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Image Similarity Search Approach Based On The Best Features Ranking

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Abstract

We propose an automatic image retrieval algorithm defining the best low level features with the purpose to become adaptive to different image categories from large databases. In conventional Content Based Image Retrieval (CBIR)systems, it is often observed that images visually similar to a query image are ranked low in retrieval results. A brief description of features and three used Databases are presented. In the first step images are retrieved using 11 known visual color, texture and shape features. We suggest an integrated features approach including features' performance comparison of 19 various image categories from the modified MSRCROID Database. We conducted a number of experiments showing that the proposed method, using integration of three common features, achieves an improvement of retrieval effectiveness of 10,1% on average compared to the corresponding best individual feature in different image categories. Further we apply this approach over two other Databases where accuracy retrieval enhancement is also shown.

Keywords: *Image retrieval, Low level features, Similarity Search.*

1. Introduction

The need for better content-based image retrieval solutions is growing due to the increasing number of digital images in the last decade.Values of the different type of features depending of the image content and their right selection for the image search process are very important.

MPEG-7 descriptors [1] for indexing and retrieval support a balance between the feature vector dimension and retrieval image score.The authors in [2] present an experimental comparison of a large number of different image features for content-based image retrieval. They compare quantitatively a large variety of features for four different tasks retrieval: stock photo, personal photo collection, and medical image, using five public image databases for retrieval performance of the different features analyzing. The article deals with features correlation as well. The color histogram feature usage is recommended for many applications.The current approach for image search is to use text annotations, describing the image content and enter this information manually into a database. The problem is that many images have hundreds of objects and each one is with a lot of attributes. Additional relationships between objects need be included in annotations also and at the end those labels are not rich enough.

Photobook system from MIT[3] applies appearance (edge geometry of a person's facefor example, car images, distribution of normalized intensity), texture (for texture-swatch images – threes, clouds, cloths, grass), and 2D shape features (for hand-tool and fish database images). The task can be to ask the computer to track that person within the video clip or findanother image with the same person. Photobook system allows using both text annotations and images directly based on their content for image search in databases.

One of the first systems QBIC (IBM) use color histograms, shape, texture and object motion features [4]. QBIC system combines visual content querying and annotations, key words and text querying.Carson et al. in [5] transform images to a small set of image regions which are coherent in color and texture and roughly correspond to objects, applying Expectation-Maximization (EM) segmentation and image retrieving by a nearest-neighbor criterion. For retrieving distinctive objects the precision is significantly higher than using color and texture histograms of the entire image. This system is named "Blobworld".

Many of the papers describe new proposed methods and features for image retrieval without giving a detailed comparison in respect to different image categories.The goal of this paper is to developa new approach for integration of the existing low level features, based on their image retrieval accuracy / performance without increasing vector length. An overview of the most popular features for content-based image retrieval is given. An analysis of feature performance for different image categories and databases as well as feature integration for obtaining better results in comparison to the individual features application is performed.

For the experiments, threedifferent databases with many publicly available image categories are used and the retrieval performance of the features is analyzed in detail.The experimental results from this paper lead to a new approach forchoosing an appropriate integration of features based on image similarity performance.

The paper is arranged as follows: In Section 2 the used low level features are described; in Section 3 the used threedifferent freely accessible image Databases are presented; in Section 4 the entire proposed by us approach for feature evaluation and integrationis given; in Section 5 are presented some experimental results, obtained using a Java program, and their interpretation, and Section 6 - the Conclusions.

2. UsedImage Similarity Search Features

A set of eleven features have been used in our experiments. All of them are implemented in Liresystem (Lucene Image Retrieval) [6].

2.1. Color Histogram

One of the important properties used in CBIR systems is the color. Color histogramis one of the most basic approaches used as a visual feature. In our experiments a 512 bin RGB histogram is utilized to represent the image. The similarity between two images *Q* and *T*is-computed as Manhattandistance(as a sum of absolute differences):

$$d(Q,T) = \sum_{i=0}^{I-1} \left| h_Q(i) - h_T(i) \right|, \tag{1}$$

Where h_Q and h_T are the image histograms, i is the index of *i-th* bin and I is the number of bins.

