IMAGE MINING BY COLOR CONTENT

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ABSTRACT

Image mining presents special characteristics due to the richness of the data that an image can show. Effective evaluation of the results of image mining by content requires that the user point of view (of likeness) is used on the performance parameters. Comparison among different mining by similarity systems is particularly challenging owing to the great variety of methods implemented to represent likeness and the dependence that the results present of the used image set. Other obstacle is the lag of parameters for comparing experimental performance. In this paper we propose an evaluation framework for comparing the influence of the distance function on image mining by colour. Experiments with colour similarity mining by quantization on colour space and measures of likeness between a sample and the image results have been carried out to illustrate the proposed scheme. Important aspects of this type of mining are also described.

Keywords: image mining, colour space, colour similarity.

1 INTRODUCTION

Image are generated at increasing rate by sources such as military reconnaissance flights; defence and civilian satellites; fingerprinting devices and criminal investigation; scientific and biomedical imaging; geographic and weather information systems; stock photo databases for electronics publishing and news agency; fabric and fashion design; art galleries and museum management; architectural and engineering design; and WWW search engines [22]. Most of the existing image management systems are based on the verbal descriptions to enable their mining [31,35]. A key-word description of the image content, created by some user on input, in addition to a pointer to the image data is the base of this systems. Image mining is then based on standard mining. However, verbal descriptions is almost always inadequate, error prone and time consuming. The majority of pictorial information in real world images (as those in figure 1) cannot be fully captured by text and numbers due to the limitation power of languages. A more efficient approach is gathered when image example is given by the user on input to the mining process. Automatically generate matching is required then for an efficient image mining. The basic idea is to extract characteristic features similar to that of object recognition schemes. After matching, images are ordered with respect to the query image according to their similarity measures and displayed for viewing. [1].

In this work, we present an framework for considering the influence of this distance function on colour mining. This framework assesses a system's quality from the viewpoints of users; it provides a basic set of attributes to characterise the ultimate utility of systems. Then we analyse examples of mining by colour and present some conclusions.

2 MINING BY COLOR

Mining in visual database is quite different from standard alphanumeric mining [21]. On current approaches, feature vectors per image is computed for evaluation distance function on the feature space. Then this function is used to retrieve images from a given set. Images with distance less then a predefined threshold or within a predefined number are retrieved (the last one is usually simpler to user because threshold values frequently depends on theoretic aspects). These feature vectors facilitate mining by colour, texture, geometric properties, shape, volume, spatial constraints, etc. [1-8,21-26].

Fig. 1. Examples of the named group 1 and 4 of similar colors real world images, these are samples compose the subset of "sunset colors" and "blue-grayish images".

Experimental results show that image mining based on colour provides high discrimination power [31-33]. Querying by colour similarity has been proposed in several systems [2,4-7,11-17,21-28,30-33]. Although, these search engines support querying based on colour, each system has special characteristics and limitations. For example, the colour space, the used colour quantization algorithms, the distance functions and indexing methods are different [22]. When one search for images that contain colours similar to an example, matching is usually performed by evaluating distance in the used colour space [3,5,10,19]. The implementation usually return a fixed-size set of nearest neighbour without regard to actual threshold of similarity. In practice, determination of an appropriate threshold of similarity is difficult, frequently it involves multiple characteristics and arbitrary weightings. Whether it really performs a good work on mining similar colours is complicated by the fact that the human perception of colours is mainly psychological and does not have suitable mathematical definition. Well-known distance measures do not exactly matches what a user fells as a similar colour [7,9]. They work in ad-hoc manner, but no one pays much attention to their real efficiency [21]. The lack of effective evaluation parameters or benchmarks for retrieval systems are identifies as a critical issue [20-22]. Without a common technique each system uses individual evaluation procedures and image-match scores are not consistently compared among the various systems. Moreover, in visual information systems, this must be defined in terms of simple human perception aspect to preserve its real objective of efficiency. User satisfaction is the most important consideration for evaluating software's effectiveness [20,29].

3 DEFINING PARAMETERS

Complexity is an useful point in comparing software systems [20]. This aspect is normally obtained from the source code, but it is completely irrelevant for the user. The mining result is a more important aspect for the user[1,4,6,8,18,20,26,31]. The factor concerning to the mining result are: the underlying colour space used to represent the colour features; the quantization approach used; the number of bins on the histogram space (its dimension or digital colour resolution); the distance function used to represent the notion of nearness on the colour space (histogram representation); the fixed number of images to be retrieved and the threshold used for matching similarity [2,5,9,10,33].

