ABSTRACT

Content Based Image Retrieval (CBIR) systems attempt to allow users to perform searches in large image repositories. Content-Based Image Retrieval (CBIR) has become one of the most progressive research areas in the past few years. In content Based Image Retrieval, images are retrieved based on color, texture and shape (low level perception). There is a gap between user semantics (high level perception/concepts) and low level perception is called ‘Semantic Gap’. Relevance Feedback (Relevance Feedback) learns association between high level semantics and low level features. While these research efforts establish the basis of CBIR, the usefulness of the proposed approaches is limited. Specifically, these efforts have relatively ignored two distinct characteristics of CBIR systems are semantic gap and human perception of visual content respectively.

In this paper, we propose different aspects of the system such as first, we analyze the nature of the Relevance Feedback problem in a continuous representation space in the context of image retrieval. Secondly, a Relevance Feedback based interactive retrieval approach, which effectively takes into account the above two characteristics in CBIR. During the retrieval process, the user’s high level query and perception subjectivity are captured by dynamically updated weights based on the user’s feedback and finally, the proposed system where user can view/understands the relevance level of the retrieved result of images to his/her given query image. The proposed approach greatly reduces the user’s effort of composing a query and captures the user’s information more specifically. We can reduce the user intervention in the CBIR retrieval system.

Keywords: Content Based Image Retrieval (CBIR), Relevance Feedback, Semantic Gap and Human Perception.

1. INTRODUCTION

Digital images are produced at an ever increasing rate from diverse sources. A content based image retrieval (CBIR) system is required to effectively tackle information from these image repositories. Content-based retrieval is characterized by the ability of the system to retrieve relevant images based on the visual and semantic contents of images.

This research has been truly interdisciplinary in nature. As impressive and synergistic this effort may appear to be, however, these investigations didn’t accrue the benefits of cumulative effect the research didn’t advance by effectively building upon one another’s work. Furthermore, there is a mismatch between these synergistic efforts and the one that is truly required to bring success to CBIR in the commercial market place.

The retrieval of images based on their contents, even though the approach is readily generalizable to other media types. Keyword annotation is the traditional image retrieval paradigm. In this approach, the images are first annotated manually by keywords. They can then be retrieved by their corresponding annotations. However, there are three main difficulties with this approach, i.e. the large amount of manual effort required in developing the annotations, the differences in interpretation of image contents, and inconsistency of the keyword assignments among different indexers [1, 2, 3]. To overcome the difficulties of the annotation based approach, an alternative mechanism, Content-Based Image Retrieval (CBIR), has been proposed in the early 1990’s. Besides using human-assigned keywords, CBIR systems use the visual content of the images, such as color, texture, and shape features, as the image index. This greatly alleviates the difficulties of the pure annotation based approach, since the feature extraction process can be made automatic and the image’s own content is always consistent. CBIR has attracted great research attention, ranging from government, industry, to universities.

In the early years of research in CBIR, the focus was on query by visual example (QBVE): a search session begins by presenting an example image (or sketch) to the search engine as a visual query, then the engine returns images that are visually similar to the query image. More recently, the concept of semantic gap has been extensively used in the CBIR research community to express the discrepancy between the low-level features that can be readily extracted from the images and the descriptions that are meaningful for the users.

The automatic association of such descriptions to the low-level features is currently only feasible for very restricted domains and applications. When searching more generic image databases, one way of identifying what the user is looking for in the current retrieval session (the target of the user) is by including the user in the
retrieval loop. For this, the session is divided into several consecutive rounds; at every round the user provides feedback regarding the retrieval results, e.g. by qualifying images returned as either “relevant” or “irrelevant” from this feedback, the engine learns the visual features of the images and returns improved results to the user. The Relevance Feedback mechanism implemented in a search engine should attempt to minimize the amount of interaction between the user and the engine required for reaching good results.

In this paper we focus on issues related to nature of the Relevance Feedback problem in a continuous representation space in the CBIR, a Relevance Feedback based interactive approach, which consider the major problems of current CBIR system (i.e. semantic gap and human perception) and we proposed a new method where user can view relevance levels of each displayed image as result for the user query image.

