of dominant colors. These colors are normally received by using clustering and color quantization. The descriptor contains the representative colors, their percentages in a region, their color spatial coherency, and variance [21]. The DCD is formulated by Equation (1).

$$F\{(C_i.p_i.V_i).s\}.i = 1.2.\cdots.N \qquad (1)$$

where, N is the number of dominant colors, each value C_i is a vector of corresponding color space, P_i is the fraction of pixels in the image or image region corresponding to color C_i, V_i is the variation of color values of pixels in the corresponding representative color and S is a single value that shows the overall spatial homogeneity of the dominant colors in the image. It is suggested that a maximum of 8 dominant colors (N) is sufficient to represent an image or an image region.

A fixed representative colors feature extraction (FRCFE) algorithm is presented in [21]. In the FRCFE algorithm, a color quantization is used in RGB space by 38 perceptual colors to demonstrate images based on dominant colors.

Table I shows these colors which are selected from RGB color space. After defining the selected colors, each pixel color is replaced by its nearest selected color to form an image array. The nearest color can be found by computing a distance measure between the pixel color i with components (P_r, P_g, P_b) and all selected colors C_i with components (C_{iR}, C_{iG}, C_{iB}) by Equation (2) [21].

$$C_d = \min\left(\sqrt{(P_r - C_{iR})^2 + \left(P_g - C_{iG}\right)^2 + (P_b - C_{iB})^2}\right)$$
$$i = 1.2.\ldots.38 \qquad (2)$$

For each image pixel, the RGB entry in color table can be assigned for which C_d is the minimum. Then, a frequency table for each assigned color is created and sorted in descending order.

Finally, the highest 8 frequent colors are selected with their percentages to create the image description. Similarity matching for retrieval purposes is done by comparing two DCDs, F_1 and F_2 given by Equations (3) and (4) [21].

$$F_1\{(C_i.P_{1i}.V_{1i}).S_1\}.i = 1.2.\ldots.N_1 \qquad (3)$$

$$F_2\{(C_i.P_{2i}.V_{2i}).S_2\}.i = 1.2.\ldots.N_2 \qquad (4)$$

Neglecting the optional color variance parameter, and the spatial coherence, S, quadratic histogram distance measure can be used to measure the dissimilarity $D^2(F_1,F_2)$ between the two descriptors given by Equation (5), where, $a_{1i.2j}$ is the similarity coefficient between two colors C_{1i} and C_{2j}, which is identified by Equation (6),

$$D^2(F_1.F_2) = \sum_{i=1}^{N_1} P_{1i}^2 + \sum_{j=1}^{N_2} P_{2j}^2 - \sum_{i=1}^{N_1}\sum_{j=1}^{N_2} 2a_{1i.2j}P_{1i}P_{2j} \qquad (5)$$

$$a_{1i.2j} = \begin{cases} 1 - ||C_{1i} - C_{2j}||/aT_d & ||C_{1i} - C_{2j}|| \le T_d \\ 0 & ||C_{1i} - C_{2j}|| > T_d \end{cases} \qquad (6)$$

where $||C_{1i} - C_{2j}||$ is the Euclidean distance between C_{1i} and C_{2j} in the CIELuv color space and T_d indicates the maximum distance for the two colors to be considered similar. Specifically, this means that any two dominant colors from one single description are more than T_d distance apart. A recommended value for T_d is between 10 and 20 in the CIELuv color space and α is between 1.0 and 1.5 [21].

Distance between the pixel color and color in Table I is calculated by using Equation (5). All pixels in the image are replaced with the nearest color value obtained from Equation (6). Figure 6 shows effect of the DCD color quantization using the FRCFE algorithm on a carpet image. The 8 dominant colors are obtained from frequency table sorted in descending order for each assigned color.

Proposed DCDIP Method

As it mentioned, most of the carpets layout includes center and margin parts. Carpets may differ in center, margin, or both parts. Therefore, to enhance the DCD retrieval results, area of a carpet image is divided into 2 regions, centre and margin. Then DCD method is applied to each region independently as following.

i. All images are resized into 499 × 374 pixels.

ii. A block including 439×296 pixels at the image centre is assigned to the centre region and remaining pixels around the centred region are assigned to the margin region. These partitions are illustrated in Figure 7.

iii. A dominant color descriptor is computed independently on each region as a feature vector.

iv. For the retrieval process, a distance is computed for each feature vector and computed distances are weighted and combined to make a new distance by Equation (7), where w_M and w_C are dedicated weights for the margin and center regions distances, respectively. d_M and d_C denote the distance measures applied for the margin and center regions, respectively.

$$d = w_M \times d_M + w_C \times d_C \qquad (7)$$

A relatively higher weight is dedicated to the centre region distance than the margin region distance. Finally, a feature vector is computed for each carpet image combining the obtained DCDs feature vectors.


