Parameter Optimization of Dominant Color Histogram Descriptor in Content-based Image Retrieval Systems

Szabolcs Sergyan

***Abstract*—**Last years the importance and abundance of image retrieval systems had a big growth. During the searching process the color feature of the images is one of the most significant characteristics. Since the color-based comparison and retrieval has a variety of widely used techniques. This paper introduces a new color based image descriptor which is a mixture of other widely used features. This descriptor takes into account the dominant colors in HSV color space, the color histogram and the spatial distribution of pixels. With the proposed feature experiments were carried out in two image databases, and that was found the precision of retrieval has significantly improved. The paper presents the best choice for the mentioned parameters.

***Keywords*—**Content-based image retrieval, Color features, Color histogram, Dominant color histogram, Parameter determination.

I. Introduction

THE importance of image databases has increased with spreading of digital cameras and everyday use of internet. The image databases are not only becoming increasingly important in specific areas (ie. medical, police, arts applications), but also in people's daily lives [22] as well. The computer users have either special image collections (family photographs, home-made landscapes, photos of cities), or on the internet they want to find images to suit specific themes or moods. [2]

There are two techniques fundamentally used to search for images. One is based on text indexing, where text descriptors (keywords, short explanations) are assigned to each image. The assigned text features are usually representatives of the images, but the assignment process and the possible re-indexing of database is very time consuming.

The other indexing and retrieval technology automatically assigns features to the image based on the content of the image. This technique allows relatively fast indexing and search, reduces the subjectivity of properties, but the generation of the proper characteristics is usually a difficult task. The latter technique is the content-based image retrieval. The method became popular in the 80s and since then has evolved considerably, is still a priority research area. [17]

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Sz. Sergyan is with the Software Engineering Department of Obuda University, Bécsi út 96/b, H-1034 Budapest (phone: 361-666-5579; fax: 361-666-5552; e-mail: sergyan.szabolcs@nik.uni-obuda.hu).

The content-based image retrieval systems usually extract features considering the color of images, and the color, shape and texture of objects in the scene. It is important that the images are properly segmented [20], [21], and can be obtained much information from the image using an image processing algorithm [14], [16]. The search can be done in many ways. The most common method is when the user gives a query image, and similar images are looked for in the database. To do this, the features of the query image and the database images are compared using an adequate similarity measure. All this shows that the most significant in CBIR systems the feature retrieval and how the generated features are compared with a similarity measure.

The content-based image retrieval systems are usable a number of scientific and development area. One possible example is the retrieval of vehicle databases [1], [5]. The CBIR systems use actual scientific results of a lot of fields: information retrieval, artificial intelligence [4], data mining, image processing and image understanding, control and systems [6], [24]. The systems are based on the novel achievements of computational modeling [26] and workflow process [27].

In this paper only the color-based comparison techniques are taken into account. In Section II the commonly used color features are presented, and a novel feature, the dominant color histogram is introduced. Based on color properties a new method is proposed, that takes into account the color locations slightly not only the colors themselves. The proposed method is described in Section III. The features usually heavily depend on parameters, so a series of tests were completed to determine the most suitable parameters. The test conditions are described in detail in Section IV. The results of the experiments stated that the proposed dominant color histogram as a feature gives better precision results than the widely used dominant color feature. In Section V the conclusion and possible improvements are presented.

II. Color-based Features

In the preparation of color-based features generally the applied color gamut used to feature generation has to be determined. The display of computers uses the RGB color space, but there is a problem with this color space. The distance of two RGB colors is not proportional to the distance of human color perception. For this reason the usage of HSV,

Fig. 1: The significant colors of bins based on the HSV color space. The H channel is divided into 8, the S and V channel into 3-3 equally wide intervals.

