Agent Based Framework for Content Based Image Retrieval

Sabyasachi Saha and Sandip Sen
Department of Mathematics & Computer Science
The University of Tulsa
sahasa, sandip@ens.utulsa.edu

Abstract

In this paper, we plan to study the viability and effectiveness of using an agent-oriented approach to developing content-based image retrieval (CBIR) systems. Image retrieval is a key technology that significantly aid the work of both professionals (medical practitioners, engineers, etc.) and has the potential of enabling a much richer interaction of the average home user with the distributed information content on the internet and the world-wide-web. CBIR focuses on using feedback from the user to facilitate the search for matching images based on the content of a query image. Some of the most practical use of agent technology results in building personalized agents to assist users with their information processing needs. Such agents have both expertise in the domain of application, e.g., travel planning, financial planning, etc. and a model of the biases, preferences, constraints of the associated user. We believe that an agent-based CBIR system has several advantages over a personal systems in terms of flexibility, ease-of-use, adaptability, transparency, and precision of recall. Our proposed *Agent for content Based Image Retrieval (ABIR)* is an interactive image retrieval system based on relevance feedback from the user. ABIR will use the preference of the current user, the usage patterns of past users, and novel feature preference combination methods to iteratively interact with the user and guide the search for satisfactory matching images.

Introduction

Huge volumes of digital images are created everyday in many application areas including E-commerce, Medical Science, Space Research, etc. Most of this information is not readily accessible to users because of lack of domain-independent efficient query retrieval mechanisms for large image collections. This underutilization of rich image repositories highlights the need for research involving innovative modalities of image retrieval. The research of image retrieval fall within the purview of Computer Vision and Multimedia Database Systems. These fields approach the problem of image retrieval from two different research angles. The Database community focused in the image indexing techniques whereas the Computer Vision people concentrates on the content analysis of the image (Rui, Huang, & Chang 1999).

While image retrieval techniques have largely concentrated on syntactical image characteristics like color, texture, shape, etc. much less attention has been paid to characterizing semantic content. An approach to address this shortcoming, content-based image retrieval (CBIR), which places equal emphasis on semantic information characterized by the structural components and organization of the image, has received increasing attention in recent years. By Content Based Image Retrieval(CBIR) we mean the retrieval of images by their visual content. While large image databases often use textual annotations, either manually generated or inferred, for indexing and retrieving images, CBIR systems rely primarily on automatically computed features from the stored images. Given an image as a query, images with the closest matching features are returned as query results. The commonly computed features are that of color, texture and shape contents of an image, where each of the feature values may be further computed based on the values of some sub-features, e.g., color histograms, texture measures like coarseness, shape features like boundary segments, etc. Other used features capture image similarities even though they do not map to easily describable features perceptible to humans, e.g., wavelet transforms.

Most CBIR systems have a single-interaction modality where the user presents an image as a query and obtains the matching images as results. This one-shot modality for querying information repositories has a history of successes ranging from decades old classical, textual database queries and information retrieval techniques to more recent web searching facilities. Though such one-shot query modality has been effective in dealing with large corpora of text-based information repositories, we believe that the same modality is undesirable, ineffective, and inefficient for a significant class of image retrieval domains. In past few years, interactive CBIR systems (Rui, Huang, & Mehrotra 1998) are gaining popularity.

The key problem with most traditional and content-based image retrieval techniques is that image content is often ambiguous, i.e., the same image may instantiate multiple concepts, and at different levels of abstraction, any of which may be the meaning associated to it by the current user. An image, as the cliche goes, is worth a thousand words. Per-

Figure 1: A sample image query with ambiguous content.

haps, and for some images, it takes much more than that do describe its content accurately. In different images, the different features may play different roles. For some image, color may play the central role, viz, search for a sky image, whereas in some feature shapes may play the key role. The goal of the CBIR research is to bridge the gap between the high-level, semantic concepts contained in an image with its low-level, syntactic features. While it may be impossible to automatically and unambiguously derive the meaning of the content of an image, a query modality that involves the user actively can disambiguate a significant subset of such problematic multiple interpretations. While various forms of user interaction can facilitate this process, an approach that involves the user ranking a subset of the images retrieved in successive iterations can be an effective mechanism while imposing relatively modest cognitive burden on the user.