The remainder of the paper is organized as follows. An overview of approaches to CBIR and nature of the Relevance Feedback in the CBIR is presented in section 2. Nature of the Relevance Feedback in CBIR systems are discussed in section 3. An interactive Relevance Feedback approach to CBIR to solve the semantic gap and human perception in the retrieval process is presented in the section 4. Section 4 contains the proposed system for displaying the relevance level to the result image set. Experimental setup and results are included in the section 5. Finally, section 6 concludes the paper and section 7 gives future directions to the researches.

2. OVERVIEW OF APPROACHES TO CBIR

At the highest level, image attributes are grouped into two categories: extrinsic and intrinsic. *Extrinsic attributes* denote the characteristics of an image (or a domain object in the image) which can only be obtained externally. In other words, extrinsic attributes cannot be derived from the image itself. For example, name of the physician who made the diagnosis of a chest X-ray is an extrinsic attribute of an X-ray image. In contrast, *intrinsic attributes* are those that can be extracted from the image manually, automatically, or by a combination of manual and automatic methods.

In the image processing and pattern recognition literature, intrinsic attributes are referred to as *features*. Intrinsic attributes are grouped into three categories: objective, subjective, and semantic. *Objective attributes* are those whose interpretation doesn’t vary from one retrieval user to another. For example, number of bedrooms, total floor area is two objective attributes in the domain of architectural design. Compared to subjective attributes, objective attributes are more precise and do not require the domain expertise either to identify or to quantify them in new image instances.

The interpretation of *subjective attributes*, on the other hand, varies significantly from one retrieval user to another. Subjective attributes are best viewed as spanning a spectrum characterized by a left hand pole and a right hand pole. A user’s subjectivity is then associated with a specific position on the spectrum. Based on the attribute taxonomy, several generic query classes have been identified in [4]. They include retrieval by: color, texture, sketch, example, shape, volume, spatial constraints, browsing, objective attributes, subjective attributes, motion, keywords, and domain concepts.

Rui, Hunag, and Chang (1999) [5] discuss CBIR techniques, research directions, and open issues as of late 1990s. In the following we describe some recent approaches to CBIR. We begin with those which employ *retrieval by browsing* as a major mode of querying. Yee et al. (2003) [6] approach to CBIR is based on navigating an image collection of size 35,000 along conceptual dimensions (or facets) that describe images in the collection. Based on experimental evidence with real users, the study concludes that facet-based approach is effective in providing access to image collections.

3. NATURE OF THE RELEVANCE FEEDBACK IN CBIR

Relevance Feedback is a powerful technique used in traditional text-based information retrieval systems and adopted it to the image retrieval systems. It is the process of automatically adjusting an existing query using the information feedback by the user about the relevance of previously retrieved objects such that the adjusted query. The key issue in Relevance Feedback is how to effectively utilize the feedback information to improve the retrieval performance.

There are two major approaches to improving retrieval effectiveness: automated query expansion, and Relevance Feedback techniques. Automated query expansion methods are based on Term co-occurrences [7] “methods involve identifying terms related to the terms in the user query. Such terms might be synonyms, stemming variations, or terms that are physically close to the query terms in the document text”, Pseudo-Relevance Feedback (PRF) [7] “In the PRF method, multiple top-ranked documents retrieved in response to the user’s initial query are assumed to be relevant.”, concept-based retrieval [8] “it treats the terms in the user query as representing domain concepts, and not as literal strings of letters.”, and language analysis [9] “Language analysis based query expansion methods”. In this section we discussed only Relevance Feedback approaches to CBIR.

A typical scenario for Relevance Feedback in content-based image retrieval is as follows Fig.1.

**Step 1.** Machine provides initial retrieval results, through query-by-keyword, sketch, or example, etc.
Step 2. User provides judgment on the currently displayed images as to whether, and to what degree, they are relevant or irrelevant to her/his request.


This procedure is iteratively executed until user gets satisfied with the results.

Fig.1. Relevance Feedback Process

The following paragraphs are discussed about the assumptions for Relevance Feedback, Relevance Feedback mechanism components and various methods exist for Relevance Feedback.