CIE L*a*b*, or LUV color space is usually proposed. [25]

The HSV is a popular selection for color manipulation. This color space is developed to provide an intuitive representation of color and to approximate the way in which humans perceive and manipulate color. The hue (H) represents to dominant spectral component of color. Adding white to the pure color changes the color itself: the less white, the more saturated the color is, so it generates the saturation (S). The value (V) corresponds to the brightness of color. [10]

A. Color histograms

The most frequently used color descriptor is the color histogram. During the histogram production the actual color space is divided into a predetermined number of bins. Figure 1 shows histogram bins, if the HSV color space is divided up. In this example the H channel is divided into 8, the S and V channel into 3-3 equally wide intervals.

If all colors are matched to the color assigned to the according bin, then of course the image is modified, but it is not significant, as shown in Figure 2.

After the production of bins the number of those pixels is determined for all bins whose color intensity belongs to the according bin. The color histogram is obtained in this manner. It is obvious that the sum of the histogram values is the same as the image size. If the histogram is to be independent of the size of the image, then all values are divided by the number of pixels to obtain the normalized histogram.

To compare histograms the L_1, L_2 and L_∞ norms are usually used. Another frequently used comparing method is the so-called histogram intersection. [18].

A problem with histogram is that the result of image retrieval is highly dependent on bin determination. Mainly a problem may be at those colors which are close to the edges of histogram bins, because in case of small color differences the colors may belong to different bins. One resolution of this problem is the use of the dominant colors.

(a) (b)

Fig. 2: (a) Original image (from Wang database [28]), (b) the original colors are replaced using the representative color of according bin in case of 72 several bins.

B. Dominant color

If dominant colors [23] are used, then only those colors are taken into account, whose frequency occurrence is greater than a predefined threshold. In this case the dominant colors (C_i), and those frequency occurrences (p_i) are stored as descriptors. The similarity measure between dominant colors [9] can be determined in the following way:

$$D(I_1, I_2) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(L_2(C_i, C_j) \cdot |p_i - p_j| \right) \quad (1)$$

where L_2 is the Euclidean distance, I_1 and I_2 are the two observed images, M and N are the number of dominant colors in I_1 and I_2, respectively.

Mojsilovic et al. [11] proposed a similarity measure as stated below:

$$D(I_1, I_2) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(L_2(C_i, C_j) + |p_i - p_j| \right). \quad (2)$$

The comparison of dominant color descriptors can be based on color clustering and similarity of appropriate clusters too. [3]

C. Dominant color histograms

As the mixture of color histograms and dominant colors the dominant color histogram can be produced. During the histogram creation only the dominant colors are considered. The advantage of this method that the histogram comparison is faster (ie. with L_2 norm) than the calculation of the dominant color comparison measures. Question to be examined, in addition to a faster running time how the hit rate of similar images varies.

III. Proposed Method

A. Description of the algorithm

The HSV color space is divided into bins. According to the individual bins the normalized color histogram is modified based on the dominant colors of the image on that way, the histogram value is set to zero in those bins, where does not fall any dominant colors.

Because images generally comprise one or more objects in a background, it may be worth to separate the object and background. This can be done by a segmentation algorithm [19], but the segmentation algorithms are generally quite time-consuming. Therefore, a simpler method is used, the like of which can be found in the article [23] as well. Because objects are usually found in the middle of the image, so a frame of the image is prepared. The pixels belonging to this frame are

Fig. 3: Dominant color can be seen in the image. Each dominant color is assigned to either the frame or the middle.

considered as background pixels, and the pixels inside the frame are the object pixels. Of course some object and also some background pixels will be classified badly. However, the really important is which color belongs to either objects or backgrounds. Therefore, the occurrence frequency of all dominant colors is examined within the frame and inside the frame. If the occurrence is higher within the frame, then the according dominant color is assigned to the frame-histogram, otherwise to the object-histogram.

In Figure 3 an image can be seen, where only the dominant colors appear. Each color is assigned to the frame or the middle.

Ultimately, therefore, there will be two histograms. The first one ($hist_{DC,f}$) is generated from the dominant colors which are more frequently occurring close the image border, by the other ($hist_{DC,c}$) is generated from those dominant colors which has higher frequency at the middle.