For images with multiple content interpretations, interpretations based on syntactic features like color and texture may not match with higher level logical components. For example, the user may present a picture of a couple of white horses running against a dark background. At the basic feature level this picture can have similarities with a lot of different pictures with varying semantic content. At the logical level, the user may be looking for horses of any color. At a more abstract level, he/she may be looking for animals in motion in the wild. For another example, consider the image in Figure 1: a user can be looking for any one of the following: images of elephant herds, images of herd of any animals, images of sunset, images of the particular tree type in the background, etc. While one-shot CBIR systems can produce basic feature level matches, interactive CBIR systems can provide effective responses for a large class of logical queries. We believe significant advances need to be made for this class of queries before addressing the issue of abstract queries.

While precisely defining the semantic content of an arbitrary image may be an impossibility, reasonable approximations can be targeted for a large class of images. Here we outline the design of an agent-based iterative query mechanism that involves the user in refining the query over a few, well-structured exchanges and argue for this being a more prudent, meaningful, and effective approach to CBIR. We envision that given an original image query, our agent-based CBIR system, ABIR, will iteratively ask the user to rate a few images for interest to eliminate content ambiguities and narrow down the set of most appropriate images in the repository. In this paper, we propose some novel techniques to integrate this critical user feedback to improve the image interpretation. We plan to study several, alternative interaction mechanisms ranging from partial selection to ranking to allow the user to give varying levels of feedback to ABIR. We also discuss the long-term adaptation of such a system to learn, using extended interaction history, general, consistent biases in the perceived similarity or syntactic-to-semantic level mapping preferences of a given user.

Background and Related Work

In last few years the research in CBIR has received an unprecedented boost. There are three fundamental bases for CBIR: visual feature, *i.e.*, content extraction, multi-dimensional indexing and retrieval (Rui, Huang, & Mehrotra 1998).

Visual Feature Extraction

Feature extraction is the fundamental basis of CBIR systems. The visual features can be classified into two classes: general features and domain-specific features. Example of important visual features are color, texture, shape etc. Because of the subjectivity in the human perception of an image, there does not exist a single best presentation for a given feature. For any given feature, there exist multiple representations which characterize the feature from different perspectives (Rui, Huang, & Chang 1999). We briefly describe research research on some of the commonly used features in CBIR systems:

Color: Color is an immediately perceivable visual feature when looking at an image. Color feature is relatively robust to background complication and independent of image size and orientation. In an image, we have a collection of points known as color stimuli in a three dimensional color spaces. There are several geometric color models, viz., Color-metric models, Physiologically inspired models, Psychological models (Wang 2001) which represents color stimuli consistently and quantitatively. In another approach the color models can be divided into the following: *Hardware oriented models* (for example RGB) and *User Oriented models* (for example HSV).

In image retrieval, the most commonly used color feature is *color histogram* as it represents the global color distribution of an image (Stricker & Orengo 1995). For similarity of images, Swain and Ballard (Swain & Ballard 1991) proposed histogram intersection, an L_1 metric, as a similarity metric. Color moments and color sets are two other well known features for color representation. MA and Zhang (Ma & Zhang 1998) shows that the color moment performs worse compared to high dimensional color histogram. But in some cases it can be an effective representation.

Texture: Image texture is also a widely used and primitive visual feature of an image. Texture feature plays important role to separate regions. Say for example texture of rivers differ from that of buildings. The most commonly used texture feature is *Tamura* texture representation (Tamura, Mori,

& Yamawaki 1978). This is widely used because it is based on human texture representation. Ma and Manjunath (Ma & Manjunath 1998) use various wavelet transformations to evaluate the texture image annotation.

