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A Novel Architecture for Personalized Image Retrieval from Social Websites

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Abstract: The social media photo sharing sites allows users to upload their photos, annotate them with tags, submit them to groups, and also to form social networks by adding other users as contacts. The site offers multiple ways of browsing or searching it. One option is tag search, which returns all images tagged with a specific keyword. If the keyword is ambiguous, e.g. jaguar could mean an animal or a car, tag search results will include many images that are not relevant to the sense the user had in mind when executing the query. This paper describes an approach to personalized image indexing and retrieval. To tackle the issue of subjectivity in Content-Based Image Retrieval (CBIR), users can extend their own tag vocabulary and make the system learn it. This tag extension concept demonstrates that content based image search can be efficiently adapted to user interests and matches personalized image retrieval.

Keywords: Sharing, Search, Upload, Photos, Tagging.

I. INTRODUCTION

The social media photo sharing sites are one of the new generations of Web sites, whose content is primarily user-driven. Using these social websites users are collaboratively creating, evaluating, and distributing information. In the near future, new information-processing applications enabled by social media will include tools for personalized information discovery. The ease with which digital cameras allow people to capture, edit, store and share high quality images in comparison to the old film cameras. This factor, coupled with the low cost of memory and hard disk drives, has undoubtedly been a key driver behind the growth of personal image archives. Furthermore, the popularity of social networking websites such as Face book and MySpace, alongside image sharing websites such as Flicker has given users an extra incentive to capture images to share and distribute amongst friends all over the world. For commercial organizations, correct key wording of images has a direct effect on their revenues and efficiency in satisfying the needs of consumers; an incorrectly or insufficiently labeled image is unlikely to be found, particularly within the stringent deadlines commonly experienced within the commercial world, thereby leading to a loss in operational efficiency.

The main purpose of tagging images is to allow for the retrieval of images based on natural language keywords and also assist in content based image retrieval (CBIR) techniques such as query by sketch or query by example. Using Social media sites users create or contribute content in a variety of media types, annotate content with tags and evaluate content. In the process of using these sites, users are adding rich metadata in the form of social networks, annotations and ratings. Availability of large quantities of this metadata will lead to the development of new algorithms to solve a variety of information processing problems, from new recommendation to improved information discovery algorithms. Content based Image search is crucial for users with varying sorts of information needs. The ultimate goal of image retrieval is to provide personalized service for individuals and satisfy user's interests.

The rest of the paper is organized as follows. Section 2 describes CBIR search levels. Related works are discussed in section 3. Section 4 describes the proposed architecture and its functionality in greater details, including its tag search capability. Section 5 concludes by discussing results and future work.

II. CBIR SEARCH LEVELS

A CBIR search could consist of three levels.

Level 1: The first level is by primitive features, these features may consist of color, texture, shape, or the location of different elements or objects in the photo. Examples of search queries from this level include

a. Find pictures with long thin dark objects in the top left-hand corner
b. Find pictures containing yellow stars arranged in a ring
c. Find more pictures that look like this (a more general form)

These types of features are derived from the photos themselves without prior knowledge. As CBIR attempts to extract information from photos or images themselves, several techniques have been used to do so. The most common techniques are color, texture, and shape based on mathematical measures.

A. Color retrieval:

For color retrieval in Level 1 CBIR, a color histogram is computed for each image. This allows a person to search for a percentage of color in an image or even submit an example image for comparison. This is especially useful when searching for images with the same background or an object of a certain color.

B. Texture retrieval:

Another technique for retrieval of images in Level 1 is texture retrieval. One significant use of texture retrieval is in the case of areas with similar color. For example, recognizing the difference between green carpet and green grass. In order to accomplish this task, second-order statistics are calculated from the images. This consists of calculating the brightness of pairs of pixels relative to each other. As a result, several areas of measuring image texture are formulated such as degree of contrast, coarseness, directionality, regularity, periodicity, and randomness. The queries for texture retrieval are similar to color retrieval in that a percentage or example is used to match images.

