Human-Centered Content-Based Image Retrieval

http://www.m4art.org

Egon L. van den Broek[a], Thijs Kok[b], Theo E. Schouten[b], and Louis G. Vuurpijl[c]

[a]Center for Telematics and Information Technology (CTIT), University of Twente
P.O. Box 217, 7500 AE Enschede, The Netherlands

vandenbroek@acm.org   http://eidetic.ai.ru.nl/egon/

[b]Institute for Computing and Information Science (ICIS), Radboud University Nijmegen
P.O. Box 9010, 6500 GL Nijmegen, The Netherlands

T.Kok@student.ru.nl   http://eidetic.ai.ru.nl/thijs/

T.Schouten@cs.ru.nl   http://www.cs.ru.nl/~ths/

[c]Nijmegen Institute for Cognition and Information (NICI), Radboud University Nijmegen
P.O. Box 9104, 6500 HE Nijmegen, The Netherlands

l.vuurpijl@nici.ru.nl   http://hwr.nici.ru.nl/~vuurpijl/

ABSTRACT

A breakthrough is needed in order to achieve a substantial progress in the field of Content-Based Image Retrieval (CBIR). This breakthrough can be enforced by: 1) optimizing user-system interaction, 2) combining the wealth of techniques from text-based Information Retrieval with CBIR techniques, 3) exploiting human cognitive characteristics, especially human color processing, and 4) conducting benchmarks with users for evaluating new CBIR techniques. In this paper, these guidelines are illustrated by findings from our research conducted the last five years, which have lead to the development of the online Multimedia for Art ReTrieval (M4ART) system: http://www.m4art.org. The M4ART system follows the guidelines on all four issues and is assessed on benchmarks using 5730 queries on a database of 30,000 images. Therefore, M4ART can be considered as a first step into a new era of CBIR.

Keywords: Multimedia for Art Retrieval (M4ART), Content-Based Image Retrieval, color categories, laypersons, experts, human color perception, texture, benchmarking, user-system interaction

1. INTRODUCTION

Par excellence, humans can function well in complex environments, which provide them with a range of multimodal cues. So far, entities that comprise artificial intelligence cannot function properly if at all in such an environment. Therefore, the performance of human intelligence and, moreover, human cognitive capabilities (e.g., perception) remain the challenging goal for the development of intelligent software applications.

The powerful human visual system is equipped with specific encoding mechanisms to optimize the use of precious processing resources. This is put in practice by enhancing relevant features and providing only a sketchy representation of the less relevant aspects of our visual environment. It utilizes features such as color, texture, and shape in recognizing objects, the environment, and photos or paintings. In an ideal situation, computer vision should have similar characteristics.

In 1992, Kato [11] introduced the term *Content-Based Image Retrieval* (CBIR), to describe his experiments on automatic retrieval of images from a database by color and shape features. Since then, CBIR arose as a new field of research [10,21,30]. However, most image retrieval engines on the world wide web (WWW) still make use of text-based image retrieval, in which images are retrieved based on their labels, descriptions, and surrounding text. Although text-based image retrieval is fast and reliable, it fully depends on the textual annotations that accompany images. Consequently, it requires every image in the database or on the WWW to be well annotated or labeled.

For collections of images that lack proper annotations, CBIR promised to be the solution. Regrettably, current CBIR systems are still far from mature, especially when compared with Information Retrieval systems.

Four arguments can be identified which sustain this claim: (i) CBIR techniques still yield unacceptable retrieval results, (ii) they are restricted in the domain that is covered, (iii) they lack a suitable user-interface and (iv) are mainly technology-driven. Consequently, CBIR systems require considerable domain knowledge and technological skills from users to be able to fulfill their information need.

In the last decade, a change in research perspective with respect to CBIR systems can be observed: from computer vision and pattern recognition to other disciplines such as cognitive science and psychology. In line with the latter statement, we have identified four areas in which a substantial improvement on CBIR can be made:

1. Improving aspects of user-system interaction;

2. Combining Information Retrieval and CBIR;

3. Devising Image processing techniques inspired by human color perception;

4. Validation of the techniques through benchmarks with human users.

Each of these four areas involve the human user and are applied in our new CBIR system called M4ART (Multimedia for Art ReTrieval). The next section will introduce the M4ART system. Subsequently, each of the four areas and how they are taken into account for the development of M4ART are discussed in a separate section. We end this paper with conclusions.