2.2. Tamura Features

One of most popular texture descriptors are Tamura texture feature histograms [7]. They represent six local statistical measures corresponding to the human visual perception. In the most cases, only the first three of them are used in the CBIR systems: coarseness, contrast and directionality of texture structures in image. Thus, in our test we calculate these three features to build a histogram. The comparison between two images Q and $T$is givenas Euclidian distance:

$$d(Q,T) = \sqrt{\sum_{i=0}^{I-1} (h_Q(i) - h_T(i))^2}. \tag{2}$$

2.3. Gabor Features

Applying Gabor Waveletfilters over the image gathers useful frequency and orientation representation of the texture [8].The Gabor features are extracted using different scale (k) and orientation (l). For each pair (k, l) the corresponding mean μ_{kl} and variation σ_{kl} of the filtered image are calculated. A feature vector is then created:

$$f = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, ..., \mu_{0K-1}, \sigma_{0L-1}, ..., \mu_{K-1L-1}, \sigma_{K-1L-1}), \tag{3}$$

where$K$ and L denotes the total number of different scales and orientations used.
The similarity between two images Q and $T$is calculated as:

$$d(Q,T) = \sum_{k=0}^{K-1} \sum_{l=0}^{L-1} \sqrt{(\mu_{kl}^Q - \mu_{kl}^T)^2 - (\sigma_{kl}^Q - \sigma_{kl}^T)^2}. \tag{4}$$

2.4. Color Correlogram

The authors in[9] present a color feature called Color correlogram. Unlike the conventional Color histogram the Color correlogram takes into account not only the color distribution in image but also the spatial correlation ofcolors.In our tests we employ the Auto Color correlogram descriptor which gives the probability to find two pixels with same colors at certain distance [10].It has been shown that this featureisrobust to large change of viewing angle, scales, etc [9].To save computation cost the Manhattan distance is used for comparing Auto color correlograms (see Eq.1).

2.5. MPEG-7 Color Descriptors

The MPEG-7 (The Moving Picture Experts Group) standard defined a set of visual descriptors[11]. In our test we use the following three of them.

Color Layout. The Color layout descriptor captures the spatial layout of color in image in very compact form. This is very fast and effective descriptor. The extraction process involves 4 steps: partitioning of image into 64 blocks, representative color selection for each block, Discrete Cosine Transform (DCT), zig-

zag scanning and quantization of the DCT coefficients for each color component (*Y*, *Cr*, *Cb*) [11]. The descriptor contains 12 coefficients (six for *Y*, three for *Cr* and three for *Cb* components). For comparison between two images *Q* and *T*represented by the descriptors, the following distance measure is used:

$$d(Q,T) = \sqrt{\sum_z w_{Yz}\left(Y^Q(z) - Y^T(z)\right)^2} + \sqrt{\sum_z w_{Crz}\left(Cr^Q(z) - TCr^T(z)\right)^2} + \sqrt{\sum_z w_{Cbz}\left(Cb^Q(z) - Cb^T(z)\right)^2}, \quad (5)$$

where *d(Q,T)* is the distance between the two images;*z* represents the zig-zagscanning order of the coefficients;w_{Yz},, w_{Crz},, w_{Cbz}, are weights for each DCT coefficient for*Y*, *Cr* and*Cb*components respectively;$Y^Q(z)$, $Y^T(z)$,$Cr^Q(z)$,$Cr^Q(z)$,$Cb^Q(z)$,$Cb^Q(z)$ are the values of the *z*-th DCT coefficient for the corresponding color component (*Y*, *Cr* or *Cb*) and the image (*Q* or *T*).