C. Shape retrieval:

One of the most intuitive techniques for CBIR is shape retrieval. Researchers have done several studies to show that natural objects have been recognized by their shape. For a CBIR system to accomplish this task, several characteristics of the shape of each object in an image are calculated. These object characteristics or features include aspect ratio, circularity and movement invariants, and consecutive boundary segments. Shape retrieval queries differ from the previous two techniques in that a user-drawn sketch can also be submitted.

D. Position retrieval:

One technique that has been around the longest is retrieval by special location. In other words, the image is analyzed based on the position of various data within the image.

Level 2:

A second level search consists of derived features. In contrast to the first level, which simply requires a content feature, the program or person requires some prior knowledge such as “more glass” or “more concrete” for the features of a building. A program or person would have to use logic to infer something about the picture. The program or person would also need to distinguish between two similar objects such as a truck and a car. Examples in this level are divided into two parts.

a. Find pictures of a type of object (a skyscraper)
b. Find pictures of a specific object (The Empire State Building)

Semantic feature retrieval Researchers today are still working on narrowing the gap between level one and level two. They have been focusing on two main areas, scene recognition and object recognition. One way to help identify objects is to be able to classify the overall scene of an image. This scene recognition can also be a filter used in searching .Along with scene recognition; object recognition can also aid the annotation process.

Level 3:

A level three search is abstract. In other words, a significant amount of knowledge about the photograph has to exist both before and after the search. Examples include

a. Retrieval of named events or types of activity
b. Retrieval of pictures with emotional or religious significance

III. RELATED WORKS

Personalized image retrieval is a hot topic and the development trend of next-generation image retrieval. The key issue of personalized image retrieval is to capture users' interests or semantic concepts. Many systems have recently been described for personalized image retrieval [1, 2, 3]. Most of the typical approaches build a user model based on predefined knowledge about a user or a group of users, e.g. in the form of stereotypes or inference rules [4, 5]. In the earlier times, CBIR systems would involve only low-level indexes such as color and texture descriptions. In such a system, queries are intrinsically restricted to low-level queries such as sketch drawing, query by example or explicit manipulation of color, texture or shape features [6, 7, 8]. These approaches are suitable in some particular cases (“I want an image which looks like this one”) but are limited and should rather be available as an alternative query tool. Sketch drawing requires a lot of efforts from the user [9].

Automatic image annotation refers to the task of assigning a few relevant keywords to an un-annotated image to describe its visual content; the keywords are then indexed and used to retrieve images. A family of image annotation methods, built on nearest-neighbor hypothesis (*i.e.*, visually similar images likely share keywords), are proposed and evaluated in [10]. Given a query image, the *k*-nearest neighbors are retrieved and their associated keywords are transferred to the query image. The accuracy of image annotation can be evaluated based on the correctness of the assigned keywords or through image retrieval by using the assigned annotations. Although image retrieval is often used to evaluate image annotation methods, the key focus of image annotation is to assign images with keywords. The dimensions in matching a textual query with the keyword-annotated images have not been systematically evaluated.

Traditionally, research on image search focuses on ingredients ranging from robust representation of visual content, semantic-sensitive visual rankers, to user-friendly visualization of search results[11,12].Content-based image retrieval (CBIR) systems intend to provide solutions for browsing and retrieval of visual data. Such systems are dedicated to automatically (or semi-automatically) index images and make possible their retrieval via a search engine.

Most CBIR systems are based upon the same framework [13] QBIC [14], the pioneer CBIR system, uses color, texture and shape features to describe images content. As for the queries, the user is given a choice between drawing a sketch and searching directly in terms of colors, shapes and textures. In such a system the abstraction level is low, which delegates a large part of the work to the user. This is also the case for Visual Seek [15] or Nitra [16].