2. THE MULTIMEDIA FOR ART RETRIEVAL (M4ART) SYSTEM

The online M4ART system is available at: `http://www.m4art.org`. Figure 1 presents an overview of all components of the system. In a MySQL database the data (containing text-based annotations and pre-indexed feature vectors) is stored of approximately 30,000 images.
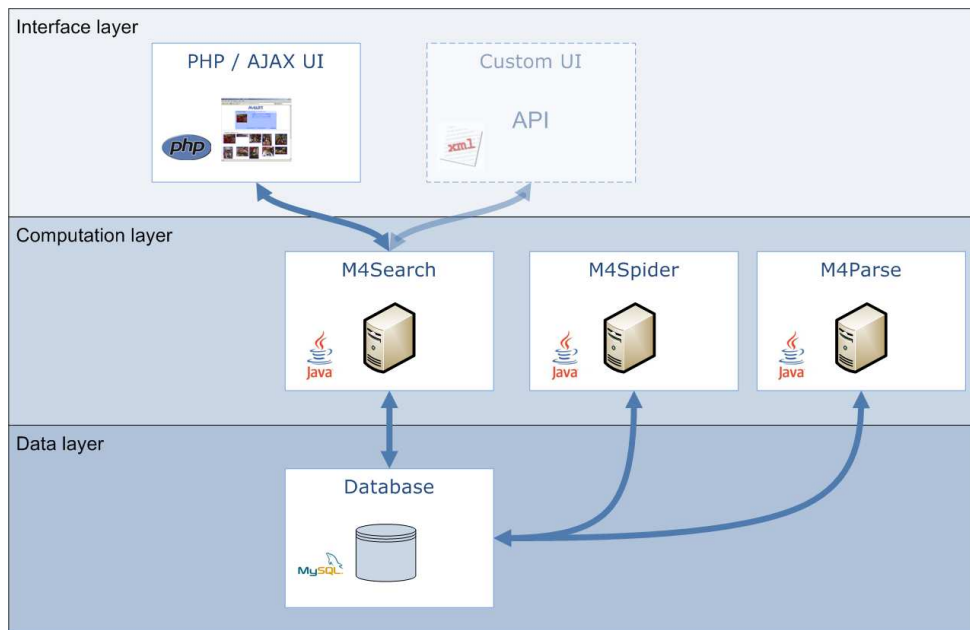

Figure 1: The basic architecture of the M4ART system. The layer structure displays the domain of every component: for example, M4Search will provide computational services, whereas the database will be used for data storage purposes only. Note that all these components can be run on one single server as well as multiple computers.

The user interacts with the system through a web-based interface. Queries are relayed to the search engine server, named M4Search. This application processes query images and compares queries to the images in the database. For example, for a CBIR-based query, M4Search will use the query image to compute a feature vector in which both color- and texture information are encoded. Subsequently, the similarities between the query vector and the pre-indexed feature vectors from the database are computed. The similarity values are ranked in descending order (the most similar results are at the top of the list) and passed back to the interface, which will display the corresponding top-ranked images.

Within M4ART a list of key components can be identified:

- M4Search: a dedicated Java server application, mainly for processing CBIR and IR queries. Any communication with the M4ART system will be routed through M4Search. A web-based interface is provided that allows the user to specify a query and displays relevant results for that particular query. A programmers API is currently being developed as well, which will allow programmers to build a custom user interface for our search engine.

- M4Spider: an application designed to maintain and extend the M4ART image database. It also supports an upload function, which allows users to upload an image from their own computer. The spider can gather various information from the image, such as EXIF data, size, and color depth, and the image's origin (such as information about the website it originated from).

- M4Parse: an extension to our spider that analyses the new, crawled images (i.e., extract color- and texture features) and optionally pre-caches queries using this image. The parsing procedure is a separate process, as it is computational complex (in contrast to spidering).

- PHP/AJAX interface: in order to provide a responsive and interactive user interface, we utilize AJAX technology to communicate with the server; this allows us to inform the user while a search is in progress, for example. These specifications will facilitate a user centered CBIR design and limit the number of technical restrictions.

Images on the web can be surrounded with "clues" that can reveal facts about their semantic representation. Every piece of information should be extracted and stored, as it could prove very useful when similarity to other images is determined. Figure 2 shows different aspects of an image that all reveal a bit of information about its semantics. It denotes classical HTML tags, keywords and a representation of both color and texture features.
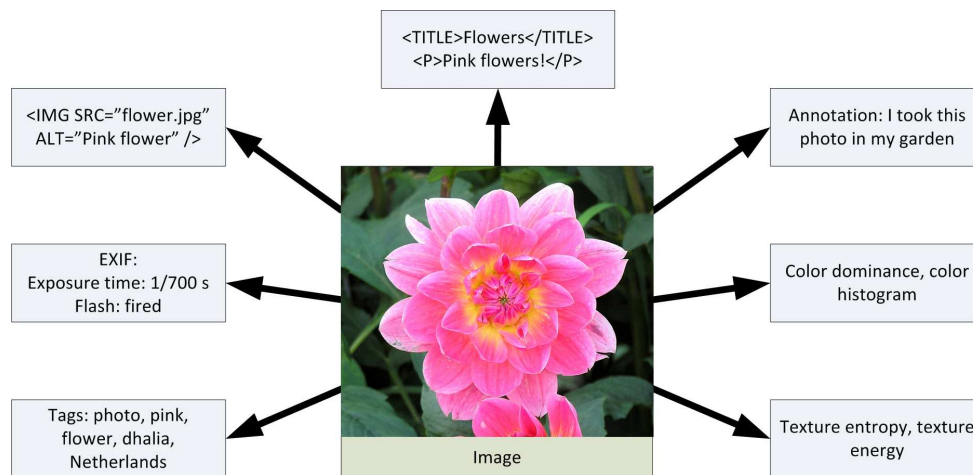

Figure 2: The information of an image, as available for the M4ART system.

3. ASPECTS OF USER–SYSTEM INTERACTION

The role of the user-interface (UI) is twofold. First, the user must be able to define his query. Second, the results of the search process must be presented in an appropriate manner.

