Top-K Retrieval Cbir Systems

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ABSTRACT: *Multimedia data is now one of the widely used information types in all the fields as the fast development of computer techniques has been made traditional database systems based on text information have the limitations when applied to multimedia information.*
One of the main problems the researchers highlighted was the difficulty of locating a desired image in a large and varied collection. While it is perfectly feasible to identify a desired image from a small collection simply by browsing, more effective techniques are needed with collections containing thousands of items.
In this paper, the problem involves entering an image as a query into a software application that is designed to employ CBIR techniques in extracting visual properties, and matching them. This is done to retrieve images in the database that are visually similar to the query image.

I. INTRODUCTION

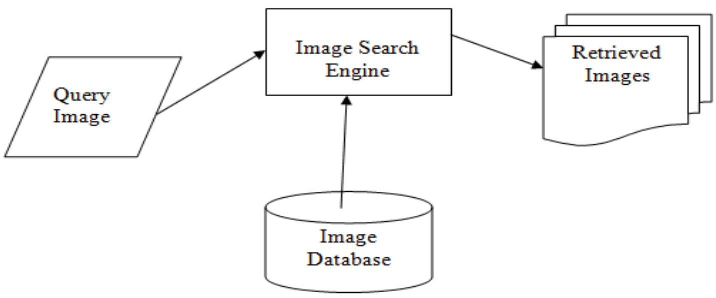
The purpose of *this* paper is to provide an overview of the functionality of temporary image retrieval systems in terms of technical aspects: querying, relevance feedback, features, matching measures, indexing data structures, and result presentation. It compares specific systems, rather than general architectures, and provides a basis for (or defense against) statements like "this or that system already does what your system does". It also is a thorough foundation for claims that most systems use low Level features, and few use high level semantic meaningful features.

Images now play a crucial role in fields as diverse as medicine, journalism, advertising, design, education and entertainment. Technology, in the form of inventions such as photography and television, has played a major role in facilitating the capture and communication of image data. But the real engine of the imaging revolution has been the computer, bringing with it a range of techniques for digital image capture, processing, storage and transmission which would surely have startled even pioneers like John Logie Baird. The involvement of computers in imaging can be dated back to 1965, which demonstrated the feasibility of computerized creation, manipulation and storage of images, though the high cost of hardware limited their use until the mid-1980s. Once computerized imaging became affordable, it soon penetrated into areas traditionally depending heavily on images for communication, such as engineering, architecture and medicine. Photograph libraries, art galleries and museums, too, began to see the advantages of making their collections available in electronic form. The creation of the World-Wide Web in the early 1990s, enabling users to access data in a variety of media from anywhere on the planet, has provided a further massive stimulus to the exploitation of digital images. The number of images available on the Web was recently estimated to be between 10 and 30 million [3].

A. Digital Image Representation

The term monochrome image or simply image refers to a two dimensional light intensity function f (i, j), where 'i' and 'j' denote the spatial coordinates and the value of 'f ' at any point (x, y) is proportional to the brightness level (gray level) of the image at that point. A digital image is an image that has been quantized both in spatial co-ordinates and brightness. A digital image can be considered a matrix whose row and column indices identifying a point in the image and the corresponding matrix element value identify the gray level at that point. The elements of such a digital array are called image elements, picture elements, pixels or pels.

B. Need for Image Retrieval: One of the main problems the researchers highlighted was the difficulty of locating a desired image in a large and varied collection. While it is perfectly feasible to identify a desired image from a small collection simply by browsing, more effective techniques are needed with collections containing thousands of items. Journalists requesting photographs of a particular type of event, designers looking for materials with a particular colour or texture, and engineers looking for drawings of a particular type of part, all need some form of access by image content.
The basic concept of image retrieval is to find out whether an image or the image-database contains the query pattern given by the user on the basis of some similarity function. The basic block diagram of Image Retrieval is shown below in figure.1



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II. RELATED WORK

CONTENT-BASED image retrieval (CBIR) has received much attention in the last decade, which is motivated by the need to efficiently handle the immensely growing amount of multimedia data. In a typical CBIR system, low-level visual image features (e.g., color, texture, and shape) are automatically extracted for image descriptions and indexing purposes. To search for desirable images, a user presents an image as an example of similarity, and the system returns a set of similar images based on the extracted features. In CBIR systems with relevance feedback (RF), a user can mark returned images as positive or negative, which are then fed back into the systems as a new, refined query for the next round of retrieval. The process is repeated until the user is satisfied with the query result. Such systems are effective for many practical CBIR applications. There are two general types of image search:

Category search

The goal of target search is to find a specific (target) image, such as a registered logo, a historical photograph, or a particular painting. The goal of category search is to retrieve a given semantic class or genre of images, such as scenery images or skyscrapers. In other words, a user uses target search to find a known image. In contrast, category search is used to find relevant images the user might not be aware ahead of time. We focus on category search in the next subsequent chapters of this project work.