Shape: Shape is an important visual feature for computing image similarity for retrieval. In general, the shape representations can be divided into two categories: boundary based and region based. The former uses only the outer boundary of the shape while the latter uses the entire shape region. The most successful representatives for these two categories are Fourier Descriptor and Moment Invariants.

Apart from the features described above, other features like color layout and segmentation are also considered in some approaches to calculating image similarity.

Multi-Dimensional Indexing

An important stage of content based image retrieval is multi dimensional indexing. Different indexing techniques are used in the literature of large image database applications. In CBIR applications an image is represented as a vector of the visual features in the multidimensional vector space where each dimension represents a feature (Fu & Teng 2000). The features of the image are extracted from the query image and stored in a feature vector and are then used to retrieve the image which has similarity with the query image. Usually, the feature vector has a high dimensionality (Essam & Mansur 2000). This makes the indexing structure complex. So, for the sake of efficiency it is important to perform dimension reduction. Karhunen-Loeve Transform (KLT) approach is the most well known approach for dimension reduction. After dimension reduction multi-dimensional indexing algorithms are used. Popular multi-dimensional indexing techniques are R-tree (Guttman 1984) and its variants R+ tree and R* tree.

Retrieval and relevance feedback

In this stage, the CBIR systems return the similar images and asks for the user for feedback on the returned images. The user may give his feedback in different forms. In some systems the feedback is boolean, *i.e.* the retrieved related or not. In other systems, the users need to rank the retrieved images based on relevance.

Existing Interactive CBIR systems

CBIR research has shown that there does not exist any universal feature for all images or any best representation for a given image. There was no unanimity for a measure even for a particular feature. For example, for the texture feature there are a number of representations viz, Tamura, Gabor filter, Wavelets and so on. It has been shown that in some domains and examples one representation is more reasonable than other and vice versa. This is a fundamental problem of recent CBIR research.

In (Rui, Huang, & Mehrotra 1998), Rui et. al. propose a relevance feedback mechanism in the Interactive CBIR. They have adopted a linear weight update mechanism through relevance feedback. IBM research implemented another CBIR system QBIC (Query by Image Content) (Niblack 1997). In this system they retrieve similar images using city-block, Euclidean distance, weighted Euclidean distance using different features such as color, texture, shape and sketch. Yang et. al. (Yang & Kuo 2000) proposed a mechanism that learns image similarities and categories from relevance feedback from users. This approach, however, mainly focus on the categorization of images. *ImageRover* is a content based image browser for the *World Wide Web*. This is a first generation image engine. It has two main subsystem viz, *Document Collection Subsystem* and *Image Query Subsystem*. The first subsystem consists of collection module and digestion module. The former module collects and stores the image informations in the database and the second module use Minkowski L_p distance based knn-rule to find similar images. They use relevant feedback approach for searching (Taycher, Cascia, & Sclaroff 1997).

Viper, Amore, Blob, SurfImage,Ikona are other important interactive content based image retrieval systems.

Learning-based approaches Su *et. al.* proposed a learning relevance feedback approach using Bayesian classifier (Z.Su, Zhang, & Ma 2000) which describes a single decision boundary. This approach is fundamentally different from weight adjusting. Shyu et. al. (Shyu *et al.* 1999; MacArthur, Brodley, & Shyu 2000) describes an interactive content based retrieval approach using decision tree learning. This is a relevance feedback approach. In the first iteration similar images are returned using unweighted *knn* algorithm. Then the user grades the images as relevant or irrelevant. The graded images, along with the query image, are used as a training example for the decision tree (MacArthur, Brodley, & Shyu 2000). Based on this training example, using $C4.5$, a decision tree for the features are build. Then an unweighted *knn* algorithm is used to return the most similar images. In each iteration the training set size increases. Based on this framework an Interactive CBIR system *ASSERT* is designed which works well in the domain of medical images.