3.1 Levels of image queries

Roughly, three levels of abstraction can be distinguished with image queries [9]. The higher the level of abstraction, the more problems CBIR systems will encounter in satisfying the user needs:

1. Primitive features; i.e., color, texture, and shape In general, CBIR techniques excel in deriving primitive features from image material. However, since not all techniques applied are intuitive for humans, the results achieved with them are not either. Nevertheless, most CBIR systems fully rely on image retrieval using primitive features.

2. Derived features:

   (a) type of objects: Types or classes of objects can be defined when they share common characteristics. Often these characteristics can be expressed by using primitive features, like color, texture or shape.

   (b) object prototypes: More general types of objects can be defined by prototypes; e.g., cars, humans. In contrast, more specific types of objects (e.g., Ferrari F40, president Bush) are impossible to describe using primitive features. Only up to a restricted level of complexity object search can be done, like in face recognition. In general, with such queries one still relies on text-based methods. For example, when searching for photos of particular objects (e.g., the "Kronenburger Park, Nijmegen, The Netherlands") by keywords, or to search for photos of a particular class of objects (e.g., vegetables), by browsing catalogs. In contrast, with general object or scene queries (e.g., when searching photos of "sunsets", "landscapes", and "red cars") one can conveniently rely on CBIR methods.

3. Abstract attributes: The highest level of abstraction is found with names of events, types of activity, and with emotional or religious significance. It is easily imaginable that such categories of photos are not suitable for CBIR methods. For instance, impressionist or abstract paintings are hard to classify. More important than color, texture, and shape characteristics of the painting, is a painting's expression and how it is experienced by its viewers. For now, such a description is far out of the reach of CBIR techniques.

3.2 Query definition

For defining a CBIR query, users will require an interface for specifying, e.g. colors, shapes, and textures. Most CBIR color selectors evolved from interfaces in graphics applications. Color selectors in the graphics industry were present, years before the first CBIR engine was born. However, color selectors for the graphics industry do have other demands than those for CBIR; e.g., subtle level crossings do not have to be made for CBIR, but are custom in graphics design.

An even more challenging issue than color selection is how users should define texture. As Celebi and Alpkoçak [4] already noted: "In forming an expressive query for texture, it is quite unrealistic to expect the user to draw the texture (s)he wants." Two alternatives are possible for drawing texture: A palette of textures can be used, which facilitates texture-by-example querying or the option to textually describe texture can be provided. Perhaps this would be possible when using a set of restricted keywords with which textures can be described. For the latter purpose, the three main characteristics (i.e., repetitivity, contrast, and coarseness) could be used. However, the descriptions and their interpretation would be subject to subjective judgments and the limitations of human cognition. So, texture description by text is hard, if possible at all. This leaves one UI that is feasible for defining texture: the palette of textures.

Shape definition by sketching is used in multiple CBIR systems [13, 17, 31]. However, drawing with a mouse is very hard. Making drawings by use of pen and tablet is easier but, for untrained users, still very hard. In addition, the quality of drawings, and with that their usability, differs substantially. Most users are not equipped with sufficient drawing techniques to draw canonical views of images. Since most photographers take photos of objects from a canonical view, this limits the mapping between segmented shapes from photos and the sketches as provided by users. All of this is only possible when CBIR systems also incorporate excellent image segmentation and object localization techniques. This is virtually impossible due to problems such as occlusion.

The complexity of the three features color, texture, and shape increases substantially due to the influence of each of these features on our percept of the scenes or objects. This influence is still not well understood although

there are multiple illustrations of it. Hence, the latter cannot by taken into account when defining a query and, subsequently, retrieving an appropriate result.

To summarize, the use of color for query by content seems feasible. Texture can probably not be employed in query by content settings. Sketch (or shape) based retrieval can be performed. However, its use has not been demonstrated on a large database, with various types of images.

3.3 Presentation of results

There is a lack of fundamental research concerning the presentation of the results of a CBIR query. Our preliminary human factors studies suggest to present images in a grid of 9–16 per screen, where the size of thumbnail images is relatively irrelevant for course recognition.