Two orthogonal issues in CBIR research are efficiency and accuracy. For instance, indexing techniques, such as R*-tree[4], may improve the efficiency of the search process. Their retrieval accuracy, however, depends on the effectiveness of the visual features used to characterize the database images. An effective CBIR system, therefore, needs to have both an efficient search mechanism and an accurate set of visual features.

The R Tree*

The R-tree, one of the most popular access methods for rectangles, is based on the heuristic optimization of the area of the enclosing rectangle in each inner node. By running numerous experiments in a standardized test bed under highly varying data, queries and operations, we were able to design the R*-tree[4] which incorporates a combined optimization of area, margin and overlap of each enclosing rectangle in the directory.

From a practical point of view the R*-tree is very attractive because of the following two reasons

- It efficiently supports point and spatial data at the same time.
- Its implementation cost is only slightly higher than that of other R-trees.

An important requirement for a spatial access method is to handle both spatial objects and point objects efficiently. Points can be considered as degenerated rectangles and in most applications rectangles are very small relatively to the data space.

A. Indexing Techniques

Hierarchical clustering

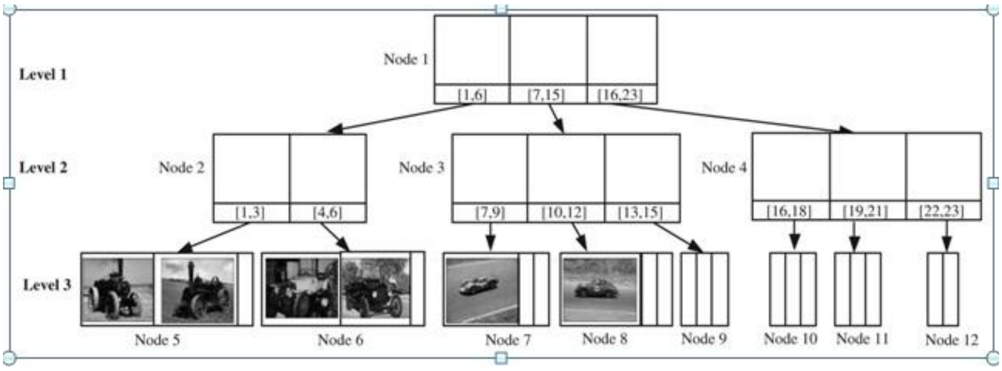


Figure. 2.1. The Hierarchical clustering index structure.

A hierarchical clustering technique, similar to the R*-tree [4], is used to organize the entire image database into a hierarchical tree structure. With each node in this hierarchy representing a cluster, the original node structure of the R*-tree is extended to include also information to identify the images in their children nodes. The hierarchical clustering is constructed as follows: When a new element (i.e., an image represented as a high-dimensional point) is inserted into the tree, this element is placed in a leaf node that requires the least enlargement in its bounding box, and a leaf node's MBB is based on all dimensions of its contained image points. If a leaf node overflows, this node is split (i.e., a portion of its entries is removed from the node and reinserted into the tree), and such splits propagate up the tree[4].

We traverse the tree in a postorder fashion. In the original R*-tree, an internal node contains an array of node entries. Each node entry is a pair (mbb, node-id), where mbb is the MBB that spatially contains the MBBs in the child node, with node-id as the child node address. In our index structure, each node entry is extended to be a tuple (mbb, node-id, imageIDrange), where imageID-range refers to the range of image identifications contained in the pointed child node and imageID-range C **[1,|S|]**. Let us describe how to augment the structure illustrated in Figure 2.1. We start from the root node (i.e., Node 1) which has three node entries. We first visit the first node entry which points to Node 2. Node 2 has two node entries, pointing to leaf nodes 5 and 6 in order. Our depth-first traversal leads us to Node 5, which contains three image points. Then, we set the imageIDrange of the first entry in Node 2 to [1, 3], and each image contained in this node can randomly pick an exclusive ID within this range. That is, the three images in Node 5 can be assigned IDs 1, 2, and 3, respectively.