IV. PROPOSED ARCHITECTURE FOR IMAGE RETRIEVAL

Tags are keyword-based metadata associated with some content. Tagging was introduced as a means for users to organize their own content in order to facilitate searching and browsing for relevant information. The distinguishing feature of tagging systems is that they use an uncontrolled vocabulary.

To eliminate this drawback we propose an extension to tag based approach where the user after specifying the tag also specifies the content eg: jaguar car. Depending on his needs or mood, the user may even extend the tag with more general or specific terms. The content specified after the tag is used for personalized search when a user issues a query.

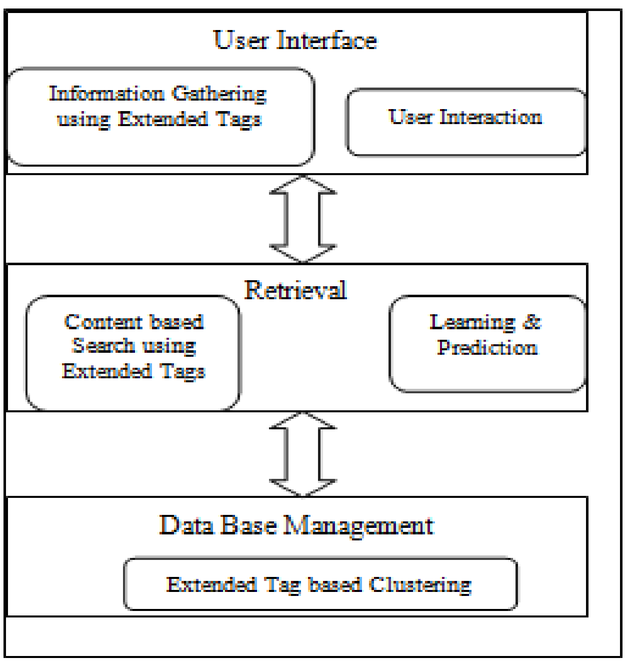

Figure 1: Extended tag based personalized image search architecture

A. Data base Management:

Personal image data contains a rich set of content information, such as color, texture and shape, and user-specific context information, such as location, time and ownership. Images are partitioned into various clusters based on extended tag contents given by the user at the time of specifying the tag.

An image X is a set of features X1... Xm,. Each feature represents a certain aspect of the image, for example the histogram, color or texture information Features can have different data types. For example, a histogram is represented as a vector of scalars. More complex features are for example a scaled-down version of the image, which is represented as a large vector of color- or gray values. But a feature can also just contain the information whether the image is black and white or color. In this case, only one binary value is needed. Now, in order to model the similarity of two images, we have to calculate the distances of the individual image features, and then sum them up to the final image score. After calculating the scores for all database images, the k images with the highest scores are returned and made as a cluster.

Text clustering requires a lot of computational effort. Sets of documents have, typically, hundreds of thousands of different terms, which make distance computation very expensive. This makes choosing an efficient algorithm very important. Hierarchical clustering algorithms are the ones that get the best clustering. Flat clustering algorithms are another option. In at clustering algorithms, the user has to provide the number of clusters prior to the clustering, which makes them not as good as hierarchical clustering algorithms, but they have a cost proportional to n, where n is the number of documents. This made us to choose a clustering algorithm: we chose K-Means for ease of implementation.

B. Image Retrieval:

Given a word/phrase in a document as a query, a contextual image retrieval system tries to return images that match the word/phrase in the given context. A contextual image retrieval system annotates the word/phrase in a document with appropriate images and can help readers learn new concepts. To capture the concreteness of a word, we use whether this word is physical or abstract given its context as a feature. The assumption is that a physical query usually corresponds to some physical existence and hence is easier to be illustrated with images than an abstract query. Since the same word can be either concrete or abstract given different context, we use word sense disambiguation (WSD) and Word Net to compute the query concreteness. To capture the commonness of a word, we use the word usage frequency on the web as a feature. More specifically, we use the Google unigram frequency count to approximate the commonness. The assumption is that the most frequently used nouns are usually simple words and might be easier to be illustrated by an image. To capture the ambiguity of a word, we use the number of noun senses for the word in Word Net as a feature. The assumption is that ambiguous words are more difficult to describe pictorially than unambiguous words.