Figure 3 provides a screenshot of the M4ART interface. In this case, a simple CBIR query by content has been conducted. Please note the information panel (tooltip), which provides additional information on the retrieved images.
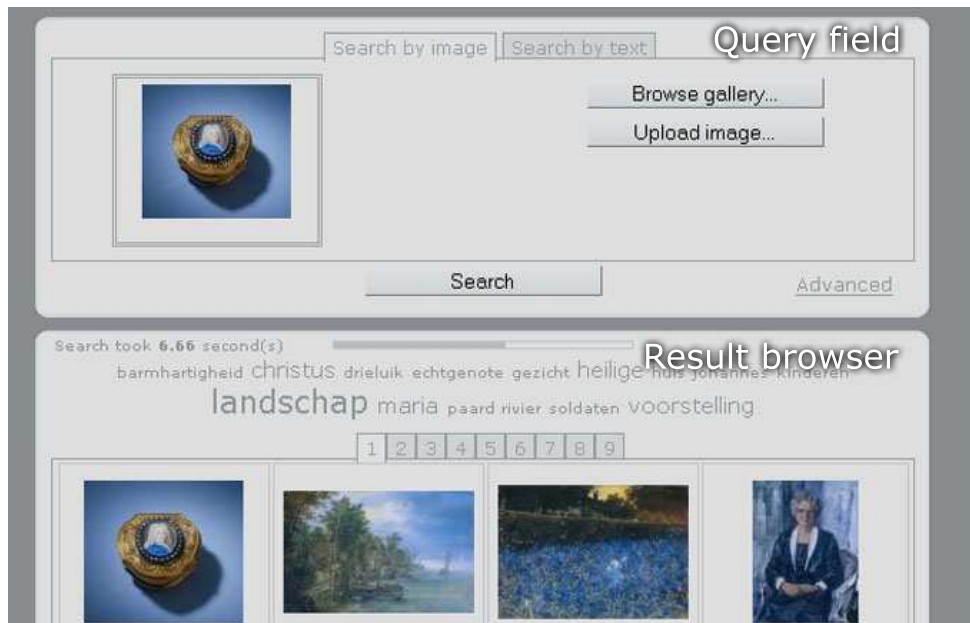

Figure 3: A screenshot of the M4ART system in its simple CBIR mode.

4. INFORMATION RETRIEVAL (IR) AND CONTENT-BASED IMAGE RETRIEVAL (CBIR)

The M4ART system combines CBIR and text-based image retrieval. This is in line with the suggestions of Lai, Chang, Chang, Cheng, and Crandell [12]: "For most users, articulating a content-based query using these low-level features can be non-intuitive and difficult. Many users prefer to using keywords to conduct searches. We believe that a keyword- and content-based combined approach can benefit from the strengths of these two paradigms." At the end of the 90s, the first results of such an approach already yielded promising results.

The M4ART system separates the two different retrieval methods – CBIR and IR – as different tabs. This method for depicting different functions is common practice among many search engines, including Google, Yahoo Search, and MSN Search. As depicted in Figure 4, the CBIR tab of M4ART provides the means to specify an example image by selecting one from the album (the existing image sets) or upload an image from the Internet or from their own computer. The IR tab facilitates a keyword-based search, similar to Google Search.
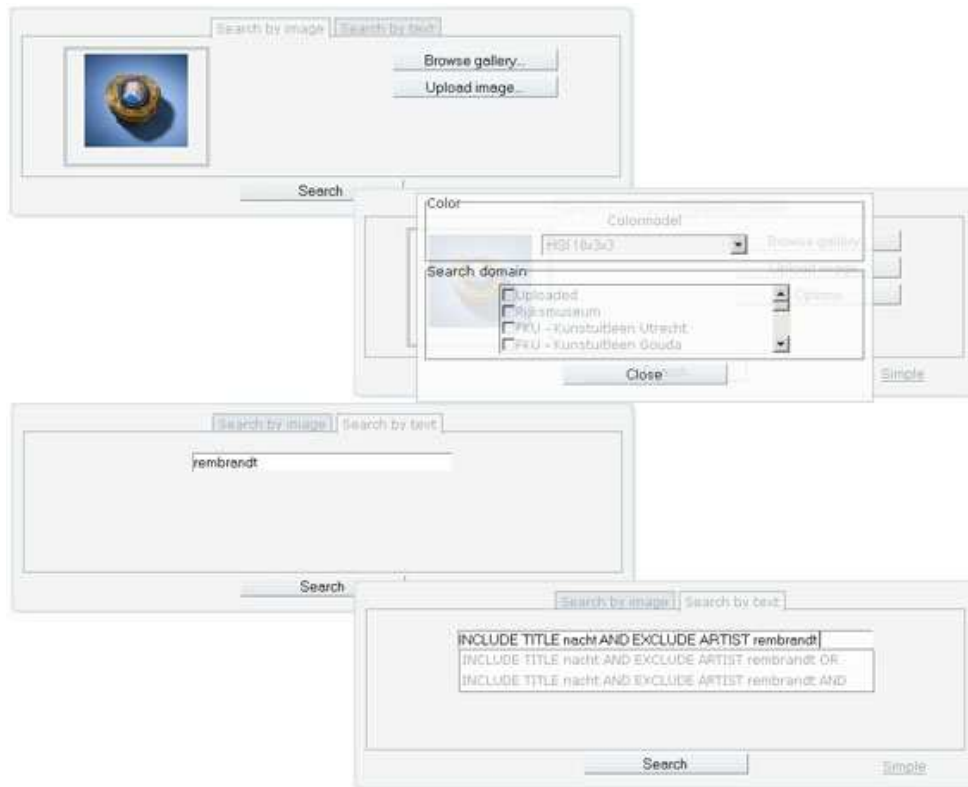
Figure 4: The CBIR and IR tabs of he M4ART system.