Several color spaces have been used for colour representation based on the perceptual concepts. There is no agreement on which is the best choice. Anyway, its desirable characteristics are completeness, uniformity, compactness, and user oriented. Completeness means that it must include all perceptible different colours. Uniformity means that the measured proximity among the colours must be directly related to the psychological similarity among them [9]. Compactness means that each colour presents a perceptual difference from the other colours. Suitable spaces must be user oriented and based on an intuitive combination of the three basic attributes of the colour (i.e. hue-H, saturation-S and intensity or value-V).

Colour quantization transforms a continuous tone picture into a discrete image [9]. The digitalisation process maps each component of a continuous colour signal into a series of limited number of (fewer) colours. This process inevitably introduces distortion. The visible distortion is a subjective and psychological notion. The questions is how to choose the colours to reproduce the original (not necessarily colours that appear in the original image). A quantization algorithm should distribute any visible distortion throughout the image so that none stands out to be found particularly objectionable by an average human observer. Empirical algorithms (as the popularity algorithms and the median-cut algorithms) present cases where significant colour shifts can be found. One of the numerical criteria for colour image quantization is to minimise the maximum variance between original pixel colour and the corresponding quantified colour, which provides better results than empirical algorithms. Another numerical criterion is to minimise the maximum discrepancy between original and quantified pixel values. Recent works use adaptive quantifiers [9]. The basic strategy employed by these is a two-step approach. The first step group original colours into clusters that are as small as possible. The second step computes a quantified colour for each cluster [19].

In our implementation the quantization used are: 216 and 162-dimensional colour vectors. This mean that each image is associated with two types of histograms in the mining process. The used colour space is the HSV [9], where H (hue) is the attribute associated with the dominant wavelength. The HSV model is based on psychophysical dada. For images already expressed in the RGB space the transformation into the hexagonal cone of HSV is performed by the well known transformations [24]. The H axis is more sensitive to colour variation than S (saturation) and V (colour intensity or value). S and V are more sensitive to lighting variation from shadows and distance from the light source. Thus, the H axis was used to be sampled more than the other two. S and V were divided into 3 sections each. The hue values range from 0^o to 360^o. Channel H was quantified in two forms: the first into 18 sections of 20^o each, and the second into 24 sections of 15^o each.

Five distance functions are used. They are "city-block" metric, Euclidean metric, histogram intersection, average colour distance, and the quadratic distance form. Denoting h_e the histogram of the example image and h_p the histogram of each image to be compared, then the "city-block" metric or (d1) [5,23], and the Euclidean metrics or (d2) are given by [23]:

$$d^{\tau}_{e,p} = \left[\sum_{m=0}^{M-1} \left| h_e[m] - h_p[m] \right|^{\tau} \right]^{\frac{1}{\tau}}$$

where if $\tau = 1$, it represents "city-block" metric and if $\tau = 2$, it corresponds to Euclidian metric.

If the images has the same number of pixels, $\{h_e\}$=$\{h_p\}$ where

$$\{h_e\} = \sum_{m=0}^{M-1} h[m]$$

then the distance function based on histogram intersection or (d3) is given by [5]:

$$d_{e,p} = 1 - \frac{\sum_{m=0}^{M-1} \min(h_e[m], h_p[m])}{\{h_e\}}$$

The average colours distance or (d4) uses the average magnitude along the three channel of the space colour [3]. The Euclidean distance between their average colours defines the distance between two images.
The quadratic distance measure form or (d5) use the expression [2,3,24,26]:

$$(d_{e,p})^2 = (h_e - h_p)^T A (h_e - h_p)$$

where A is a matrix of similarity weights, $A=[a_{ij}]$, $0 \leq a_{ij} \leq 1$ and $a_{ii} = 1$. Each entry is given by $a_{ij} = (1 - d_{ij} / d_{max})$, where d_{ij} is the Euclidean distance between colours i and j, and d_{max} is the greater distance between colours on the normalised HSV space. That is, the coefficient aij for two colours:

$$m_0 = (h_e, s_e, v_e) \text{ and } m_1 = (h_p, s_p, v_p)$$

that determines each element of $A=[a_{ij}]$, is given by [3]:

$$a_{m_0 m_1} = 1 - \frac{\left[(v_e - v_p)^2 + (s_e \cos(h_e) - s_p \cos(h_p))^2 + (s_e sen(h_e) - s_p sen(h_p))^2\right]^{\frac{1}{2}}}{\sqrt{5}}$$