iterations) when they again fall within the search range of the current iteration. This strategy leads to the following disadvantages:

Local maximum trap problem

In this type problem there is no guarantee that the target can be found. The search operation generally takes several iterations of RF to examine a number of regions in the feature space, before it reaches the target image. During this iterative process, the search advancement might get trapped in a region as illustrated in Figure 2.2. It shows s

B. **Searching Methods**

Target search

We assume that the Euclidean distances between the images reflect their semantic similarity, and focus on investigating new search techniques to improve the efficiency of category search. Existing search techniques re-retrieve previously examined images (i.e.,thoseretrieved in the previous

and t as the starting point p_s and the target point p_t, respectively. Initially, the 3-NN search with p_s as the query point yields three points p_s, p_1, and p_2 as the query result. Let us say, the user marks points p_1 and p_2 as relevant. This results in point p_r, their centroid, as the new query point. With p_r as the refined query, the next 3-NN computation again retrieves points p_1, p_2, and p_s as the result. In this

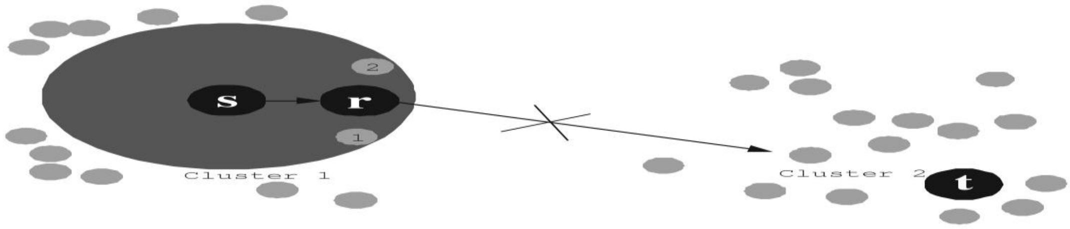


Figure. 2.2. Local maximum trap in existing approaches.

scenario, the search process is trapped in this local region, and can never reach the target point p_t. Although, the system can escape the local maximum trap with a larger k, it is difficult to guess a proper threshold (k = 14 in this example). Consequently, the user might not even know a local maximum trap is occurring.

Slow convergence problem

Including previously examined images in the computation of the current centroid results in repeat retrieval of some of the images. This prevents a more aggressive movement of the search in the feature space. This drawback is illustrated in Figure. 2.3, where k = 3. It shows that it takes six iterations for the search operation to reach the target point p_t. This slow convergence incurs

longer search time, and significant computation and disk access overhead.

III. Proposed System Architecture

In most approaches image features are extracted, stored in a database and compared with the features of a particular search image. In CBIR, each image in the database has its features extracted and compared to the features of the query image. It involves two steps:

Feature Extraction: The first step in the process is extracting image features to a distinguishable extent.

Matching: The second step involves matching these features to yield a result that is visually similar.

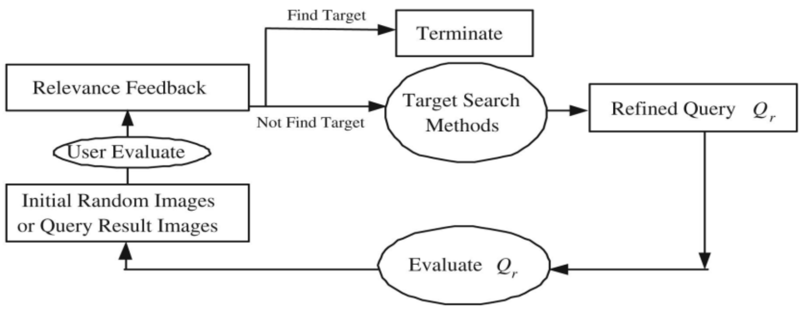


Figure. 3.1. Overview of the target search systems

In the architecture shown in figure.3.1 the user first submits a query image to the system. The features of the query image is calculated. Then the system search the feature database with the help of the target search methods described in the previous chapter. In each iteration the system extracts some refined images based on the relevance feedback. If the target image is found from the result images, then the process terminates otherwise the user again selects some of the images from the result image set relative to the target image. Then the Query is prepared and the search process is continued in an iterative fashion till the target image is found.