The main functionality can be divided in four modes, based on two dimensions. Both the IR and the CBIR component of M4ART provide a standard mode and an advanced mode. Each of these four modes are illustrated in Figure 4. The advanced mode allows experts to specify additional parameters such as color model selection and optional texture analysis. The advanced mode provides a guided Boolean search method: A combination of selecting the correct operator (i.e., NOT, AND or OR) and typing keywords. Below, each of the four modes is briefly discussed:

1. Search by image

   (a) Simple mode
       i. Browse the catalog: This will open a new window, containing images from the catalog. These images can also be part of the results.
       ii. Use image by providing URL: This will open a new window, in which you can specify an URL that refers to an image. This image will be used as your query.
       iii. Use image from my computer : This will open a new window, in which you can upload an image that resides on your computer. This image will be used as your query.
   (b) Advanced mode will display the same buttons as in the simple mode, but additionally:
       i. Vector model: The vector model to be used; you can specify the color model and number of quantization bins.
       ii. Distance evaluation: Method of distance measurement, either Euclidean or Intersection distance.
       iii. Texture analysis: When this option is checked, texture analysis will be performed.

2. Search by text

   (a) Simple mode

     i. Text field, in which you can specify one or more keywords. M4ART searches every field (title, artist, material, etc.) for one of these keywords.

(b) Advanced mode (contains five rows that all have the same controls):

     i. Include/Exclude: Determines whether the keyword should exist or not in the field.

     ii. Field selection: Can be used to search in a specific field (such as title or description)

     iii. Text field in which one or more keywords can be specified.

     iv. AND/OR: Determines whether the next row should be true as well (AND) or either this or the next row should be true (OR).

5. COGNITIVE COMPUTER VISION TECHNIQUES

5.1 Color

Color is the sensation caused by light as it interacts with our eyes and brain [7]. In image processing, the use of color is motivated by two principal factors. First, color is a powerful descriptor that facilitates object identification and extraction from a scene. Second, humans can discern thousands of color shades and intensities, compared to about only two dozen shades of gray.

The color histogram is the most frequently used method for describing the color content of an image. It counts the number of occurrences of each color in an image. The color histogram of an image is rotation, translation, and scale-invariant; therefore, it is very suitable for color-based CBIR.

In order to produce color histograms, color quantization has to be applied. Color quantization is the process of reducing the number of colors used to represent an image. A quantization scheme is determined by the color space and the segmentation (i.e., split up) of the color space used. A color space is the representation of color. Typically (but not necessarily), color spaces have three dimensions and consequently, colors are denoted as tuples of (typically three) numbers.

The implementation of our M4ART color space quantization is based on human color categorization. It is founded on the work of Brown and Lenneberg [3], who showed that English color naming and color recognition are related. Subsequent research identified 11 color categories [2, 7]. Compared to traditional color quantizations, 11 color categories yield an enormous reduction; e.g., IBM's QBIC uses 16^3 color categories [17]. Moreover, such a human-based quantization was expected to result in better results than an arbitrary quantization scheme (e.g., [17]) of comparable precision [24].
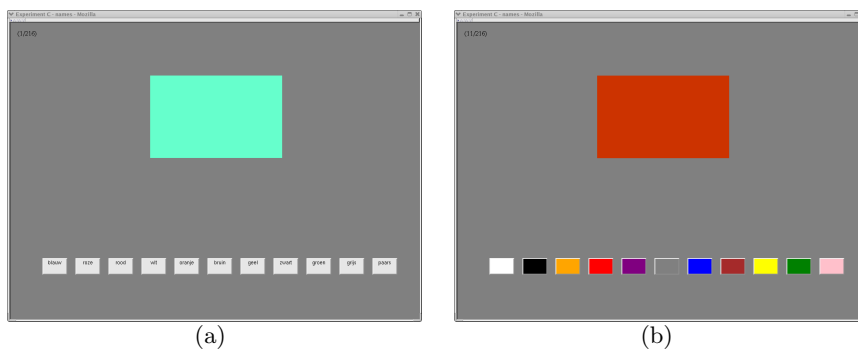

Figure 5: Screendump of the user interface of (a) the color memory experiment (gray buttons, labeled with a color name) and (b) the color discrimination experiment (colored buttons without a label).

To collect data on human color categorization, two experiments were conducted. With one experiment, information on human color categorization by memory was gathered. In the other experiment, subjects were able to compare prototypical colors with the color presented; based on this comparison, they could make their choice of categorization. Figure 5 presents the user interfaces of both experiments.

The data gathered was used to assign parts of color space to color categories. To enable a complete categorization of color space, a newly developed Fast Exact Euclidean Distance (FEED) transform was applied [19]. This transform categorized each color to its closest color category. This process is visualized in Figure 6 of a slice of color space. Subsequently, a lookup table was generated that provided a pointer for each color to its color category. With that, a new, complete human-based color quantization scheme was introduced [25].
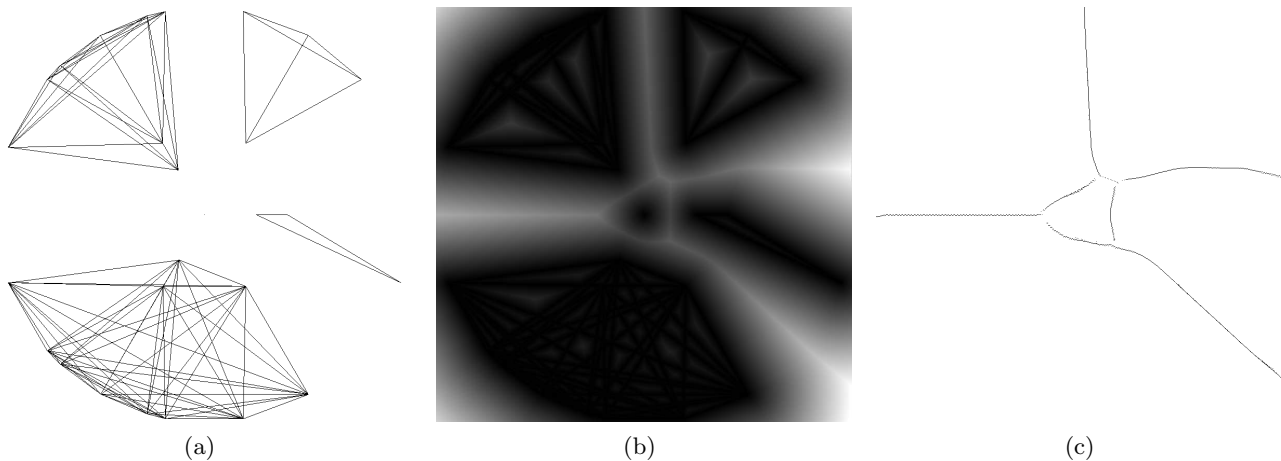