Figure 6. (a) carpet image, (b) Its color quantization using FRCFE

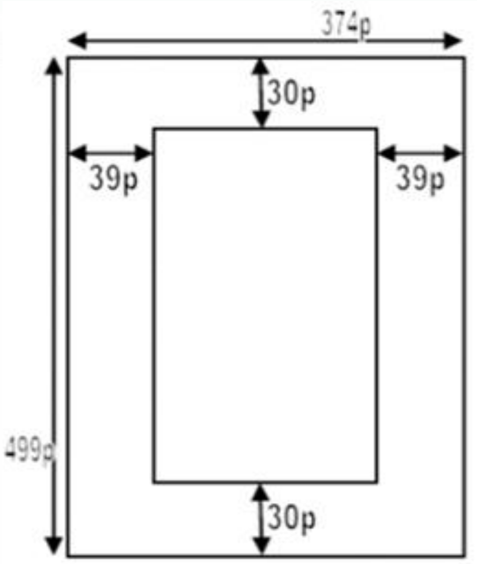

Figure 7. Carpet image partitioning

V. EXPREMENTAL RESULTS

Evaluation Criterion

The rank of retrieved information is an important issue in performance of a retrieval system. This subject is addressed in the MPEG-7 by defining the ANMRR (average normalized modified retrieval rank) as the retrieval performance [22]. The normalized modified retrieval rate (NMRR) is measured for each query by using Equation (8), where NG(q) is size of the ground truth set for a query image q, Rank(k) is ranking of the ground truth images retrieved by the retrieval algorithm and K(q) specifies the "relevance rank" for each query.

$$\mathrm{NMRR(q)} = \frac{\left\{\sum_{k=1}^{NG(q)} \frac{Rank(k)}{NG(q)}\right\} - 0.5 - \frac{NG(q)}{2}}{k(q)=0.5(1-NG(q))} \qquad (8)$$

As size of the ground truth set is normally unequal, a suitable K(q) is determined by Equation (9), where GTM is the maximum of NG(q) for all query sets. NMRR is in range of [0,1] and its smaller values means a better retrieval performance.

$$k(q) = \min\,(4 \times NG(q).2 \times GTM) \qquad (9)$$

Hence ANMRR can be defined as Equation (10), where NQ is number of query images [22].

$$ANMRR = \frac{1}{NQ} \sum_{q=1}^{NQ} NMRR(q) \qquad (10)$$

Simulation results and Performance Comparison

All mentioned methods are implemented in MATLAB and executed on a Laptop computer with Intel Core2Duo-2GHz CPU and 1GB RAM. The methods are also applied to our carpet image database and retrieval performance of each method is evaluated in terms of the ANMRR.

The retrieval rate of original CLD and proposed QCLD methods are depicted in Table II. A downward trend can be observed for ANMRR in the last row of Table II. The ANMRR results of proposed QCLD is 0.216 for all 110 query sets while this value is 0.247 for the original CLD.

TABLE II. NMRR AND ANMRR RESULTS OF PROPOSED QCLD IN COMPARISON WITH ORIGINAL CLD

Query Num.	NG(q)	K(q)	CLD	QCLD (proposed)
100	7	28	0.410	0.424
489	4	16	o.471	0.471
511	7	28	0.502	0.506
630	9	36	0.222	0.216
635	11	44	0.000	0.000
659	7	28	0.133	0.129
714	11	44	0.111	0.126
832	13	52	0.008	0.009
854	18	56	0.027	0.047
931	14	56	0.001	0.000
959	18	56	0.001	0.001
1000	28	56	0.155	0.126
1079	19	56	0.284	0.359
1113	14	56	0.630	0.617
ANMRR			**0.247**	**0.216**

Table III represents the retrieval results of the original DCD and proposed DCDIP methods. As an example for query image number 511, the value of NMRR for DCD is 0.626 while this value is 0.387 for DCDIP. The number of query sets which resulted in the zero value of NMRR is considerable.
The DCDIP provides the ANMRR value of 0.125 over all 110 sets while the DCD provides the ANMRR value of 0.148. The lower value for ANMRR means higher retrieval performance and accuracy. In this research, T_d and α parameters in Equation (6) were set to 10 and 1, respectively.