Use the obtained histograms the similarity of image I_1 and I_2 can be determined:

$$D(I_1, I_2) = d_{L_2}\left(hist_{DC,f}(I_1), hist_{DC,f}(I_2)\right) + d_{L_2}\left(hist_{DC,c}(I_1), hist_{DC,c}(I_2)\right) \quad (3)$$

where d_{L_2} is the distance based on L_2 norm, namely

$$d_{L_2}(hist_1, hist_2) = \sqrt{\sum_{i=0}^{NoB}\left(hist_1(i) - hist_2(i)\right)^2} \quad (4)$$

if *NoB* is the number of histogram bins.

B. Parameters of the algorithm

The effectiveness of the procedure expectedly largely depends on the choice of the following parameters.

The HSV color space is divided into several bins. The first parameter is the number of the applied bins. One property of HSV color space is that the S and V channels contain less (color) information than the H channel. So 3-3 bins for S and V channels are sufficient. In case of H channel it is worth to consider more possible divisions as well. Because of the characteristics of this color space we consider the division into 6, 12 and 18 equal parts. In [8] eigth bins was suggested.

During dominant color determination a threshold value must be taken into account. The colors with higher frequency than this threshold are considered as dominant colors. The following thresholds are examined: 0.1, 0.05, 0.025 and 0.0125.

When we assign the pixels to either the frame (background) or the middle (object), we take into account which width (or height) ratio of the image is used. To determine this the following ratios are applied: 1/10, 1/8, 1/6 and 1/4.

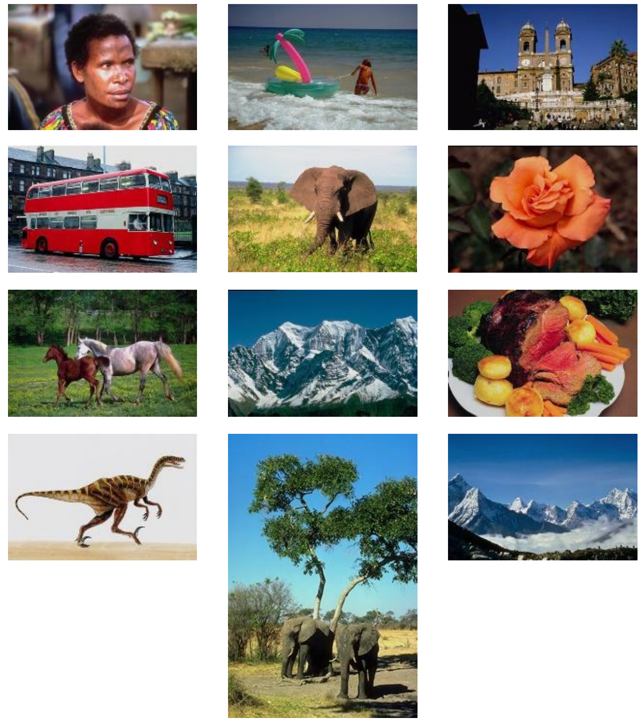

Fig. 4: Sample images form the Wang database.

IV. Experiments

A. Applied databases

To test the algorithm and to find to proper parameters two test databases were used.

The first is the so-called Wang database [7], [28], which is widely used in testing content-based image retrieval algorithms. The database contains images related to 10 several topics, as indigenous, beach vacation, historical buildings, buses, extinct reptiles, elephants, flowers, horses, snowy mountains and set tables. Some images of the database can be seen in Figure 4.

The other one is the Coil-100 database [13]. It contains images of 100 several objects in homogeneous background. The objects can be seen in Figure 5. Shots are made of each object from different directions with 5° deviation. In experiments only every sixth image of each object was used, so twelve several images of each object were in the used sub-database.

Fig. 5: The COIL-100 database contains images of 100 objects.

B. Performed tests

For both databases each image was compared to all other images. In comparison the dominant color descriptor and the dominant color histogram descriptor was used. The dominant colors were compared by (1) formula and the dominant color histograms by the (2) formula.