| (a) | (b) | (c) |

Figure 6: (a) The original image in which all data points (of five color categories) assigned to the same color category are connected with each other, using a line connector. (b) The basic ED map of (a), in which the intensity of the pixels resembles the weight. (c) The boundaries between the five classes, derived from the ED map as presented in (b). A hill climbing algorithm was used to extract these boundaries. Note that (c) is the Voronoi diagram of (a).

In parallel with the color quantization scheme discussed, various other laboratories developed alternative color categorization and color quantization schemes. In 2005, Mojsilović [15] introduced her "computational model for color", founded on "the National Bureau of Standards' recommendation for color names". Recently, Menegaz, Le Troter, Sequeira, and Boi [14] introduced their "discrete model for color naming", "starting from the 424 color specimens of the OSA-UCS set", they "propose a fuzzy partitioning of the colorspace".

5.2 Texture

Human texture perception is highly complex and not well understood. Various disciplines attempt to unravel the phenomenon of texture perception. Possibly most striking is the neglect of color in texture analysis in most research. Even when color images are present, gray scale texture analyses are employed. However, in the last decade interest in color induced texture analysis has grown. In M4ART, the 11 color categories have proved to be promising as well [26]. Using the 11 color categories, both good retrieval results are found and a low computational complexity is achieved [25].

Texture analysis is not only employed for classification based on texture features, it is also used for the segmentation of images. Using color induced texture analyses, successful studies on object segmentation are conducted [5, 28]. The 11 color categories processing scheme for both color and texture of images has also been employed to conduct computationally cheap image segmentation [28].

In the same year as the papers of Van den Broek et al. [26, 28], Chen, Pappas,Mojsilović, and Rogowitz [5] introduced an alternative approach that "combines knowledge of human perception with an understanding of signal characteristics in order to segment natural scenes into perceptually/semantically uniform regions." They provide a processing scheme "for image segmentation that is based on low-level features for color and texture." The latter approach has already been applied by Depalov, Pappas, Li, and Gandhi [6] on a database of 9,000 segments obtained from 2,500 photographs of natural scenes.

In past few years, color induced texture processing has received more attention [27, 29]. However, intensity-based texture analysis, using texture samples instead of real world images, is still dominant [1, 8, 18, 20]. It
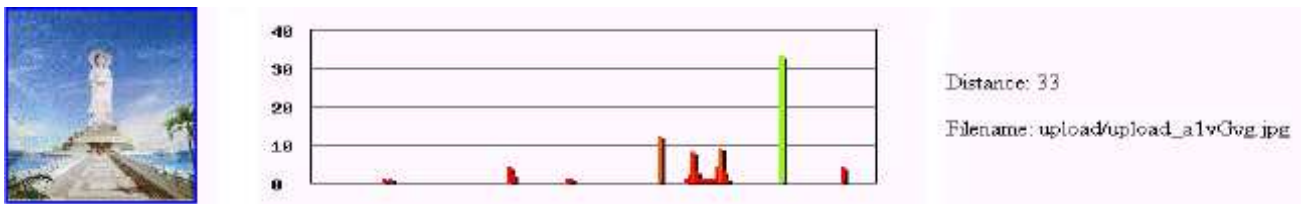
Figure 7: A result as presented when using the advanced CBIR user interface. The image features are depicted using a histogram. Moreover, the distance to the query image is provided.

illustrates the complexity of color induced texture analysis, compared with intensity induced texture analysis. Moreover, it illustrates the problems that arise with image segmentation algorithms when applied beyond their domain. Hence, no generic solution for image segmentation, especially object detection, has been developed. This is where a true understanding of human perception of scenes and objects would provide a solution. However, there is still a long way to go before such an understanding will be present. Then and only then, a required next step in CBIR can be made.

5.3 The challenge of launching CBIR technology

The pre-mature stage of development of CBIR technology makes it questionable whether CBIR should be launched for the general public; this is a clear argument against such a launch. However, technology rapidly changes and the new digital media have taken over house holdings. The amount of image and video data exploded last decade and is still growing. To handle these data, even limited CBIR technology could provide essential services to its users. Therefore, we are of the opinion that CBIR technology should be introduced to the general public.