Edge Histogram. The Edge histogram describes the spatial distribution of the present non-directional edge parts, non-edge parts and four directional edge parts in the image[12]. The image is partitioned in 16 sub-regions and the extraction process is done over them.For each sub-region a local edge histogram of 5 bins is built. This is done by division sub-region on small square blocks and categorization of the edge type in it. The final histogram contains 16x5=80 bins.Each bin value is then normalized and quantized. As standard similarity measure of two edge histograms, the sum of absolute differences of the corresponding bins is used [13] (Eq. 1).

Scalable Color. The Scalable color descriptor is a color histogram in the HSV (Hue, Saturation, Value) color space based on the Haar transforms. This type of encoding allows scalable description presentation as well as complexity scalability in both the feature extraction and matching parts [13]. Comparison between two histograms is done using Eq. 1.

2.6. Compact Composite Descriptors

The Compact composite descriptors (CCD) combine both color and texture information in a very compact representation. In Lire system there are three implemented algorithms of such descriptor types named Fuzzy Color and Texture Histogram (FCTH), Color and Edge Directivity Descriptor (CEDD) and a combination of them – Joint Composite Descriptor (JCD). We briefly discuss the extraction stage of these features.

CEDD. The CEDD extraction procedure is described in [14]. This feature represents the color and the texture description in a histogram. The image is divided in sub-regions and the color information in HSV color space is then extracted using fuzzy logic. A 10 bin quantized histogram is then created. Each bin corresponds to a particular color. A feature vector stores the number of sub-regions assigned to each bin. The histogram is extended to 24 bins by adding two additional fuzzy rules to each bin of the histogram. This involves information related to the hue of each color. To capture texture information five digital filters are also used over each sub-region. This process is derived from the procedure of Edge Histogram detection from MPEG-7 standard. The result is 144 bins histogram that is then quantized. The feature is finally represented in 144-dimentional vector.

FCTH.The FCTH descriptor extraction is described in [15]. This process is very similar to that of CEDD. The part of color information extraction follows the same steps as these in CEDD. To present the texture in FCTH a Haar Wavelet transform is applied over each sub-region. This information is then imported to the 24-bins histogram which forms 192 bins histogram. Thus the FCTH feature is presented as192-dimensional vector.

JCD. The authors in [16] effectively combined the two descriptors CEDD and FCTH into a single one – JCD. The goal is to utilize the texture information captured by each descriptor, generating a 168-dimentional vector.

The Similarity*S*between the images for all CCD descriptors is done usingTanimoto coefficient [14, 15][1]:

$$S(x_Q, x_T) = \frac{x_Q^T x_T}{x_Q^T x_Q + x_T^T x_T - x_Q^T x_T}, \qquad (6)$$

wherex_Q and x_T are the feature vectors for the first *Q*and second *T*image respectively, x_Q^T and x_T^T are transposed feature vectors.

2.7. DCT Coefficients Histogram

The vector of this descriptor is a histogram of the DCT coefficients of different frequencies for the three different image components / channels (*Y*, *Cr*, *Cb*). The DCT coefficients represent 8 x 8 = 64 spatial frequencies. For each frequency, the DCT coefficients for all blocks are scanned to form a histogram. Thus the histogram consists of at most 64 × 3 = 192 bins [17]. To compare two feature vectors of the images *Q* and *T*the sum of squared differences of the corresponding bins is used:

$$d(Q,T) = \sum_{i=0}^{I-1} (h_Q(i) - h_T(i))^2, \qquad (7)$$

Where h_Q and h_T are the image histograms respectively, *i* is the index of *i-th* bin and *I* is the total number ofbins.

3. UsedImage Databases

In this section we briefly describe threedifferent freely accessible imageDatabases (DB) used for CBIR benchmarking. The first one– MSRCORID*(Section 3.1) allows forevaluation

1 http://chatzichristofis.info/?page_id=15

of particular feature performance for different image categories and we use it.Then we combine these features that bring best performance.The same tests have been conducted using other twoimage Databases: UCID (Section 3.2),ZuBuD (Section 3.3). A summary of these Databases is given on Table 1.