I examined, which 12 images are the closest to the query image (in case of Wang database), and which 11 images (in case of COIL-100 database). The precision of retrieval was determined [15] as the number of pixels from the same class as the qurey image divided by the number of hits (12 or 11). In Figure 6 one search result can be seen. The top image is the query image, and the other 12 images are the mentioned hits.

Fig. 6: The 12 closest images to the top (query) image using the dominant color histogram descriptor with a proper parameterization. 10 hits belong to the same class as the query image.

The test was carried out with all images of the database, so a precision value is achieved for all images. The precision of total search was determined as the average of the precision of each database image.

The test were performed for all earlier mentioned parameters (see Subsection III.B), thus the average precision of each search was obtained for all parameterizations. Tables 1-4 contain the obtained precision values. Clearly, the usage of dominant color histogram yields better precision values for all

		$thresh_{DC}$			
Bins #	$thresh_{frame}$	**0.0125**	**0.025**	**0.05**	**0.1**
6	**1/10**	0.5571	0.5477	0.5072	0.4176
	1/8	0.5608	0.5523	0.5059	0.4225
	1/6	0.5637	0.5541	0.5099	0.4252
	1/4	0.5613	0.5545	0.5183	0.4332
8	**1/10**	0.5647	0.5494	0.4773	0.3924
	1/8	0.5670	0.5507	0.4810	0.3908
	1/6	0.5737	0.5540	0.4900	0.4018
	1/4	0.5729	0.5583	0.4938	0.4059
12	**1/10**	0.5522	0.5272	0.4691	0.3752
	1/8	0.5583	0.5332	0.4768	0.3738
	1/6	0.5636	0.5404	0.4793	0.3817
	1/4	0.5637	0.5415	0.4836	0.3892
18	**1/10**	0.5359	0.5028	0.4438	0.3401
	1/8	0.5381	0.5071	0.4441	0.3420
	1/6	0.5425	0.5114	0.4504	0.3458
	1/4	0.5551	0.5213	0.4610	0.3537

Table 1: Average precision values for all examined parameters using dominant color histogram descriptor in the Wang database.

		$thresh_{DC}$			
Bins #	$thresh_{frame}$	**0.0125**	**0.025**	**0.05**	**0.1**
6	**1/10**	0.3117	0.2699	0.2060	0.1871
	1/8	0.3076	0.2715	0.1978	0.1814
	1/6	0.3094	0.2687	0.2084	0.1789
	1/4	0.3160	0.2755	0.2104	0.1793
8	**1/10**	0.3130	0.2487	0.1951	0.1840
	1/8	0.3151	0.2553	0.1903	0.1792
	1/6	0.3174	0.2583	0.1934	0.1746
	1/4	0.3188	0.3662	0.1991	0.1715
12	**1/10**	0.3157	0.2421	0.1917	0.1619
	1/8	0.3157	0.2452	0.1982	0.1620
	1/6	0.3202	0.2487	0.1975	0.1573
	1/4	0.3132	0.2518	0.2009	0.1568
18	**1/10**	0.3172	0.2132	0.1852	0.1563
	1/8	0.3142	0.2086	0.1922	0.1557
	1/6	0.3209	0.2245	0.1968	0.1547
	1/4	0.3249	0.2311	0.1942	0.1470

Table 2: Average precision values for all examined parameters using dominant color descriptor in the Wang database.