3.1 General assumptions

One can customize Relevance Feedback mechanism if one knows the characteristics of the scenario, of the target application and of its users. It is nevertheless important to remind some general assumptions that are usually made when developing Relevance Feedback mechanisms for CBIR:

1. The discrimination between “relevant” and “irrelevant” images must be possible with the available image descriptors.
2. There is some relatively simple relation between the topology of the description space and the characteristic shared by the images the user is searching for.
3. “Relevant” images are a small part of the entire image database.
4. While part of the early work on Relevance Feedback assumed that the user could (and would be willing to) provide a rather rich feedback, including “relevance notes” for many images, the current assumption is that this feedback information is scarce: the user will only mark a few “relevant” images as positive and some very different images as negative.

3.2 Components of Relevance Feedback

Relevance Feedback mechanism has two components: a learner and a selector. At every feedback round, the user marks the images returned by the search engine as “relevant” or “irrelevant”. The learner exploits this information to re-estimate the target of the user. With the current estimation of the target, the selector chooses other images that are displayed by the interface of the search engine; the user is asked to provide feedback on these images during the next round. In the following, we briefly present the evolution of the learners and selectors.

3.2.1 Learners

In Relevance Feedback, the learner must use the training data, i.e. the images marked by the user during subsequent feedback rounds, and sometimes prior knowledge in order to estimate the target of the user. The task of the learner is particularly difficult in the context of Relevance Feedback for several reasons:

1. The amount of training data is very low, usually much lower than the number of dimensions of the description space.
2. There are usually much fewer positive examples (images marked by the user as “relevant”) than negative examples (images marked as “irrelevant”). The learner must have a low sensitivity to this imbalance in the training set or some corrective must be found.
3. The target class may have a rather complex shape or even several, rather disconnected modes. Together with the fact that training data is scarce, this can severely limit the generalization we can expect.
4. To preserve interactivity, both learning from the training examples and the evaluation of the remaining images according to the selection criterion must be very fast. The computation cost can then be a very important criterion in the choice of a learning method.

In Relevance Feedback, SVMs appear to be the learners of choice for several reasons such as: For most choices of the kernel, SVMs avoid too restrictive assumptions regarding the data, SVMs are very flexible, SVMs allow
fast learning and relatively fast evaluation for medium-sized databases, SVMs are usually less sensitive than
density-based learners to the imbalance between positive and negative examples in the training data.