To relief the problems of introducing a CBIR system to the general public, some additional user feedback systems are included in the M4ART system, as is illustrated in Figure 7. M4ART provides an overview of the image features of the retrieved images by way of a histogram. In addition, for each retrieved image, the distance to the query image is provided.

Another approach would be to make use of IR efforts in image retrieval, in order to improve semantically correct results. The popular photo uploading service Flickr (`http://www.flickr.com`) has introduced a new technique called "tagging": annotation by specifying a number of relevant keywords. This method relieves the strain of writing a lengthy description and thus simplifies the annotation process. Methods such as these could be adopted by CBIR search engines to enrich the image material; e.g., see: Figure 3.

6. VALIDATION: BENCHMARKING CBIR SYSTEMS

The field of CBIR technology lacks a generally accepted methodology on benchmarking (parts of) systems [16,22]. This despite several efforts to introduce standards; e.g., IAPR TC-5 on implementing and benchmarking pattern recognition systems, IAPR TC-12 on Multimedia and Visual Information Systems that incorporates a section on benchmarking, including TRECVID, and the Benchathlon network, which was initialized specifically for CBIR benchmarking.

CBIR benchmarking is starting to get some substance. However, in most cases the user is ignored. This, despite the fact that CBIR systems will be used and judged by their users. This emphasizes the need for the incorporation user interface aspects. Moreover, users should judge techniques developed to sustain their usage. User interface aspects are already discussed. This section will describe a setup for the evaluation of CBIR technologies by users, as has been applied twice so far [23,24].

A valid CBIR benchmark should satisfy the following characteristics:

1. The subjects should be naive with respect to the research goal. In particular, they should not be aware of the fact that multiple engines are judged.

2. All engines should be supplied with the same results interface, unless the interface is topic of research;

3. The aspects under research should be assessed in isolation. Hence, each aspect can separately judged on its contribution to the overall performance of the engine;

4. A valid design of the benchmark should be developed. Therefore, the following aspects have to be satisfied:

   (a) Randomization of all queries;

   (b) A set of standardized queries should be selected and subsets should be assigned in different arrangements to each of the engines under research. This should be done in such a manner that all subsets are assigned in equal amounts to each of the engines;

   (c) The amount of queries judged should be large; then, variations in settings can be regarded as noise. Alternatively, the benchmarks should be run in a controlled setting. Then variability in environment, display, light, etc. are under control.

5. The results of the engines should be cached to overcome possible preferences due to differences in retrieval speed, among the engines.

So far, we have conducted two benchmarks in which 10 engines were judged with in total 5730 queries [23, 24]. The benchmarks were conducted online. Due to the large number of queries, it was possible to regard differences in settings as noise. The engines tested differed in three aspects: color space, color quantization scheme, and distance measure used.

Next to the judgments, the computational complexity of the calculations underlying each engine can be taken into account. Not seldomly, a trade-off will have to be made between precision, recall, and time needed for retrieval.

7. CONCLUSION

This paper has underlined that users of CBIR systems are mostly ignored in the development of CBIR techniques. This despite the fact that human perception could help the development of new image processing techniques. In contrast with the current trend in technique, usability issues of CBIR systems are only seldom acknowledged as an important aspect of development. Moreover, benchmarks that examine users' preferences for systems are applied seldomly. The M4ART system, as introduced in this article, illustrates the feasibility of a human-centered approach on CBIR. The identification and implementation of human-centered CBIR systems as discussed in this paper may be regarded as a first step toward a new era for advanced CBIR techniques.

Acknowledgments

REFERENCES

1. C. A. Z. Barcelos, M. J. R. Ferreira, and M. L. Rodrigues. Retrieval of textured images through the use of quantization and modal analysis. *Pattern Recognition*, 40(4):1195–1206, 2007.
2. R. M. Boyton. Eleven colors that are almost never confused. *Proceedings of SPIE (Human Vision, Visual Processing, and Digital Display)*, 1077:322–332, 1989.
3. R. W. Brown and E. H. Lenneberg. A study in language and cognition. *Journal of Abnormal and Social Psychology*, 49(3):454–462, 1954.
4. E. Celebi and A. Alpkoçak. Clustering of texture features for content based image retrieval. *Lecture Notes in Computer Science (Advances in Information Systems)*, 1909:216–225, 2000.
5. J. Chen, T. N. Pappas, A. Mojsilović, and B. E. Rogowitz. Adaptive perceptual color-texture image segmentation. *IEEE Transactions on Image Processing*, 14(10):1524–1536, 2005.
6. D. Depalov, T. Pappas, D. Li, and B. Gandhi. Perceptually based techniques for semantic image classification and retrieval. *Proceedings of SPIE (Human Vision and Electronic Imaging)*, 6057:60570Z, 2006.

7. G. Derefeldt, T. Swartling, U. Berggrund, and P. Bodrogi. Cognitive color. *Color Research & Application*, 29(1):7–19, 2004.

8. M. A. García and D. Puig. Supervised texture classification by integration of multiple texture methods and evaluation windows. *Image and Vision Computing*, 25(7):1091–1106, 2007.