In the above we have discussed some major CBIR systems along with their approaches to retrieving images. The list is not exhaustive (for a more complete survey see (Veltkamp & Tanase 2000)), but given the space limitations we have highlighted the approaches more relevant to our approach. Though some of these systems have produced effective results in particular domains, we still do not have a powerful, generic mechanism that is able to effectively bridge the gap between the high level semantics of an image and low level features. In this paper we propose a novel agent-based relevance feedback approach that we believe overcome the shortcomings of the existing systems. We discuss our approach in the next section.

ABIR

In the above we have seen a number of different CBIR systems. We believe our agent-based approach to developing an effective CBIR system is complementary to the current efforts and will be more flexible, scalable, and easy-to-use than most of these systems. ABIR is designed to answer logical image queries from the user by a systematic and flex-

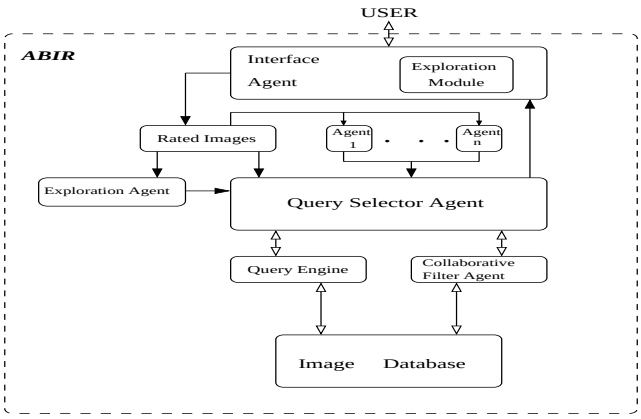

Figure 2: The architecture of ABIR.

ible iterative feedback process. The goal is to improve recall and user satisfaction by carefully incorporating and balancing past history of usage and current relevance feedback.

System architecture

We now discuss the proposed architecture of ABIR shown in Figure 2. ABIR is an interactive, agent-based CBIR system that encapsulates an image database and will be designed to allow users to interactively retrieve images. The user interacts with an interface agent which can retrieve the summary of the history of past interactions with the user. This summary will be used to model the similarity biases exhibited by the user and accordingly influence the selection of matching images. The interface agent will also contain an explanation module that can explain the choice of images to the user as an itemized list. The user will have the option to support or reject an explanation that will, in turn, influence future retrievals. The user is expected to rate the selected images (a few different rating schemes will be evaluated, ranging from selecting a preferred subset to ranking all the returned images). Based on this ranking, other images will be returned. This process is repeated until the user is satisfied with one or more of the returned images and terminates the query/search process. We envision typical queries to result in between 4-6 rounds of interaction with ABIR.

The query process is started by the user presenting an image as a query. In response ABIR returns a set of matching querying with some variance to allow for exploration. The variance is introduced by the `Exploration agent` and is a directed attempt to prevent *premature concept convergence*. This condition happens when a highly similar set of images is presented as a first response to a query, and this homogeneous set leads the user to believe that the only relevant images are those shown and resultantly leads the search process along a very narrow and restrictive path. By rating a few of the highly similar images, the user is unlikely to explore beyond a narrow local region of the image space. Rather, we want to present some diversity in the initial response, most likely emphasizing similarity with the presented image based on non-overlapping feature subsets. Such a diverse, but relevant set of images allow the user to choose between several alternative exploration paths for desired images. Subsequent rounds of interactions will produce increasingly more homogeneous images (correspondingly, less exploratory choices). Such a graded exploration scheme is more likely to effectively guide the user's search for a satisfactory image.

The feature agents 1 through n correspond to agents that specializes in matching images based on particular feature values. Each feature agent will retrieve and rank k images from the image database through the `Query Selector Agent`. The query selector agent will take inputs from the feature agents and the exploration agent, and take into consideration the images ranked by the user, to retrieve and filter images from the image database by using the `query engine`. This agent incorporates the weighted voting procedure to effect tradeoffs between preferences between the feature agents.