3.2.2 Selectors
Relevance Feedback session is open-ended, since the user is supposed to be able to provide feedback any time
during the session. It is then difficult to define two distinct stages in the session: the identification of the target
class, followed by the presentation of its images to the user.
As a consequence, the selection strategy has two different and potentially conflicting goals during each feedback
round:
1. Given the current state of knowledge of the learner, provide the user with as many “relevant” images as possible.
2. Derive from the user as much information as possible regarding the distinction between “relevant” and
“irrelevant” (maximize the transfer of information from the user to the system).
Rui, Huang, and Mehrotra (1998) [10] have presented a relevance-feedback based approach to CBIR, in which a
human and a computer interact to refine high-level queries to representations based on low-level features, which
addresses the gap between high level concepts and low level image features; and, subjectivity in human
perception of image content. The evaluation parameter used was convergence ratio. Benitez, Beigi, and Chang
(1998) [11] described MetaSeek, which is a metasearch engine to query distributed image collections on the
Web. The metasearch engine interfaces with four image search engines: VisualSeek, WebSeek, QBIC, and
Virage. User feedback was used to evaluate the quality of search results returned by each engine, and this
history was preserved in a database.
Vasconcelos and Lippman (2000) [12] used a Bayesian learning algorithm that integrate relevance feedback
provided by the user over a retrieval session. Through experimental results, they demonstrate a significant
improvement in the rate of convergence to the relevant images is possible by the inclusion of learning in the
relevance feedback by using self-organizing maps. The Self-Organising Map (SOM) is an unsupervised, self-
organising neural algorithm widely used to visualize and interpret large high-dimensional data sets.
Sean D. MacArthur, Carla E. Brodley, and Avinash C. Kak (2002) [14] proposed a relevance feedback
technique that uses decision trees to learn a common thread among instances marked relevant. The technique
was applied in preexisting content-based image retrieval (CBIR) system that was used to access high resolution
computed tomography images of the human lung. The experimental evaluation was done on image database
of HRCT scans of different cross-sections of the lung. The average precision was used to evaluate the results at
different iterations. Su, Zhang, Li, and Ma (2003) [15] have given an approach to relevance feedback based
CBIR using a Bayesian classifier. Positive examples in the feedback were used to estimate a gaussian
distribution that represents the desired images for a given query. Ranking of retrieved images was determined
based on the negative examples in the relevance feedback.
Zhong Su, Hongjiang Zhang, Shaoqing Ma (2004) [16] have proposed a new relevance feedback approach based
[17] have suggested a new concept semantically based feature space modification which achieves feature
adaptive relevance feedback (FA-RF). FA-RF is a RF-based approach and uses two iterative techniques to
exploit the relevance information: query refinement and feature re-weighting. Image database was built from
UC Berkeley digital library project. Wei Bian and Dacheng Tao (2010) [18] have represented images by low-
level visual features. They have designed a mapping to select the effective subspace from for separating positive
samples from negative samples based on a number of observations. They have proposed the biased
discriminative Euclidean embedding (BDEE) which parameterizes samples in the original high-dimensional
ambient space to discover the intrinsic coordinate of image low-level visual features.
Peter Auer, Zakria Hussain, Samuel Kaski, Artto Klami, Jussi Kujala, Jorma Laaksonen, Alex P. Leung, Kitzuchart Pasupa, John Shawe-Taylor (2010) [19] have described Pinview, a content-based image retrieval
system that exploits implicit relevance feedback during a search session. Dorota G lowacka, John Shawe-Taylor
(2010) [20] have presented a new approach to content-based image retrieval based on multinomial relevance
feedback. Ja-Hwung Su, Wei-Jyun Huang, Philip S. Yu, Vincent S. Tseng (2011) [21] have proposed a novel
method, Navigation-Pattern-Based Relevance Feedback (NPRF), to achieve the high efficiency and
effectiveness of CBIR. In terms of effectiveness, the proposed search algorithm NPRF Search makes use of the
discovered navigation patterns and three kinds of query refinement strategies, Query Point Movement (QPM),
Query Reweighting (QR), and Query Expansion (QEX), to converge the search space toward the user’s
intention effectively. By using NPRF method, high quality of image retrieval on RF was achieved in a small
number of feedbacks.
4. An Interactive Relevance Feedback approach to CBIR
Before we describe how the Relevance Feedback technique can be used for CBIR, we first need to formalize
how an image object is modeled [22].
4.1. The Multimedia Object Model

An image object $O$ is represented as:

$$O = O (D, F, R)$$  \hspace{1cm} (1)

- $D$ is the raw image data, e.g. a JPEG image.
- $F = \{ f_i \}$ is a set of low-level visual features associated with the image object, such as color, texture, and shape.
- $R = \{ r_{ij} \}$ is a set of representations for a given feature $f_i$, e.g. both color histogram and color moments are representations for the color feature [24]. Note that, each representation $r_{ij}$ itself may be a vector consisting of multiple components,

$$i.e. \quad r_{ij} = [r_{ij1}, \ldots, r_{ijk}, \ldots, r_{ijK}]$$  \hspace{1cm} (2)

where $K$ is the length of the vector.

In contrast to the computer centric approach’s single representation and fixed weights, the proposed object model supports multiple representations with dynamically updated weights to accommodate the rich content in the image objects. Weights exist at various levels. $W_i$, $W_{ij}$, and $W_{ijk}$, are associated with features $f_i$, representations $r_{ij}$, and components $r_{ijk}$, respectively.

4.2. Articulating Relevance Feedbacks in CIBR

An image object model $O(D,F,R)$ together with a set of similarity measures $M = \{ m_{ij} \}$, specifies a CBIR model $(D,F,R,M)$. The similarity measures are used to determine how similar or dissimilar two objects are. Different similarity measures may be used for different feature representations. For example, Euclidean is used for comparing vector-based representations, while Histogram Intersection is used for comparing color histogram representations. Based on the image object model and the set of similarity measures, the retrieval process is described below and also illustrated in Fig. 2.