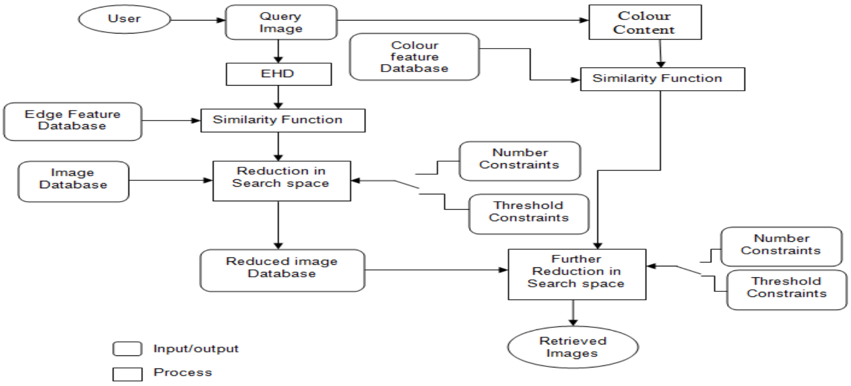


Figure 3.4: Hierarchical Architecture

This architecture is used to retrieve similar images based on edge features and colour features of the query image. Unlike combining the features, a hierarchical retrieval system is proposed which improves the retrieval performance and minimizes the search time.

When the user submits a query image the system asks the user to enter the desired colour (foreground colour). Hence the background colour is automatically neglected. Edge histogram containing 5 types of edges (point, horizontal, vertical, 45° diagonal, 135° diagonal) is extracted and compared with the edge feature database. Relevant images are retrieved in the order of similarity. The number of images retrieved by the system depends on the threshold or number constraint given to the system.

IV. Features Used For Proposed Hierarchical Method

A. Colour Histogram

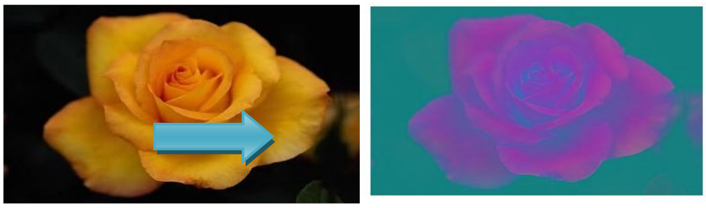
Intensity transformation functions based on information extracted from image intensity histograms a basic role in image processing. The histogram of a digital image with gray levels in the range [0, L-1] is a discrete function [35].

$$h(r_k)= n_k \qquad (k=1, 2..........L)$$

Where r_k is the k^{th} gray level and n_k is the number of pixels in the image whose intensity level is r_k.

In this approach, extraction algorithms follow a similar progression:

(1) each image is first transformed from the standard RGB colour space into the YCbCr space for the purpose of easy extraction of the features based on colour tone;
(2) Quantization of colour space,
(3) Computation of histograms,
(4)Normalization of the histogram.



rgb image rgb2YCbCr image

Figure 4.6: rgb2YCbCr conversion of an image

The colour histograms for the images are computed by quantizing the colours within the image. Each colour image is split up in to 3 two-dimensional images such as Luminance (Y), Blue chrominance (Cb) and Read Chrominance (Cr) respectively. Number of bins in the colour histogram can be set to obtain the feature vector of desired size [5].

Colour histogram (Image)=
[0.4214 0.1040 0.4646 0.0101 0]

4.4.2. Colour Content Histogram:

B. Colour Content Histogram

Colour content shows the dominant colour present in the image. The entire RGB colour space is described using small set of colour content categories. This is summarized into a colour content look up table.

Table 4.2: Color Content look-up Table

Color Content	R	G	B

Black	<50	<50	<50
Blue	<50	<100	>100
Red	>150	<50	<100
Yellow	>100	>100	<50
Magenta(Violet)	>80	<50	>80
Cyan(Indigo)	<50	>150	>100
Green	<100	>80	<50
Gray	<50 & >150	<50& >150	<50 & >150
White	>180	>180	>180

V. EXPERIMENTS AND RESULTS

The image database used in this experiment is downloaded from WBIIS database [48]. The database consists of 1000 images. The image set comprises 100 images in each of 10 categories. The images are of the size 256x384 or 384x256. The types of images include flowers, buses, animals, constructions, tribal photos, natural sceneries, beaches, fruits etc. Accuracy of the retrieval scheme is calculated by Precision & recall graph.