The possibilities of find all the relevant content of database is an important aspect for interpreting the queries results and also for classifying the quality of each metric. The possibility of "no-show" an image characterises false negative results [2], i.e. not all images on the set with similar colour composition can be retrieval by the environment, because it does not take colour similarity into account adequately. On this case some significant image can never be mining and the user concludes that such image does not exist. False negative can be related to deficient consideration of colour similarity by the metric [3]. The parameter named Retrieval Robustness (RE) was built [24] to show the ability of mining all images on the set that are of the same type of a given sample. On a query, each time a correct image (with colour in the same group of the image query) appears it is considered a significant answer. The maximum number of significant images, *Ns*, that can appear depends on the number of images of the group on consideration, *Ng*, and the number that the user request, *n*. A measure of the completeness of the inquiry is then defined by:

$$\text{RE} = Ns / (Ng \times n) \,\%$$

On RE evaluation, the significant mining results are considered over the first *n* request number of results [8,24-28]. It is presented on percentage for easy comparison between each combination of possibility.

4 PROPOSED FRAMEWORK

For comparing the quantization and distance function influence we develop the system shown in figure 2. Each mining result returned from the system have the value of RE computed. That is the evaluation procedure automatically compute all possible combination of metrics, histograms and colour set types (figures 3 to 6 show some results). On comparing two approaches the best one is that with grades closer to 100% for RE. This makes ease to compute a grade on simulating query by a virtual user on the specific conditions on test.
A unique set must be used to compare the performance of each parameter (metric or quantization) [11-18]. The used set presents different categories of photographic images with the same size, collected among the most used publics domain images databases. On this set, subsets or groups of images with similar colour were identify, like those presented on figure 1. For finding the similarity subsets, we asked four users to rank the image set with reference to their colour similarity [18]. The interviewed people confirmed the groups of same colour images.

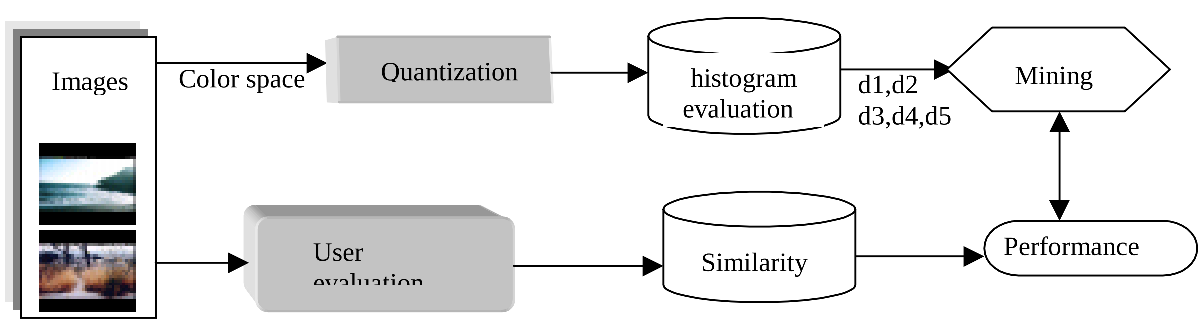

Fig. 2. Diagram of the performance evaluator

5 EXPERIMENTS

In this section we analyse the performance of the two different colours quantization and the five distance functions. Each combination is evaluated with respect to the percentage of Retrieval Robustness (RE) using the same image set and the similar colour groups [24]. Figure 3 compares plots of the RE for group 4 images using 162 histograms bins considering the 4 possible combination of metrics on the mining of 5 to 50 relevant images. Figure 4 do the same but using 216 histograms bins. On figure 5, the colour in the images are those of the group 1 and 162 histograms bins are considered on the 4 possible combination of metrics. Figure 6 compares plots of the RE for the same group of figure 5, but using 216 histograms bins. These figures and the others considering all image colour groups show that the results are related with the images colour composition more than with the number of bins on the histogram (results for other colour subsets can be seen on http://caa.uff.br/~aconci/colors/effectiveness.html or http://caa.uff.br/~aconci/colors/efficiency.html). They depend also of the number of images the user wants to find. On average, better results concerning retrieval robustness (RE) were obtained using Euclidian metric, which is also an easy computed value. Great difference of metric performance can be seen if few number of images are asked. On increasing the number of wanted images almost all metric presents quite the same performance (compare the figures for 45 or more images).