The `collaborative filter agent` is responsible for capturing perceived similarity of images in the image database by all users of the system. The goal is to create an affinity based clustering on the image database where the relevance feedback given by the users incrementally change the affinity between the images. Whereas ABIR primarily uses the past history of interaction of the current user to tailor the retrieval process to the particular user, summary of usage by all past users of the system will also impact the matching process. We believe that the tradeoff of individual and collective preferences will provide the right blend of exploitation-exploration in the search of matching images.

Key research issues

We now outline the key research issues to be explored within the architecture of ABIR to address the effective CBIR problem.

Agent Based CBIR in ABIR: Our premise that an agent-based CBIR system can be an effective approach stems from the fact that CBIR requires a matching of user preferences to stored images. As a result, an effective matching mechanism must be knowledgeable in both apersonal image characteristics and, at the same time, must take into consideration biases and preferences of the user that has not been explicitly specified, but can be partially inferred from usage patterns. We also posit that personal user biases can be inferred indirectly from a summary of past usage and an iterative query process where the current query is refined from relevance feedback from the user over multiple interactions.

In our design, a feature agent specializes in matching images based on that particular feature. A feature agent is further composed of sub-feature agents each of which specializes in matching images by a sub-feature of that feature. While a feature agent is responsible for trading off conflicting recommendations from sub-feature agents, the `Query`

`Selector agent` is responsible for coordinating recommendations from the feature agents.

Voting on images: Most CBIR systems use some kind of linear weighted voting of the low-level feature values while matching images. While these techniques are well-understood, they cannot reasonably approximate user preferences that may not be linear. While general non-linear combinations are difficult to work with, we believe a particular class of approaches motivated by techniques from voting theory can be used to better represent user requirements. While voting mechanisms are traditionally used to arrive at a compromise candidate based on preferences of multiple voters (Straffin 1980), in our research, we have successfully applied variations of these techniques to conflicting preferences of a given user (Mukherjee, Sajja, & Sen 2003; Sen, Haynes, & Arora 1997). In the context of CBIR, we will consider each feature agent to retrieve a set of matching images from the image database based on feature values of the query and subsequently rated images and that of the images in the image databases. Each feature agent, A_i is allowed to nominate a set I_i of images as a match. Thereafter each agent further ranks all the images in the set $I = \cup_{i=1,\ldots,n} I_i$ (where n is the number of agents). Then a voting procedure will combine the rankings of all feature agents to form a total ordering of the retrieved images. The voting mechanism will incorporate both the preferences of the user based on usage, both past choices and current ratings, and recommendations of the collaborative recommendation component. In particular, the voting procedure uses weights for the different syntactic features of the image. A learning mechanism that uses a graded history of past interactions will be used to tune the general preference of a particular user. The resultant weight set will determine the initial bias when retrieving matching images for a given image presented by the user. Subsequent interactions with the user for a particular query will adjust the weights on the features for this query given the feedback provided by the user on the retrieved images. The deviation of the weight vector through these iterations will be used to modify the default weight vector for the user through a reinforcement learning procedure. A gradual adaptation mechanism will enable the system to track any change in preferences of the user. The top k of the ranked images will be returned together with l other images as dictated by the exploration facility in ABIR. The sum of $k + l$ is held a constant, with the number of images chosen by the exploration facility decreasing over the iterations of a given query.

Exploration: Premature concept convergence can be a key problem in the search for matching images. For example, consider the case of a user searching for animals in the wild, and presented a picture of a group of horses in a meadow. If the CBIR system was to return only pictures of horses as matching results, the user will be led to believe that these are the only relevant pictures and hence miss out on the possibility of retrieving other wild animal pictures. To alleviate this problem, ABIR will incorporate a novel exploration scheme where, in addition, to matches generated from stated image and past usage, a biased exploration scheme will highlight the importance of different image features to select other images to add to the diversity of the images returned. In the above example, these might return some images of other animals, and even images of nature without animals in it. While the last result may appear superfluous, it might be relevant in the less likely case of the user being interested in nature photos. The influence of the exploration component will be steadily decreased over iterations as user selection will indicate the sub-space of images where the matching should be concentrated.