TABLE III. NMRR AND ANMRR RESULTS OF PROPOSED DCDIP IN COMPARISON WITH ORIGINAL DCD

Query Num.	NG(q)	K(q)	DCD	DCDIP (proposed)
100	7	28	0.396	0.350
489	4	16	0.242	0.228
511	7	28	0.626	0.387
630	9	36	0.347	0.291
635	11	44	0.003	0.026
659	7	28	0.000	0.000
714	11	44	0.061	0.057
832	13	52	0.000	0.000
854	18	56	0.000	0.000
931	14	56	0.000	0.000
959	18	56	0.000	0.000
1000	28	56	0.000	0.000
1079	19	56	0.000	0.000
1113	14	56	0.000	0.000
ANMRR			**0.148**	**0.125**

TABLE IV. LINKING BETWEEN SEMANTIC RATING AND NMRR VALUES

Subjective Rating	NMRR
Very good – good	0.0 – 0.28
Good – fair	0.281 – 0.64
Fair – poor	0.641 – 1

TABLE V. PERCENTAGE OF EACH SEMANTIC RATE FOR ALL THE 110 NMRR RESULTED FROM APPLIED METHODS

Method/rating Percentage	Very good-good	Good-fair	Fair-poor
CLD	58.2	33.6	8.1
QCLD (proposed)	68.2	26.4	5.4
DCD	75.5	24.5	0.0
DCDIP (proposed)	80	19.1	0.9

Table IV shows the linking between semantic rating and the NMRR of each query. Table V shows the percentages of those queries which have the same semantic for each of the retrieval algorithm.

As a number of results, Figure 8 shows the first 18 retrieved images by proposed QCLD method for query image number 959 with NMRR value of 0.0018. As it can be seen, all the 16 related images are retrieved and ranked in the first 18 results.

Figure 9 shows retrieved images by the DCDIP method for query image number 832. Zero value of NMRR indicates that all 12 ground truth images are retrieved and ranked in the first 18 results. As the number of ground truth sets is 110, a semantic rating is introduced in order to clarify the overall NMRR for each query.

For example, in the original DCD method, those queries with NMRR values between 0 and 0.28, cover 75.5% of all 110 query sets, those have NMRR values between 0.281 and 0.64, cover 24.5% and those have NMRR values between 0.641 and 1 cover 0.0% of all 110 query sets which 0.0% means no query set has this range of NMRR when the original DCD method is applied on our carpet image database.

For the original CLD method, those sets with NMRR values in the range of ‘very good – good’ cover 58.2% while in the QCLD method, it is 68.2%. To evaluate different methods from computational complexity point of view, the running times required for extracting feature vectors in each methods are measured and listed in Table VI.

Figure 8. Retrieved images by using the proposed QCLD method for the query image number 959, NMRR=0.0018, all the 16 ground truth images were found in the first 18 retrieved images