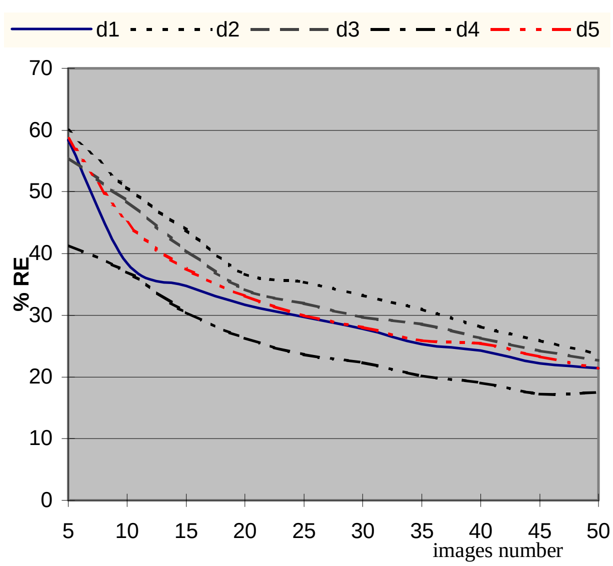

Fig. 3. Percentage of average Retrieval Robustness (RE) for group 4 images using 162 histograms bins

6 CONCLUSIONS

We proposed an framework for mining images by colour content. The implementation was built using CGI, Java and C languages. The framework provides the possibility of use 5 distance function for evaluation of similarity among images and 2 type of quantization. For comparing the influence on system performance of these parameters an simulating engine was implemented and all possible combinations have been tested considering sets of similar images. This framework can be try on line at html://www.caa.uff.br/~mathias/visual.htm.

The framework has been used to evaluate the results of mining from 5 to 50 images. To measure mining performance (in the quality of the results, it cannot be understood as response time) the distance between each image on a given group and each image on the image set must be calculated by the approach under evaluation (that is quantization type and metrics). Some examples of the performance evaluator (considering the quality of the results) used can be seen on figure 4 to 6, where two subset of image colour are considered The procedure here presented considers only retrieval aspects. Considerations like complexity or time performance are not treated here. The ideas presented are only a small step in a very rich research direction. Others visual features such as texture, shape, and use of compressed images [30,34] can be identified for further extension of this problem.

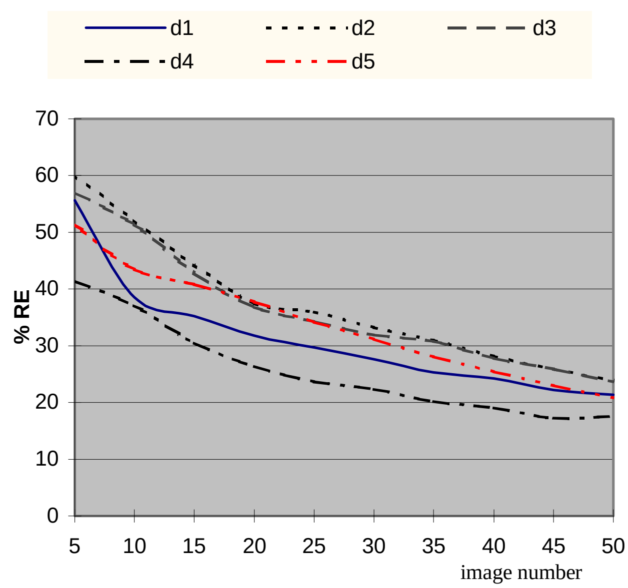

Fig. 4. Percentage of average Retrieval Robustness (RE) for group 4 images using 216 histograms bins

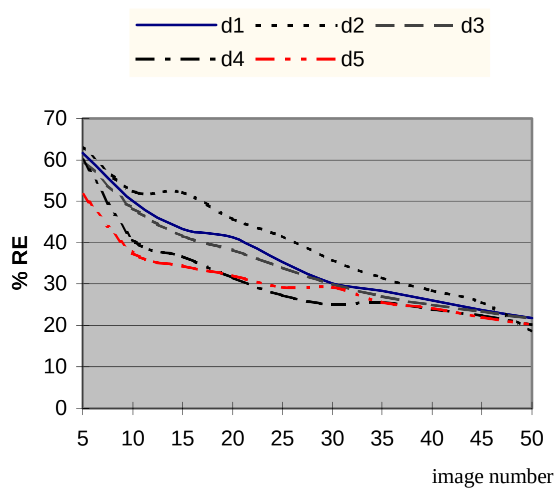

Fig. 5. Percentage of average Retrieval Robustness (RE) for group 1 images using 162 histograms bins