Retrieval has been classified as accurate if for a given query image the system retrieves the perceptually (to human) most similar image as the topmost retrievalFor each query, images similar to the query image are manually listed from the database by their dominant colours present in the query.to evaluate the retrieval performance, the standard evaluation method, i.e., precision-recall pair [49] is used. Precision (P) is defined as the ratio of number of relevant images retrieved (N) to the total number of images are retrieved (K).
Recall (R) is defined as the ratio of number of relevant images retrieved (N) to the total number of relevant images in the whole database (T).

Precision $$P = \frac{N}{K} \quad \text{………………………. (6.1)}$$

Recall $$R = \frac{N}{T} \quad \text{…………………………..(6.2)}$$

Where
N is the number of relevant images retrieved
K is the total no. of images retrieved.
T is the total no. of relevant images in the database.

Figure 6.1(c): Retrieved Images

Table-6.1: No. of retrieved images vs. No. of relevant retrieved images

Method	K=1	K=8	K= 20
Euclidean Distance	N=1	N=3	N=10
Normalized Absolute Difference	N=1	N=5	N=10

Min-Max Ratio	N=1	N=6	N=12

From the above table the precision reacall Graph is plotted below.

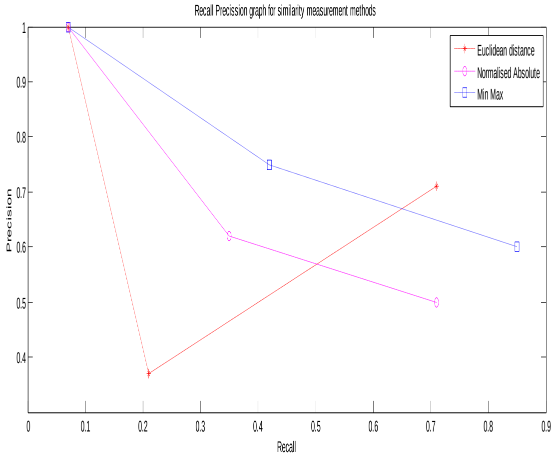


Figure-6.2: Precision and Recall Graph of the different types of similarity measurement method

rom the above observation it can be concluded that min-max ratio is better than the other similarity measurement method. For further experiments the Min-Max ratio is taken for the similarity measurement method.

Comparison between Colour Histogram and Colour Content Histogram

Results of two different colour features, Colour Histogram and Colour Content Histogram are shown in figure 6.3a & 6.3b. Image number 641 is considered as the query image. Total number of relevant images in the database for the above query image is 14.

VI. CONCLUSION

In this paper, we proposed a new paradigm inspired in one of the ways people can find objects. To implement and test this approach, two level descriptors are selected and organized into a hierarchical structure. The proposed hierarchical retrieval method is less time consuming than the combined features method. In the proposed hierarchical method colour feature and edge features are considered in different stages.For colour features we have considered Colour Content Histogram (CCH).The proposed technique of dominant colour identification based on CCH is a meaningful technique to retrieve the images based on colour. Selection of prominent colour by the use of, helps in segmenting the foreground from the background of the image. Hence the colour content feature is giving better retrieval results than the colour histogram.

REFERENCES

[1]. D. Liu, K.A. Hua, K. Vu, and N. Yu, "Fast Query Point Movement Techniques for Large CBIR Systems IEEE Transactions on Knowledge and data Engineering, VOL. 21, NO. 5, MAY 2009.

[2]. P. R. Snoeren and N. Karssemeijer. "Thickness correction of mammographic images by means of a global parameter model of the compressed breast.", IEEE Transactions on Medical Imaging, 23(7): pp 799-806, 2004.

[3]. Sclaroff S et al (1997) "ImageRover: a content-based image browser for the World-Wide Web" in Proceedings of IEEE Workshop on Content-Based Access of Image and Video Libraries, San Juan, Puerto Rico, June 1997, pp 2-9.

[4] Norbert Beckmann, Hans-Peter Kriegel, Ralf Schneider, Bernhard Seeger "The R*-tree: An Efficient and Robust Access Method for Points and Rectangles" ACM 1990.