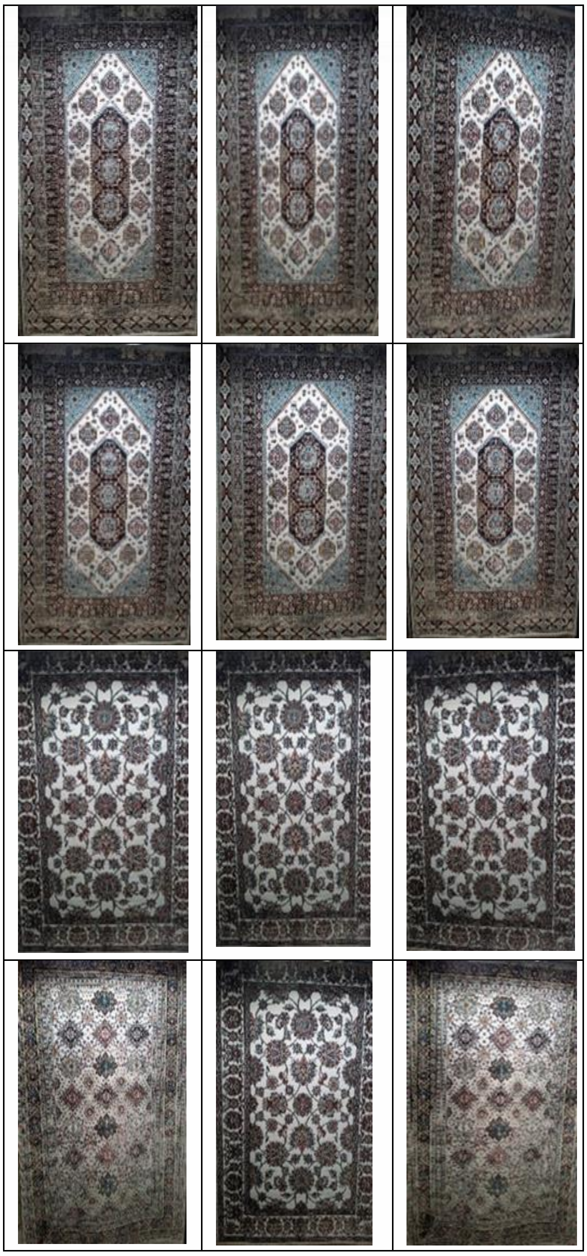

Figure 9. A number of retrieved images by using the proposed DCDIP method for the query image number 832, NMRR=0

TABLE VI. ANMRR AND FEATURE EXTRACTION RUNNING TIME

Method	**ANMRR**	**Time (s)**
CLD	0.247	0.4
QCLD (proposed)	0.216	2.84
DCD	0.148	7.5
DCDIP (proposed)	0.125	8.15

As it is shown in Table VI, the original CLD method took only 0.4 second to extract the color layout descriptor which is by far the lowest value among all the running times. While the proposed DCDIP method results in the lowest ANMRR value, it needs 8.15 seconds to be run. In overall the original CLD method is the best in terms of running time and the proposed

DCDIP is the best in ANMRR results although, the proposed QCLD appears proportionate in both terms of running time and accuracy.

VI. Conclusion

In this paper, a content-based image retrieval system was introduced for carpet e-commerce application. This system can be used in carpet e-commerce where an image is used instead of any tags. The carpet image database containing various Persian carpet images was also made for this application. Several content-based image retrieval methods were applied to the Persian carpet image database and evaluated in terms of the retrieval accuracy, speed and computational complexity.

Finally, based on the studied methods, two suitable methods of CLD for its speed and DCD for its higher accuracy were selected among all. Then these two methods were modified and the QCLD and DCDIP methods were proposed in order to have higher retrieval performance and speed for carpet e-commerce application.

According to the simulation results, a downward trend observed for the retrieval accuracy of the original CLD and proposed QCLD methods. The proposed DCDIP method also presented the higher retrieval accuracy in comparison with the original DCD method. To evaluate the methods from computational complexity point of view, the running times required for extracting feature vectors in each methods were measured.

The original CLD method took only 0.4 second to extract the color layout descriptor. The proposed DCDIP method resulted in the lowest ANMRR, while it needed 8.15 seconds to extract features.

In overall the original CLD is the best method in terms of running time and the proposed DCDIP is the best in the ANMRR results, although the proposed QCLD appears proportionate in both terms of running time and accuracy. Therefore, the simulation results reflected a higher retrieval performance for the two proposed methods of QCLD and DCDIP in content based carpet image retrieval for carpet e-commerce.

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Mehdi Reza Shahabi received the B.Sc. degree in Electrical Engineering from Islamic Azad University, Dezful, Iran in 2010 and the M.Sc. degree in Electrical Engineering from University of Sistan and Baluchestan, Zahedan, Iran in 2013. He currently works as an online Application and Solution Architect. His research interests include Neural Networks, Machine Learning Algorithms and Computer Vision.

Mehdi Rezaei (M'04) received the B.Sc. and M.Sc. degrees in electronics engineering from the Amir Kabir University of Technology and Tarbiat Modares University, Tehran, Iran in 1992 and 1996, respectively, and also Ph.D. degree in Signal Processing from the Tampere University of Technology, Finland in 2008. His research interests include Multimedia Signal Processing and Communications. He has published several papers in these fields. During his Ph.D. program, he had a close collaboration with the Nokia Research Center and he filled several patents. He also received the Nokia Foundation Award in 2005 and 2006. Now, he is an Associate Professor of Communications Engineering Department, University of Sistan and Baluchestan, Iran.

Farahnaz Mohanna received the B.Sc. degree in Electronics Engineering from the University of Sistan and Baluchestan, Zahedan, Iran in 1987, and M.Sc. degree in Electronics Engineering from the University of Tehran, Tehran, Iran in 1992, and Ph.D. degree in data processing from the University of Surrey, Guildford, UK in 2002. She continued working as a research fellow at the Centre for Vision, Speech and Signal Processing (CVSSP) at the Surrey University, UK in 2003. She is currently an Assistant Professor of Communication Enginnering Department at the University of Sistan and Baluchestan. Her research interests include image, and Video Processing, Computer Vision, and Communications. She has published several journal and conference papers in these fields.