C. User Interface:

Provides the user to specify the extended version of tag with the content or context type as extension. During the search process at each retrieval step, given a user's feedback, The interface traverses through the data clusters stored in the database and predicts and identifies a potential match, and returns the candidate thumbnail images of the matched cluster to the user.

V. RESULT ANALYSIS

A photo sharing site contains the options for Uploading an image as shown below.

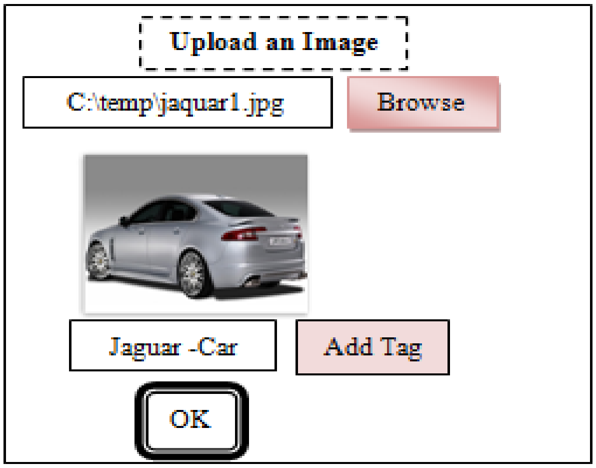

Figure 2: Uploading an image by specifying the extended tag.

A Normal Search based on tag retrieves all the images that are stored in the database under the specified tag.

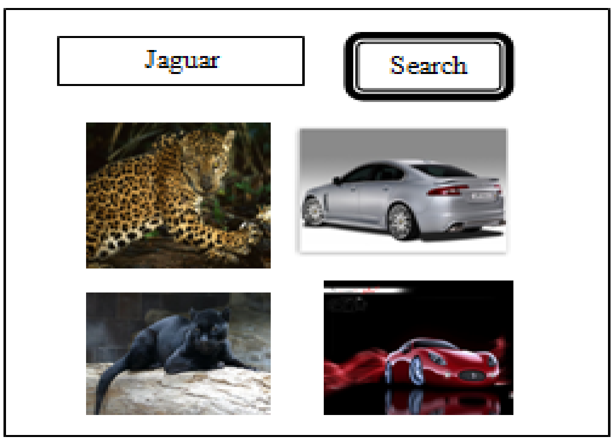

Figure 3: Normal Search by specifying the tag.

The extended tag based approach simplifies our content based search for personalization as the search query filters the results based on custom data specified after the tag.

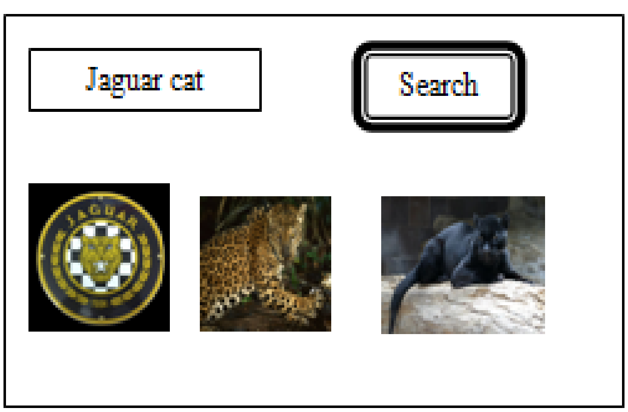

Figure 4: Personalized Search by specifying the extended tag.

VI. CONCLUSIONS

A novel approach for content based image retrieval is proposed in this paper. The proposed approach extends the definition of tag based approach and makes the system learn it. This tag extension concept can be used by the search engines to retrieve the images based on content. Our future work will be based on extending the tag based approach for personal image data management, search, and sharing on mobile devices.

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