1. Initialize the weights $W = \{ W_i, W_{ij}, W_{ijk} \}$ to $W_0$, which is a set of no-bias weights. That is, every entity is initially of the same importance.

$$W_i = W_0 = 1/I$$  \hspace{1cm} (3)

$$W_{ij} = W_0 = 1/J_i$$  \hspace{1cm} (4)

$$W_{ijk} = W_0 = 1/K_{ij}$$  \hspace{1cm} (5)

where $I$ is the number of features in set $F$; $J_i$ is the number of representations for feature $f_i$, $K_{ij}$ is the length of the presentation vector $r_{ij}$.

2. The user’s information need, represented by the query object $Q$, is distributed among different features $f_i$ according to their corresponding weights $W_i$.

3. Within each feature $f_i$, the information need is further distributed among different feature representations $r_{ij}$ according to the weights $W_{ij}$.

4. The objects’ similarity to the query, in terms of $r_{ij}$, is calculated according to the corresponding similarity measure $m_{ij}$ and the weights $W_{ijk}$:

$$S(r_{ij}) = m_{ij}(r_{ij}, W_{ijk})$$  \hspace{1cm} (6)

5. Each representation’s similarity values are then combined into a feature’s similarity value:

$$S(f_i) = \sum_j W_j S(r_{ij})$$  \hspace{1cm} (7)

6. The overall similarity $S$ is obtained by combining individual

$$S = \sum_i W_i S(f_i)$$  \hspace{1cm} (8)

7. The objects in the database are ordered by their overall similarity to $Q$. The $N_{RT}$ most similar ones are returned to the user, where $N_{RT}$ is the number of objects the user wants to retrieve.

8. For each of the retrieved objects, the user marks it as highly relevant, relevant, no-opinion, non-relevant, or highly non-relevant, according to his information need and perception subjectivity.

![Fig. 2. The Retrieval Process](image-url)
9. The system updates the weights according to the user’s feedback such that the adjusted Q is a better approximation to the user's information need.

10. Go to Step 2 with the adjusted Q and start a new iteration of retrieval.

In Fig. 2, the information need embedded in Q flows up while the content of O’s flows down. They meet at the line, where the similarity measures m_i are applied to calculate the similarity values S(r_j)'s between Q and O's. Following the Information Retrieval theories, the objects stored in the database are considered objective and their weights are fixed. Whether the query is considered objective or subjective and whether its weights can be updated distinguishes the proposed Relevance Feedback approach from the computer centric approach. In the computer centric approach, a query is considered objective, the same as the objects stored in the database, and its weights are fixed. Because of the fixed weights, this approach cannot effectively model high level concepts and human perception subjectivity. It requires the user to specify a precise set of weights at the query stage, which is normally not possible. On the other hand, queries in the proposed approach are considered as subjective. That is, during the retrieval process, the weights associated with the query can be dynamically updated via Relevance Feedback to react the user's information need. The burden of specifying the weights is removed from the user.

5. PROPOSED SYSTEM

Fig. 3 shows the general scheme of the proposed system using Relevance Feedback in CBIR. The basic idea of Relevance Feedback is to shift the burden of finding the right query formulation from the user to the system.

Algorithm for proposed system is as follows:

Step 1: User will give the input query image to the proposed system

Step 2: From this image system extracts the low-level features, from this constructs the feature vector of the given image and then finds the similarity measure value (using Euclidean distance measure) with Feature database images (Image Database).

Step 3: Displays the set of images which is having less value when comparing the similarities between input image and database images. Highest ranked images will be displayed to the user; the number of images displayed will be dependent on the size of the display window or the threshold value given in the code of experiment. Generally, the people use to display up to maximum 20 images per iteration.

Step 4: In our proposed system, the displaying images are appeared along with the relevance level value of image, which shows the relevance information with the given input image (query image). In the implementation section we are given an output screen, shows the images displayed along with the level. For example, if

level = 1, means image is most relevant to the given image.
level = 2, means image is moderately relevant to the given image.
level = 3, means image is less relevant to the given image.
level = 0, means image is displayed with no option.
level = -1, means image is less irrelevant to the given image.
level = -2, means image is gently irrelevant to the given image.
level = -3, means image is most irrelevant to the given image.