Personalized biases: The essence of personal agents is to provide information tailored according to the needs and biases of the user. In the first few interactions with the user, ABIR, will have very little past information to bias its search according to this particular user's preferences. But, over time, the type of queries submitted, the relevance feedback provided, and the final images accepted by the user as match can be used to approximate the bias of the users with regards to different image features. Such implicit inference is to be preferred over explicit low-level feature ratings required of the user in some existing CBIR systems. Our approach has the desired features of increasing precision of recall without increasing the cognitive load on the user.

Collaborative filtering: Collaborative filtering techniques (Breeze, Heckerman, & Kadie 1998) use recommendations from a group of users while recommending products and services to a user who is estimated to belong to the corresponding group. In ABIR, relevance feedback and selection of final images in response to a query will be used to define an *affinity matrix* between the images in the database. The affinity between two images will capture the content similarity between two images as perceived by the users of the system. We will evaluate the effectiveness of such a representation in bridging the gap between high-level concepts and low-level features of an image. The affinity matrix is likely to be sparse and hence sparse-matrix encoding techniques can alleviate storage space concerns for this information. Though we plan to initially investigate a single affinity matrix to capture the summary ratings of all users, at a later stage of the project we plan to group users into multiple clusters based on their usage (similarity of their stored preferences) and hence the corresponding number of affinity matrices will be stored in the image database.

Relevance Feedback options: We plan to investigate two different types of relevance feedback scheme: (a) the user categorizes each of the returned images into one of a few specific categories, e.g., relevant and non-relevant, and (b) the user re-ranks the set of ranked results. We believe that the latter results will enable us to produce more satisfactory matching images in less iterations, even though each iteration may incur somewhat more cognitive load on the user compared to the first approach. The feedback from these user ratings will be used to alter the influence of different feature agents in the voting procedure to determine the ranking of matching images in the next round. This information will also be used to update the personal bias of the user.

Evaluation: We will evaluate ABIR and its components across a few well-characterized image databases. One of the criteria that we plan to vary is the degree of homogeneity of the images in the database. For this reason, we will first prepare a large database consisting of collections of many different types of images. Next, we will partition this database hierarchically into succeeding levels of more homogeneous images. We would carefully study the number of iterations required and the amount of feedback given to retrieve satisfactory images from databases with different homogeneity levels. We also plan to experiment with one or more different image databases used by professionals in specific disciplines with a relatively high degree of homogeneity compared to arbitrary images available on the web. Candidate databases for this part of our study includes the following: (a) Automated Plate Scanner: images of stars and galaxies, (b) Dermatologic Image Database (available from University of Iowa's College of Medicine), (c) Glacier Image Database Cities and (d) Buildings database (available from the University of Washington and funded by NSF under the Digital Libraries Initiative Program). We will compare the performance of ABIR with other linear weight-based iterative CBIR techniques.

Research goals

In this paper we have argued for an agent based CBIR system that uses multiple interactions and feedback from the user on retrieved images to disambiguate semantic contents of images. We have presented the architecture of the proposed ABIR system which uses novel applications of voting mechanisms in CBIR. Additionally, we have outlined a learning process that adjusts to a particular user's image similarity preferences by incorporating feedback from the user over various retrieved images in response to user queries over past interactions. As a result, the more a user uses ABIR, the less effort he/she is expected to spend for retrieving matching images. We also provide an interesting exploration-oriented retrieval process which will enable the user to look for related images which may not have been his/her original intention. We believe that in a number of domains this might lead to interesting discoveries of images that otherwise would not be retrieved.

An area of ABIR that we would like to expand on is the use of multiple weight vectors per agent, where each weight vector corresponds to a particular class of images, e.g., the same user may have different preferences for image similarities for nature pictures versus sports events pictures, etc.