Table 1.Overview of image Databases used

Database	Number of images	Number of queries	Avg. number of imagesperquery	Queryapproach
MSRCORID*	4135	4135	216.6	Leaving-one-out
UCID	1338	262	2.5	Leaving-one-out
ZuBuD	1005	115	5	TestandDatabaseimagesareseparated

3.1. MSRCORID*Image Database

The MSRCORID[2](Microsoft Research Cambridge Object Recognition Image Database version 1.0) consists of 4323 images - 18 categories (top level), such as: "Airplanes", "Bicycles", "Kitchen utensils", "Scenes", etc. Some of them are further divided into subcategories (second level), i.e. "Kitchen utensils": "Forks", "Knives", and "Spoons". In our tests we made slight modifications of the distribution of the images per categories. We moved "Scenes" subcategories ("Countryside", "Office", and "Urban") in the top level division, because the images belonging to these particular categories don't seem enough visually similar. Also we excluded "Miscellaneous" since there is no visual similarity among all images in it. Thus the modified version -"MSRCORID*" contains 4135 images (19 categories).

3.2. UCID Image Database

The UCID Database[3]is an Uncompressed Color Image Dataset of 1338 photos[18].It can be used as evaluation Database for image compression, color quantizationalgorithms. It is also appropriate for testing CBIR systems as well as the image compression effect on their performance.UCID comes together with aground truth file where 262 images from the Database have been manually assigned to their similar ones. This Database contains a pool of different photo categories, not limited to: "Cars", "Man", "Flowers", "Building", etc.

3.3. ZuBuDImage Database

The ZuBuDDatabase[4] (Zurich Buildings Database for Image Based Recognition) depicts 201 buildings in Zurich city[19].Five images for each building were taken from different angles of view or weather conditions. This results to a set of 1005 images - training part. Another 115 images each of which describes one building from the training part forms the query part. When testing CBIR on given query only returned images that show the same building as the one in the queryare considered relevant.

[2] ftp://ftp.research.microsoft.com/pub/download/orid/msrcorid.tar.gz
[3] http://www-staff.lboro.ac.uk/~cogs/datasets/UCID/ucid.html
[4]http://www.vision.ee.ethz.ch/datasets/index.en.html

4. Developed Approach of Automated Evaluation for Features Integration

For performance evaluation first all images from the Database are indexed. That is for each feature of interest a feature vector that corresponds to each DB image is extracted and stored using Lucene index created by LIRe. Next for each query a feature vector is also extracted and compared with each image feature vector from the Database using appropriate distance. Further the Database images are sorted in ascending order with respect to the distances. In the combined feature approach a linear combination of distances (determined for the desired features for combination) is carried out to calculate similarity and accomplish ranking.

For retrieval effectiveness of CBIR systems the performance measurements Precision (P) and Recall (R) are commonly used [20]:

$$P = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}, \quad (8)$$

$$R = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in database}}. \quad (9)$$

These are usually given as form of precision-recall (P-R) graph. It is convenient to use measure parameters rather than P-R graph. In our investigations the following three parameters are examined for each Database and each feature and for the combined features approach:

Precision at the first N results (p@N) is determined as follows:
For each query image qa precision Pq(N) from the first Nresults is calculated. Then the p@N value is given as average sum of precisionsfor all queries:

$$p@N = \frac{1}{Q}\sum_{q=1}^{Q} P_q(N), \quad (10)$$

where$N = 10$ and $Q$is the number of all queries for the current Database[5] (
Table **1**).

0 Mean Average Precision (MAP) is given with the equation:

$$MAP = \frac{1}{Q}\sum_{q=1}^{Q}\frac{1}{N_{rel}(q)}\sum_{N=1}^{N_{rel}(q)} P_q(N).rel(N), \quad (11)$$

where $N_{rel}(q)$ is the total number of relevant images in the Database for the q-th query, $rel(N)$ has value of 1 if the current N image is relevant to the query and 0 if not.