		$thresh_{DC}$			
Bins #	$thresh_{frame}$	**0.0125**	**0.025**	**0.05**	**0.1**
6	**1/10**	0.4498	0.4292	0.3651	0.2511
	1/8	0.4566	0.4355	0.3714	0.2559
	1/6	0.4589	0.4402	0.3761	0.2611
	1/4	0.4617	0.4467	0.3845	0.2672
8	**1/10**	0.4825	0.4522	0.3668	0.2417
	1/8	0.4927	0.4671	0.3802	0.2501
	1/6	0.5055	0.4817	0.3877	0.2511
	1/4	0.4915	0.4700	0.3890	0.2532
12	**1/10**	0.5217	0.4833	0.4017	0.2311
	1/8	0.5250	0.4874	0.4031	0.2314
	1/6	0.5254	0.4918	0.4083	0.2319
	1/4	0.5189	0.4804	0.4036	0.2214
18	**1/10**	0.4978	0.4588	0.3505	0.1914
	1/8	0.5074	0.4673	0.3624	0.1877
	1/6	0.5175	0.4764	0.3690	0.1920
	1/4	0.5118	0.4703	0.3639	0.1909

Table 3: Average precision values for all examined parameters using dominant color histogram descriptor in the COIL-100 database.

		$thresh_{DC}$			
Bins #	$thresh_{frame}$	**0.0125**	**0.025**	**0.05**	**0.1**
6	**1/10**	0.0461	0.0497	0.0618	0.0636
	1/8	0.0470	0.0530	0.0655	0.0640
	1/6	0.0502	0.0542	0.0642	0.0670
	1/4	0.0614	0.0651	0.0653	0.0673
8	**1/10**	0.0539	0.0205	0.0283	0.0250
	1/8	0.0556	0.0242	0.0302	0.0270
	1/6	0.0587	0.0316	0.0345	0.0306
	1/4	0.0651	0.0364	0.0345	0.0356
12	**1/10**	0.0515	0.0289	0.0326	0.0566
	1/8	0.0546	0.0324	0.0343	0.0584
	1/6	0.0555	0.0380	0.0433	0.0611
	1/4	0.0629	0.0398	0.0481	0.0616
18	**1/10**	0.0441	0.0298	0.0393	0.0465
	1/8	0.0484	0.0361	0.0426	0.0483
	1/6	0.0520	0.0344	0.0482	0.0524
	1/4	0.0638	0.0496	0.0542	0.0550

Table 4: Average precision values for all examined parameters using dominant color descriptor in the Wang COIL-100.

parameters and both databases. From tables the best parameter settings can be found.

Subsequently, the three parameters were examined separately. Using the Wang database the average of average precisions were generated for two parameters meanwhile the third parameter were fixed.

In Figure 7 can be seen that the best precision value belongs to the threshold value 0.0125 of dominant color threshold in case of both descriptors.

In case of the selection of frame ratio parameter the value 1/4 gives the best average precision value, but in Figure 8 can be seen that there is no significant difference among the average precision belonging to the parameters.

When the intensities in H color channel are divided into bins, the 6 number case yields the best average precision value, as it can be seen in Figure 9.

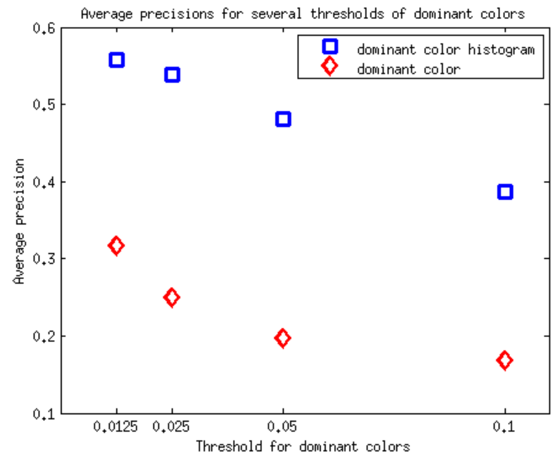

Fig. 7: Average of average precisions using each dominant color threshold values, with the dominant color histogram and dominant color descriptors.