9. L. Hollink, A. T. Schreiber, B. J. Wielinga, and M. Worring. Classification of user image descriptions. *International Journal of Human-Computer Studies*, 61(5):601–626, 2004.

10. M. Israël, E. L. van den Broek, P. van der Putten, and M. J. den Uyl. *Visual Alphabets: Video Classification by End Users*, chapter 10 (Part III: Multimedia Data Indexing and Retrieval), pages 185–206. Springer-Verlag: Berlin - Heidelberg, 2007. ISBN-13: 978-1-84628-436-6.

11. T. Kato. Database architecture for content-based image retrieval. In A. A. Jambardino and W. R. Niblack, editors, *Proceedings of SPIE Image Storage and Retrieval Systems*, volume 1662, pages 112–123, San Jose, CA, USA, February 1992.

12. W.-C. Lai, C. Chang, E. Chang, K.-T. Cheng, and M. Crandell. PBIR-MM: multimodal image retrieval and annotation. In L. Rowe, B. Merialdo, M. Muhlhauser, K. Ross, and N. Dimitrova, editors, *Proceedings of the tenth ACM international conference on Multimedia*, pages 421–422, 2002.

13. M. Lew. Next generation web searches for visual content. *IEEE Computer*, 33(11):46–53, 2000.

14. G. Menegaz, A. L. Troter, J. Sequeira, and J. M. Boi. A discrete model for color naming. *EURASIP Journal on Advances in Signal Processing*, 2007:Article ID 29125, 10 pages, 2007. doi:10.1155/2007/29125.

15. A. Mojsilović. A computational model for color naming and describing color composition of images. *IEEE Transactions on Image Processing*, 14(5):690–699, 2005.

16. H. Müller, W. Müller, S. Marchand-Mallet, T. Pun, and D. M. Squire. A framework for benchmarking in CBIR. *Multimedia Tools and Applications*, 21(1):55–73, 2003.

17. W. Niblack, R. Barber, W. Equitz, M. Flickner, E. Glasman, D. Petkovic, P. Yanker, and C. Faloutos. The QBIC project: Querying images by content using color, texture, and shape. In W. Niblack, editor, *Proceedings of Storage and Retrieval for Image and Video Databases*, volume 1908, pages 173–187, February 1993.

18. L. Qin and W. Gao. Unsupervised texture classification: Automatically discover and classify texture patterns. *Image and Vision Computing*, [in press].

19. T. E. Schouten and E. L. van den Broek. Fast Exact Euclidean Distance (FEED) Transformation. In J. Kittler, M. Petrou, and M. Nixon, editors, *Proceedings of the 17th IEEE International Conference on Pattern Recognition (ICPR 2004)*, volume 3, pages 594–597, Cambridge, United Kingdom, 2004.

20. A. Schubö and C. Meinecke. Automatic texture segmentation in early vision: Evidence from priming experiments. *Vision Research*, 47(18):2378–2389, 2007.

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):1349–1380, 2000.

22. J. Trant. *Image Retrieval Benchmark Database Service: A Needs Assessment and Preliminary Development Plan.* Archives & Museum Informatics, Canada, 2004.

23. E. L. van den Broek, P. M. F. Kisters, and L. G. Vuurpijl. The utilization of human color categorization for content-based image retrieval. *Proceedings of SPIE (Human Vision and Electronic Imaging IX)*, 5292:351–362, 2004.

24. E. L. van den Broek, P. M. F. Kisters, and L. G. Vuurpijl. Content-based image retrieval benchmarking: Utilizing color categories and color distributions. *Journal of Imaging Science and Technology*, 49(3):293–301, 2005.

25. E. L. van den Broek, T. E. Schouten, and P. M. F. Kisters. Modeling human color categorization. *Pattern Recognition Letters*, 28(x):xxx–xxx, 2007.

26. E. L. van den Broek and E. M. van Rikxoort. Parallel-sequential texture analysis. *Lecture Notes in Computer Science (Advances in Pattern Recognition)*, 3687:532–541, 2005.

27. E. L. van den Broek, E. M. van Rikxoort, T. Kok, and T. E. Schouten. M-HinTS: Mimicking Humans in Texture Sorting. *Proceedings of SPIE (Human Vision and Electronic Imaging XI)*, 6057:332–343, 2006.

28. E. L. van den Broek, E. M. van Rikxoort, and T. E. Schouten. Human-centered object-based image retrieval. *Lecture Notes in Computer Science (Advances in Pattern Recognition)*, 3687:492–501, 2005.

29. E. M. van Rikxoort, E. L. van den Broek, and T. E. Schouten. Mimicking human texture classification. *Proceedings of SPIE (Human Vision and Electronic Imaging X)*, 5666:215–226, 2005.

30. N. Vasconcelos. From pixels to semantic spaces: Advances in content-based image retrieval. *IEEE Computer*, 40(7):20–26, 2007.

31. L. Vuurpijl, L. Schomaker, and E. L. van den Broek. Vind(x): Using the user through cooperative annotation. In S. N. Srihari and M. Cheriet, editors, *Proceedings of the Eighth IEEE International Workshop on Frontiers in Handwriting Recognition*, pages 221–226, Ontario, Canada, 2002. IEEE Computer Society, Los Alamitos, CA.