Error rate (ER) takes into account only the first retrieved image for each query and is calculated as:

[5] For the MSRCORID* Database the $p@N$ is calculated for each category.

$$ER = \frac{1}{Q}\sum_{q=1}^{Q}\begin{cases}1 & \text{if the first result is relevant to the query}\\ 0 & \text{otherwise}\end{cases} \qquad (12)$$

4.1. Performance Comparison of AllFeatures

Eleven features are evaluated for 19 image categories from MSRCORID* Database. Table 2 shows the precision at top ten retrieved results for each image category and each feature. Bolded values mean the best performance reached for the certain image category and feature. Table 3 represents MAP, Precision at the first 10 results and Error Rate for each feature for the whole Database. Fig. 1 shows the same results in a graph.

Table 2.Precisionat 10 perfeatureforeachcategoryoftheMSRCORID*Database (bestvalues in bold)

Name	Precision at 10, % per feature										
	ColorHistogram	Tamura	Gabor	Color Correlogram	ColorLayout	ScalableColor	EdgeHistogram	CEDD	JCD	FCTH	DCTCoeffs
Airplanes	37,4	38,3	4,0	57,9	61,0	15,2	62,9	**67,1**	66,9	53,3	53,6
Animals	76,7	38,4	14,5	**83,7**	77,1	35,8	61,9	81,5	83,5	80,2	79,1
Benchesandchairs	10,9	6,0	0,9	21,6	10,3	6,5	10,9	16,3	16,5	14,9	**25,0**
Bicycles	50,9	25,4	10,8	66,2	42,0	29,1	54,4	57,1	66,4	62,4	**66,6**
Birds	20,1	6,3	1,9	19,4	**24,6**	6,4	13,9	19,4	20,7	17,8	15,7
Buildings	16,0	6,4	5,8	19,9	19,9	9,5	24,2	23,3	**26,8**	24,9	17,7
Cars	67,5	60,5	25,0	66,6	57,0	49,2	**91,9**	83,8	83,5	77,5	86,5
Chimneys	75,6	37,6	27,9	81,9	80,0	32,5	72,1	82,6	**84,1**	76,8	76,8
Clouds	89,5	40,9	34,1	**99,4**	86,5	89,8	73,9	94,3	95,2	95,7	87,9
Countryside	44,9	14,1	5,9	**54,6**	39,6	31,7	24,8	51,1	53,8	52,3	40,5
Doors	26,8	24,4	6,3	21,8	19,4	11,3	31,8	34,0	33,1	28,4	**38,9**
Flowers	25,3	25,2	7,5	30,6	19,7	17,5	32,1	30,2	28,6	25,4	**49,3**
Kitchenutensils	84,4	41,2	20,7	72,1	78,6	52,7	73,5	91,0	**91,5**	85,9	88,3
Leaves	41,3	16,4	8,8	**54,3**	32,9	19,9	18,4	46,6	44,2	44,2	39,6
Office	33,4	6,6	3,5	35,9	13,7	11,9	17,8	37,5	40,6	36,3	**61,3**
Signs	6,8	**21,2**	4,6	5,5	8,4	4,9	20,4	13,9	12,5	8,2	16,9
Trees	58,8	26,3	10,9	**82,0**	57,9	30,2	62,8	63,6	62,7	59,7	54,4
Urban	37,2	8,1	3,3	33,9	22,2	5,8	23,6	35,8	38,1	**40,3**	26,9
Windows	64,3	50,2	22,1	**78,4**	75,8	43,2	73,2	74,2	74,5	68,9	65,8

Table 3.Mean Average Precision, Precision at 10and Error Rate for each feature of the MSRCORID*Database (bestvaluesarein bold)

Name	MAP, %	p@10, %	ErrorRate, %
ColorHistogram	28,53	57,47	31,32
Tamura	20,24	35,29	60,00
Gabor	10,90	16,98	80,31
Color Correlogram	34,90	64,72	22,56
ColorLayout	28,78	56,27	30,98
ScalableColor	24,87	37,52	57,20
EdgeHistogram	30,98	58,30	34,17
CEDD	33,93	65,35	24,67
JCD	35,12	**66,42**	**22,37**
FCTH	**35,34**	62,50	27,52
DCTCoeffs.	33,16	63,53	25,42