[5]. Eakins, J P (1996) "Automatic image content retrieval – are we getting anywhere?" Proceedings of Third International Conference on Electronic Library and Visual Information Research (ELVIRA3), De Montfort University, Milton Keynes, pp 123-135

[6]. Eakins J P (1998) "Techniques for image retrieval" Library and Information Briefings, in press

[7]. Stian Edvardsen, "Classification of Images using Colour, CBIR Distance Measures and Genetic Programming. An evolutionary Experiment." (2006) Norwegian University of Science and Technology.

[8]. Dengsheng Zhang, "Improving Image retrieval Performance by using both Colour and Texture Features.", Proceedings of the third International Conference on Image and Graphics (ICIG'04). (2004) IEEE.

[9]. W.Niblack et al. "The QBIC project: Querying Images By Content using Colour, Texture and Shape.", SPIE Conf. on storage and Retrieval for image and video Databases, vol.1908, San Jose, CA, pp.173-187, 1993.

[10]. M. Swain and D. Ballard, "colour Indexing", International Journal of Computer Vision, 7(1): pp 11-32, 1991

[11]. Kato T (1992) "Database architecture for content-based image retrieval" in Image Storage and Retrieval Systems, Proc SPIE 1662, pp112-123.

[12]. Gudivada V N and Raghavan V. V. , "Content-based image retrieval systems" IEEE Computer 28(9), pp18-22.

[13]. Jain, R (1995) "World-wide maze" IEEE Multimedia 2(3), pp 3

[14]. Enser P G B (1995) "Pictorial information retrieval" Journal of Documentation, 51(2), pp126-170

[15]. Flickner, M et al "Query by image and video content: the QBIC system" IEEE Computer 28(9), pp23-32
[16]. Gupta, A et al "The Virage image search engine: an open framework for image management" in Storage and Retrieval for Image and Video Databases IV, Proc SPIE 2670, pp 76-87
[17]. P. J. Werkhoven, J. M. Schraagen, and P. A. J. Punte. "Seeing is believing: Communication performance under isotropic teleconferencing conditions. Displays", 22(4): pp 137-149, 2001.
[18]. Remco C. Veltkamp, Mirela Tanase, "Content-Based Image Retrieval Systems: A Survey", Technical Report UU-CS-2000-34, October 2000.
[19]. T. Kato. "Database architecture for content-based image retrieval.", Proceedings of SPIE Image Storage and Retrieval Systems, volume 1662, pages 112-123, San Jose, CA, USA, February 1992.
[20]. Del Bimbo, A., "Visual Information Retrieval". Morgan Kaufmann Publishers, Inc
[21]. A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain. "Content-based image retrieval at the end of the early years." IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(12): pp1349-1380, 2000.
[22]. Y. Rui, T. S. Huang, and S.-F. Chang. "Image retrieval: Past, present, and future." Journal of Visual Communication and Image Representation, 10:1.23, 1999.
[23]. L. Schomaker, L. Vuurpijl, and E. de Leau. "New use for the pen: outline-based image queries." In Proceedings of the 5th IEEE International Conference on Document Analysis, pages 293-296, Piscataway (NJ), USA, 1999.
[24]. L. H. Armitage and P. G. B. Enser. "Analysis of user need in image archives." Journal of Information Science, 23(4):pp 287-299, 1997.
[25]. G. Ciocca and R. Schettini. "Using a relevance feedback mechanism to improve content based image retrieval." In D. P. Huijsmans and A. W. M. Smeulders, editors, Visual Information and Information Systems: Third International Conference (VISUAL'99), volume 1614 of Lecture Notes in Computer Science, pages 107-114. Springer-Verlag GmbH, 1999.
[26]. N. Ikonomakis, K. N. Plataniotis, and A. N. Venetsanopoulos. " User interaction in region-based color image segmentation". In D. P. Huijsmans and A. W. M. Smeulders, editors, Visual Information and Information Systems: Third International Conference (VISUAL'99), volume 1614 of Lecture Notes in Computer Science, pages 99-106. Springer- Verlag GmbH, 1999.
[27]. C. J ¨orgensen. Access to pictorial material: "A review of current research and future prospects". Computers and the Humanities, 33(4):pp-293-318., 1999.