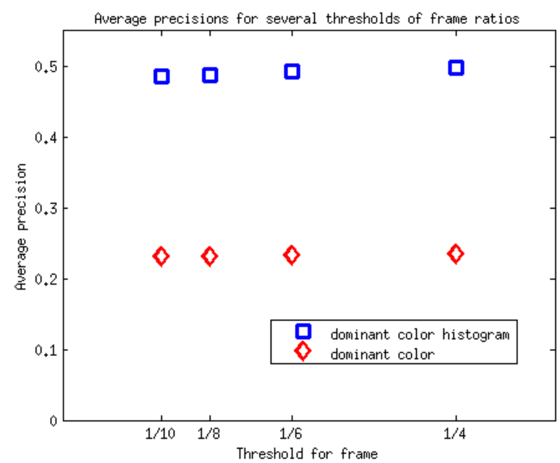

Fig. 8: Average of average precisions using each frame ratio parameters, with the dominant color histogram and dominant color descriptors.

V. Conclusion

A new color-based descriptor is defined, as a mixture of color histogram and dominant color features. The proposed color-based descriptor does not depend on image direction and resolution [12]. The generation of proposed descriptor depends on two parameters. The first one is the number of bins during histogram generation, and the other is the threshold value at dominant color determination. In order to taking into account dominant color locations, for all images two dominant color histograms were produced, one for pixels close to the image border and the other for pixels at the center of the image. The third parameter of the applied algorithm is the frame ratio.

The proposed method was tested with two widely used image databases, and based on the experimental result can be stated, that the usage of new dominant color histogram descriptor gives significantly better precision values as the dominant color descriptor. The test results also show how should be chosen the values of the three applied parameters.

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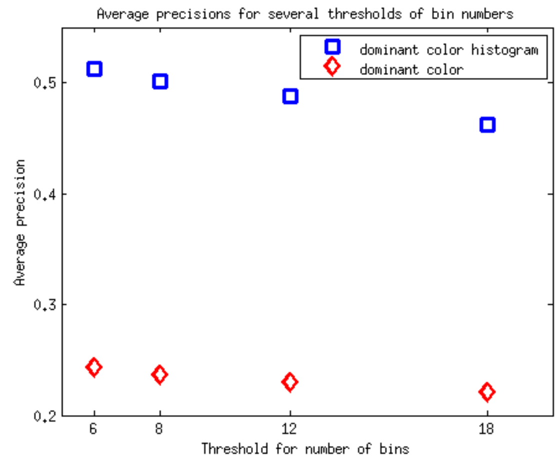

Fig. 9: Average of average precisions using each ben parameters, with the dominant color histogram and dominant color descriptors.

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Sz. Sergyan was born in Pecs, Hungary on 9 May 1973, and received his MSc degree in 1997 on MATHEMATICS AND PHYSICS at Lorand Eotvos University of Science in Budapest, Hungary. He received PhD degree in 2011 at the APPLIED COMPUTER SCIENCE Doctoral School of Obuda University, in Budapest, Hungary. The title of his PhD thesis was "Content-based retrieval algorithms in image databases".

After receiving the MSc degree he worked as a grammar school teacher on Mathematics and Physics. Since 2000 he works at Obuda University. He taught some fields of Mathematics, ie. calculus, discrete mathematics, probability theory and statistics. Since 2012 he is an associate professor at Software Engineering Department of Obuda University in Budapest, Hungary, and responsible for introductory course of programming and algorithm theory. He has some courses on computer vision and image processing, and the expert of MATLAB programming. He was an invited lecturer the Intensive Program on Computer Vision and Summer School of Image Processing summer courses. Since 2005 he is the responsible person for medical image processing on the Biomedical Engineering Summer Course at Jade University of Applied Sciences in Germany. Since 2012 he is the departmental Erasmus co-ordinator at John von Neumann Faculty of Informatics at Obuda University. He is a co-writer of a chapter of a Hungarian language book in the field of programming languages. The title of the chapter is "Object Oriented Programming". His research interest focuses on content-based image retrieval especially color based descriptors of image databases.

Dr. Sergyan is the member of IEEE. He was the editor of Advances in Image, Audio and Signal Processing conference proceedings of the WSEAS multi-conference in 2013. He is a reviewer of several journals and conferences.