Acknowledgements

This work has been supported in part by an NSF award IIS-0209208.

References

Breeze, J. S.; Heckerman, D.; and Kadie, C. 1998. Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of Fourteenth Conference on Uncertainty in Artificial Intelligence*. San Francisco, CA: Morgan Kaufmann Publishers.

Essam, A., and Mansur, R. 2000. Efficient content-based indexing of large image databases. *ACM Transactions on Information Systems (TOIS)* 18(2):171–210.

Fu, Y., and Teng, J.-C. 2000. Improving high-dimensional indexing with heuristics for content-based image retrieval. *Lecture Notes in Computer Science* 1737:249–.

Guttman, A. 1984. R-tree: a dynamic index structure for spatial searching. In *ACM SIGMOD*.

Ma, W.-Y., and Manjunath, B. S. 1998. A texture thesaurus for browsing large aerial photographs. *JASIS* 49(7):633–648.

Ma, W. Y., and Zhang, H. 1998. Benchmarking of image features for content-based retrieval. In *IEEE 32nd Asilomar Conference on Signals, Systems,Computers*, volume 1, 253–257.

MacArthur, S. D.; Brodley, C. E.; and Shyu, C. 2000. Relevance feedback decision trees in content-based image retrieval. In *IEEE Workshop on Content-Based Access of Image and Video Libraries*.

Mukherjee, R.; Sajja, N.; and Sen, S. 2003. A movie recommendation system: An application of voting theory. *User Modeling and User-adapted Interaction* 13(1–2):5–33. (special issue on "User modeling and Intelligent Agents").

Niblack, W. 1997. Updates to the qbic system. In *SPIE Storage and Retrieval for Image and Video Databases VI*.

Rui, Y.; Huang, T.; and Chang, S. 1999. Image retrieval: current techniques, promising directions and open issues.

Rui, Y.; Huang, T. S.; and Mehrotra, S. 1998. Relevance feedback techniques in interactive content-based image retrieval. In *Storage and Retrieval for Image and Video Databases (SPIE)*, 25–36.

Sen, S.; Haynes, T.; and Arora, N. 1997. Satisfying user preferences while negotiating meetings. *International Journal of Human-Computer Studies* 47:407–427.

Shyu, C.; Brodley, C.; Kak, A.; Kosaka, A.; Aisen, A.; and Broderick, L. 1999. Assert: A physician-in-the-loop content-based image retrieval system for hrct image databases. *Computer Vision and Image Understanding* 75(1):111–132.

Straffin, P. D. J. 1980. *Topics in the theory of voting*. The UMAP expository monograph series. Boston, MA: Birkhauser.

Stricker, M., and Orengo, M. 1995. Similarity of color images. In *Proceeding of SPIE Storage and Retrieval for Image and Video Databases*.

Swain, M. J., and Ballard, D. 1991. Color indexing. *International Journal of Computer Vision* 7(1):11–32.

Tamura, H.; Mori, S.; and Yamawaki, T. 1978. Texture features corresponding to visual perception. *IEEE Trans. on Systems, Man, and Cybernatics* 8(6):460–473.

Taycher, L.; Cascia, M. L.; and Sclaroff, S. 1997. Image digestion and relevance feedback in the ImageRover WWW search engine. In *Second International Conference on Visual Information Systems*, number 1997-014, 85–94.

Veltkamp, R., and Tanase, M. 2000. Content-based image retrieval systems: A survey. Technical Report UU-CS-2000-34, Department of Computing Science, Utrecht University,.

Wang, J. Z. 2001. *Integrated Region-based Image Retrieval*. Kluwer Academic Publishers.

Yang, Z., and Kuo, C.-C. J. 2000. Learning similarities and categories from relevance feedback. In *SPIE's International Symposium on Voice, Video and Data Communications, Boston, MA*.

Z.Su; Zhang, H.; and Ma, S. 2000. Using bayesian classifier in relevant feedback of image retrieval. In *IEEE International conference on Tools with Artificial Intelligence*.