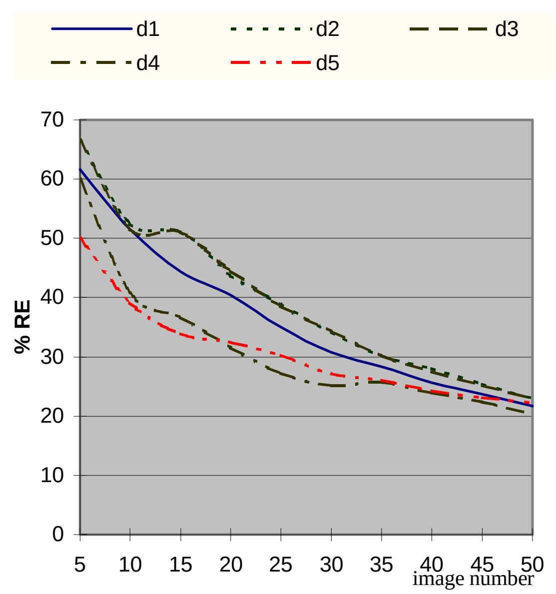

Fig. 6. Percentage of average Retrieval Robustness (RE) for group 1 images using 216 histograms bins

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REFERENCES

[1] V. N. Gudivada, V. V. Raghavan, “Content-Based Image Retrieval Systems”, IEEE Computer, September, 18-22, 1995.

[2] S. A. Stricker, “Bounds for discrimination power of color indexing techniques”, Proc. SPIE, pp. 15-24, 1994.

[3] J. Hafner, H. S. Sawhney, W. Equitz, M. Flickner and W. Niblack, “Efficient Color Histogram Indexing for Quadratic Form Distance Functions”, IEEE Trans. Pattern Analysis Machine Intell., Vol. 17, No.7, pp. 729-736, 1995.

[4] A. Pentland, R. W. Picard, S. Sclaroff, “Photobook: content-based manipulation of databases”, Int. J. Computer Vision, Vol. 18 , No. 3, 233-254, 1996. http://www-white.media.mit.edu/~tpmink/photobook

[5] M. J. Swain, D. H. Ballard, “Color Indexing”, Int. J. Comp.Vision, Vol. 7 , No. 1, 11-32, 1991.

[6] M. Flickner, H. Sawhner, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petrovic, D. Steele, P. Yanker, “Query by image video content: the QBIC system”, IEEE Computer, September, 23-32, 1995. http://wwwqbic.almaden.ibm.com/~qbic/

[7] P. K. Kaiser, R. M. Boyton, Human Color Vision, Second Ed., Washington, D.C.: Optical Society of America, 1996.

[8] J. R. Bach, C. Fuller, A Gupta, A Hampapur, B. Horowits, R. Humphrey, R. C. Jain, C. Shu, “Virage image search engine: an open framework for image management”, Symposium on Electronic Imaging: science and technology-storage & retrieval for image and video databases IV, IS&T/SPIE, 76-87, 1996. - http://www.virage.com

[9] B. Hill, Th. Roger, F. W. Vorhagen, “Comparative analysis of the quantization of color spaces on the basis of the CIELAB color-difference formula”, ACM Transaction on Graphics, Vol. 16, No. 2, April, 109-154, 1997.

[10] H. Zhang, Y. Gong , C. Y. Low, S. W. Smoliar, “Image retrieval based on color features: an evaluation study:, Proc. of SPIE, 2606, pp. 176-187, 1997.

[11] C. Z. Ren, R. W. Means, “Context Vector Approach to Image Retrieval”, Proc. IEEE ICIP, Vol. 1, No 407, 1997.

[12] T. Randen, J. H. Husoy, “Image Content Search by Color and Texture Properties”, Proc. IEEE ICIP, Vol. 1, pp. 580-583,No 417, 1997.

[13] W. Y. Ma, Y. Deng B. S. Manjunath, “Tools for texture/color based search of images”, of SPIE, vol 3106, 1997.