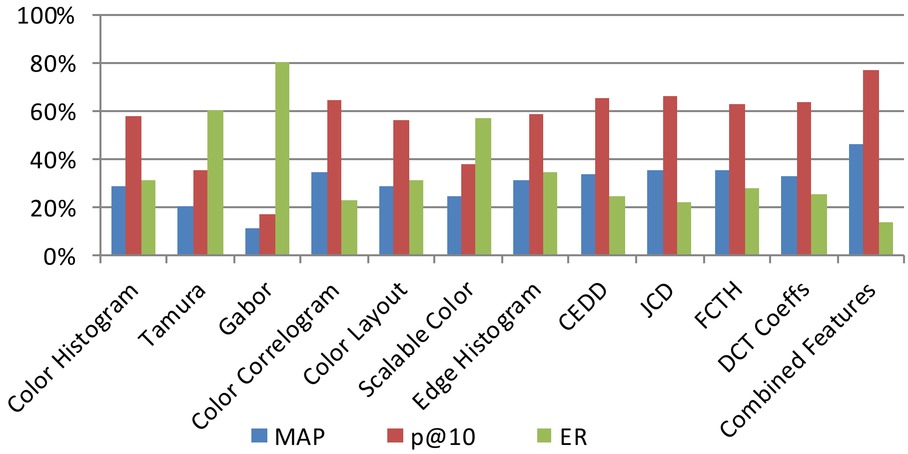

Figure1.Comparison of Mean Average Precision, Precision at 10 and Error Rate for each feature of the MSRCORID* Database

4.2. Proposed Features Integration and Performance Evaluation

The combination approach is based on sorting of the features in descendant order regarding their performance and selection of the best three features. We take into account that CEDD and FCTH are combined in one – JCD. Therefore we ignore CEDD and FCTH and add the next two best features into the desired set. The three features considered for combination JCD, Color correlogram (CC) and DCT Coeffs. are shown in table 3.

It is important to note that JCD provides both color and texture description of the image. On the other hand Color correlogram represents the spatial color distribution and the DCT coefficients histogram deals with the color frequency distribution of the image. It can be assumed that such combination of features provides more authentic image description that serves to better results.

The combined approach defines a new distance $D_{comb}(Q,T)$, utilizing linear combination of three distances $D_{JCD}(Q,T)$, $D_{CC}(Q,T)$,$D_{DCTCoeffs}(Q,T)$, calculated for the particular features:

$$D_{comb}(Q,T) = \frac{D_{JCD}(Q,T) + D_{CC}(Q,T) + D_{DCTCoeffs}(Q,T)}{3} \qquad (13)$$

The performance evaluation involves comparison between individual feature performances and our feature combined approach. In Table 4 and Fig. 2 are given the values of p@10 for all categories and the corresponding features that gives the best p@10's compared to values of p@10's reached by ourcombined feature approach. It can be seen that for 14 of categories (19 tested) our approach gives better results compared to the best individual feature performance. For example for the "Benches and chairs" category the best individual feature is DCT Coeffs. with value of p@10 equals to 25%. Using our integration approach the value of p@10 is raised to 32,35% which is 29,41% improvement for this category (Table 4 in green). The increasing of p@10 performance measure is 10,1% on average for all image categories. The improvement of p@10 performance measure is 10,1% on average.