Along this information the screen is having two options shows in (the radio buttons) as relevant and irrelevant. Upon this user will give feedback.

Step 5: After this step the system will learn the user preferences using a learning method.

Step 6: If the user is satisfied with system result (retrieved images) then stops the process, else according to the user feedback the system will adjust the weights of the image and repeats the procedure once again from the step 3 onwards. Until user gets satisfaction with the result set.

6. EXPERIMENT SETUP AND RESULTS

The test image dataset used in our experiments is selected from the COREL image datasets and it has 1000 natural images. Ten categories of images are selected and each category contains 100 images. These categories are natives people, beaches, monuments, busses, texture, dinosaurs, elephants, roses, horses, snow capped mountains, and food dishes.

The test database contains 1000 images. The reason that we have chosen this test set is that it allows us to explore all the color, texture, and shape features simultaneously in a meaningful way. Even though there exists larger test sets, they do not provide the ability to test multiple visual features simultaneously. In our current retrieval system, the visual features used include color, texture and shape of the objects in the image. That is

\[ F = \{f_i\} = \{\text{color}, \text{texture}, \text{shape}\} \quad (9) \]

To validate the proposed approach, multiple representations are used for each feature. E.g. color histogram and color moments [24] are used for color feature; Tamura [25, 26] and co-occurrence matrix [27, 28] texture representations are used for texture feature; Fourier descriptor and chamfer shape descriptor[40] are used for shape feature.
\[ R = \{r_{ij}\} = \{r_1, r_2, r_3, r_4, r_5, r_6\} = \{\text{color histogram, color moments, Tamura, co-occurrence matrix, Fourier descriptor, chamfer shape descriptor}\} \]  

Fig. 3. Proposed System Architecture

The proposed Relevance Feedback architecture is open retrieval architecture. Other visual features or feature representations can be easily incorporated, if needed.

The Fig. 4 shows an expected result of proposed system on the Corel dataset where the query is an image (in texture category) and all retrieved images shows with a relevance level (value) and feedback option for user. Here the output shows totally five images with relevance level and feedback form. For example in the Fig. 4, top left image having level=1, which means this image is most relevant to the user given query, top right image having level= -3, means this image is most irrelevant to the user given query and bottom image having level = 0, means this image is having no option. And with feedback form, if user thinks that image is not relevant to his/her given image then he can select one of the options according to his/her view. Then the system will learn the user preferences according to his/her feedback. In learning process, the system will re-weight the features of image and reconstruct the feature vector of that image using the existing methods which are not discussed in this paper (not in the scope of this paper).

7. CONCLUSION

In this paper we proposed a new method to reduce the semantic gap in CBIR using relevance feedback with displaying the set of images with corresponding relevance level with the given query image. Here we analyze the nature of the Relevance Feedback problem. Secondly, a Relevance Feedback based interactive retrieval approach, which effectively takes into account the above two characteristics in CBIR and finally, the proposed system where user can understands the relevance level of the retrieved result of images for his/her given query image. The proposed approach greatly reduces the user’s effort of composing a query and captures the user’s information need more specifically. We can reduce the user intervention in the CBIR retrieval system.

8. FUTURE DIRECTIONS

Research issues in CBIR encompass algorithms for feature extraction, retrieval models, retrieval effectiveness and efficiency, query reformulation techniques, Relevance Feedback, usability and retrieval system evaluation. Many existing CBIR systems stop at lower levels of feature abstractions due to difficulty in automatically extracting higher level image features.

- Researchers working in the area of CBIR dealing with very large data sets the Relevance Feedback technique can be improved by incorporating with parallel and distributed computing techniques.
- Research can be done in the area of CBIR system to improve precision, convergence, execution time using Relevance Feedback.
- Researchers can design a CBIR system for different applications like Crime prevention, The military, Intellectual property, Architectural and engineering design, Fashion and interior design, Journalism and advertising, Medical diagnosis, Geographical Information and Remote sensing systems, Cultural heritage, Education and training, Home entertainment, Web searching.
Researchers can improve the retrieval performance of CBIR system using Relevance Feedback technique for the images having same semantic category.

Fig.4. Expected output Result for Proposed System

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