[14] J. R.Smith, S.F. Chang, “Local color and texture extraction and spatial query”, Proc. IEEE ICIP, Vol. 3, pp. 1011-1014, 1996.

[15] Q. Lu, R. W. Conners, D. E. Kline, P. Araman, “A real-time algorithm for color sorting edge-glued panel parts”, Proc. IEEE ICIP, Vol. 1, pp. 822-825, 1997.

[16] G. Iyengar, A B.. Lippman, “Videobook: an experiment in characterization of video”, Proc. IEEE ICIP, Vol. 3, pp. 855-858, 1996.

[17] F. Liu R. W. Picard, “Periodicity, directionality and randomness: world features for image modeling and retrieval”, IEEE Trans. Pattern Analysis Machine Intell., Vol. 18, No.7, July, pp. 722-733, 1996.

[18] A. Del Bimbo P. Pala, “Visual Image Retrieval by Elastic Matching of User Sketches”, IEEE Trans. Pattern Analysis Machine Intell., Vol. 19, No.2, February, pp. 121-132, 1997.

[19] Z. Xiang, “Color Image Quantization by Minimizing the Maximum Intercluster Distance”, ACM Transaction on Graphics, Vol. 16, No. 3, July, 260-276, 1997.

[20] G. Boloix, P. N. Robillard, “A software system evaluation framework”, IEEE Computer, December, 17-26, 1995.

[21] W. I. Grosky, “Managing Multimedia Information in Database Systems”, Communications of the ACM, Vol. 40, No. 12, December, pp. 72-80, 1997.

[22] S.-F. Chang, J. R. Smith, M. Beigi, A. Benitez, “Visual Information Retrieval from Large Distributed Online Repositories:, Comm. of the ACM, Vol. 40, No. 12, December, pp. 63-71, http://www.ctr.columbia.edu/web-seek,1997.

[23] A.Gupta, S. Santini, R. Jain, “In Search of Information in Visual Media”, Communications of the ACM, Vol. 40, No. 12, pp. 34-42, 1997.

[24] E. Mathias, A. Conci, “Pesquisa de Imagens em Banco de Dados por Semelhança de Cor”, Proc. of SIBGRAPI’97 - X Simpósio Brasileiro de Computação Gráfica e Processamento de Imagens, Campos do Jordão, Brazil, pp. 2 , http://www2.lncc/br/sibgrapi97, 1997.

[25] S.-F. Chang, W. Chen, H. Meng, H. Sundaram, D. Zhong, “VideoQ: an automatic content-based video search system using visual cues”, Proc. ACM Multimedia , Seattle, Wa., Nov., http://www.ctr.columbia.edu/videoq.,1997.

[26] Y. Deng, B. S. Manjunath, “Content-based search of video using color, texture and motion”, Proc. IEEE ICIP, http://copland.ece.ucsb.edu/Demo/video/. 1997.

[27] MIT Vision and Modelling Group. http://www.media.mit.edu/vismod/.

[28]Content Based Image Retrieval from Digital Libraries, Vision and Media Laboratory, Simon Fraser University- Canada, 1997. http://jupiter.cs.sfu.ca/cbird/CBIRD.cgi

[29]Alberto del Bimbo - Visual Information Retrieval, Morgan-Kauffman Pub., Cambridge, U.K., 1999.

[30]"Multiresolution Query by Image Content", http://www.visgraf.impa.br/Courses/ipcg-query-1998/image_query.html

[31]Gevers, T., "Interactive Content-Based Image Retrieval (IBV99001)", demo on the WWW (PicToSeek) http://www.wins.uva.nl/research/isis/zomax/, Jan 2001.

[32]Gevers, T., Smeulders, A.W.M., "Color Based Object Recognition", Patterrn Recognition, 32, 457-464, 1999.

[33]Panchanathan, S., Park, Y.C., Kim, K.S., Golshani, F., "The Role of Color in Content-Based Image Retrieval", Proceedings of ICIP'00, Vancouver, Canada, p. 3202, September, 2000.

[34]Ruey-Feng C., Wen-Jia, K., Hung-Chi Tsai, "Image Retrieval on Uncompressed and Compressed Domains" Proceedings of ICIP2000, Vancouver, Canada, p. 2664, September, 2000

[35]Del Bimbo, A., "Semantic-based Retrieval by Content", Proceedings of ICIP2000, Vancouver, Canada, p. 3804, September, 2000