Table 4.Precisionat 10 ofthebestfeaturesforeachcategory, precisionat10 andimprovementofthecombinedapproachforeachcategoryofthe MSRCORID* Database (bestvalues in bold)

Category – Thebestfeatureforthiscategory	p@10 perbestfeaturepercategory, %	p@10 of ourapproach percategory, %	p@10 improvementfor our approach. %
Airplanes - CEDD	67,07	**79,48**	18,51
Animals - Color Correlogram	83,74	**90,81**	8,44
Benchesandchairs - DCTCoeffs	25,00	**32,35**	29,41
Bicycles - DCTCoeffs	66,58	**82,13**	23,36
Birds - ColorLayout	24,58	**27,22**	10,74
Buildings - JCD	26,78	**35,14**	31,20
Cars - EdgeHistogram	**91,94**	89,64	-2,50
Chimneys - JCD	84,10	**93,16**	10,77
Clouds - Color Correlogram	**99,42**	99,25	-0,16
Countryside - Color Correlogram	54,57	**66,20**	21,32
Doors - DCTCoeffs	38,92	**42,11**	8,20
Fowers - DCTCoeffs	**49,34**	40,30	-18,31
Kitchenutensils - JCD	91,49	**95,14**	4,00
Leaves - Color Correlogram	54,32	**65,25**	20,12
Office - DCTCoeffs	61,32	**66,91**	9,11
Signs - Tamura	**21,21**	18,30	-13,71
Trees - Color Correlogram	**82,03**	78,25	-4,61
Urban - FCTH	40,28	**49,72**	23,45
Windows - Color Correlogram	78,42	**88,25**	12,54

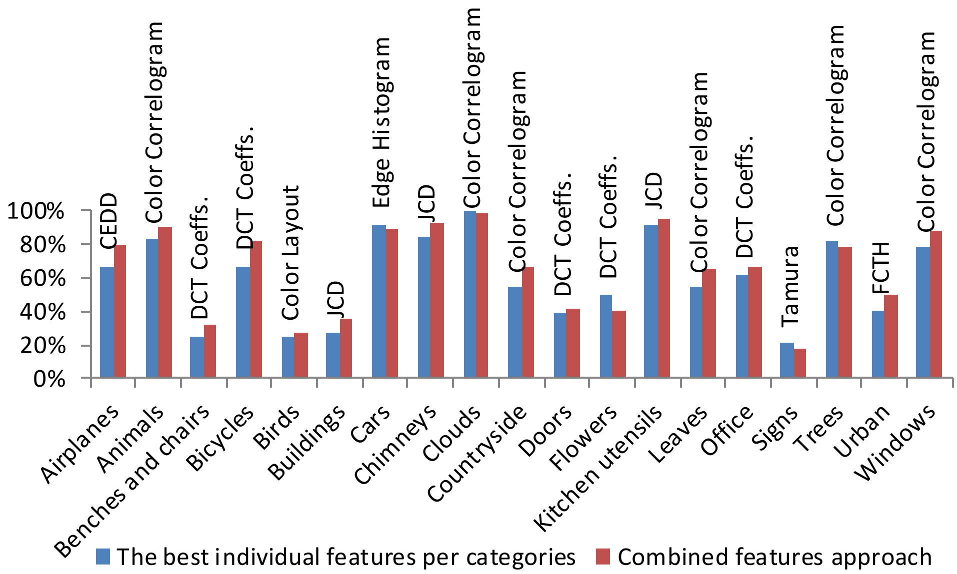

Figure2.Comparison of precision at 10 [%] reached by the best feature for each category and the precision at 10 [%] of the combined approach of the MSRCORID* Database

We also investigated our combination approach over two other Databases (UCID and ZuBuD). Table 5 shows that our approach reaches the highest performance according to p@10 measure (values in bold) for all databases and highest MAP for two of them (MSRCORID* and UCID).

Table 5.Meanaverageprecisionandprecisionat 10, foreachfeatureandthecombinedapproachforeach Database (thebestvaluesarein bold, thebestvaluesofthe individual features - underlined)

Database	MSRCORID*		UCID		ZuBuD	
Feature	MAP, %	p@10, %	MAP, %	p@10, %	MAP, %	p@10, %
ColorHistogram	28,53	57,47	39,23	10,53	**74,60**	38,70
Tamura	20,24	35,29	5,48	2,02	14,75	10,17
Gabor	10,90	16,98	2,29	0,65	2,86	1,22
Color Correlogram	34,90	64,72	53,50	13,97	69,44	36,96
ColorLayout	28,78	56,27	26,13	8,24	59,53	31,48
ScalableColor	24,87	37,52	18,01	5,92	35,12	21,13
EdgeHistogram	30,98	58,30	17,47	5,61	38,19	21,57
CEDD	33,93	65,35	44,46	12,79	71,79	37,57
JCD	35,12	66,42	47,07	13,17	71,78	37,74
FCTH	35,34	62,50	44,70	12,56	68,79	35,57
DCTCoeffs	33,16	63,53	25,90	8,13	1,49	0,26
CombinedApproach	**45,85**	**76,60**	**63,15**	**15,84**	69,93	**38,78**

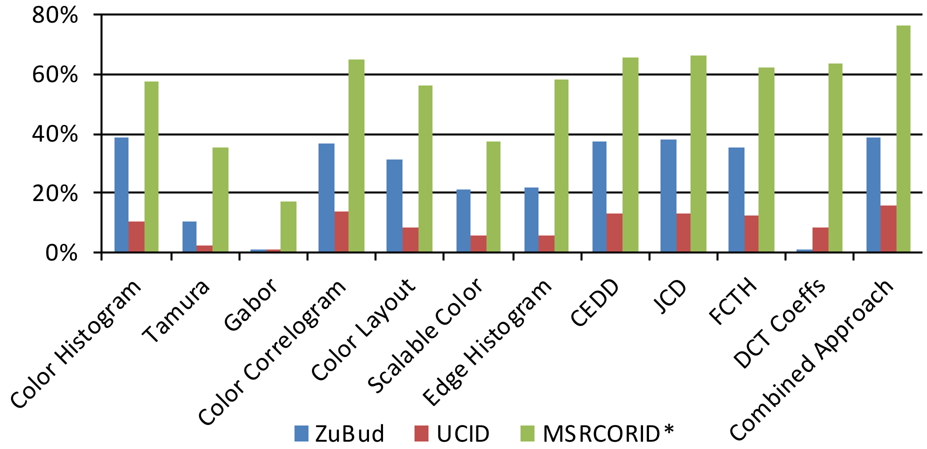

Figure3.Precision at 10 for each feature and our combined approach for each Database

On Fig. 3 is depicted the visual representation of the p@10 per feature for each databases and for the combined approach (Table 5).

(a)

(b)

(c)

Figure4.Top 10 retrieval results for the query (a) from the MSRCORID* Databaseusing the Color correlogram feature (b) and ourapproach (c)

5. Experimental Results of Similar Images Retrieval

The selected search image / query from the MSRCORID* Database is shown on Fig. 4.a.Using our feature integration approach nine relevant images from the first ten results are retrieved (Fig. 4.c). This result can be compared to the effectiveness of the individual Color correlogram feature where only four relevant images are extracted (Fig. 4.b). For the shown example the image retrieval accuracy of the automatically defined integrated approach is significantly improved 2,25 times (9/4) corresponding to the individual Color correlogram feature.

6. Conclusions

In this paper, we examine how much improvement can be achieved by integration of the best individual features per image categories for the image retrieval process.

The basic goal in content-based image retrieval is to bridge the gap from the low-level image properties ("features") and the image objects that users want to find in image databases.

The basic idea of our approach is that the images similar to a query image should be ranked higher than the initial ranking based on the individual features. First, we retrieve images using a traditional image retrieval method with each one of the features and then estimate individual features' performance. Next, we analyze the retrieved images and then suggest a method ofintegration of the best three features according to their performance. The developed approach automatically re-ranks the results according to the leastdistance from a query image. In the experiments, we show that our method can significantly improve the retrieval effectiveness in CBIR systems comparing to the individual features.

In the future we plan to apply weighting factors in the proposed method andto explore automatic classification of images into categories to search each one image collection based on image content.

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