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An Enhanced Approach for Content Based Image Retrieval System

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ABSTRACT:

Content Based Image Retrieval (CBIR) overcomes the traditional text-based image retrieval technology where search is based on automatic or manual explanation of images. For Image retrieval it's an active research field. Content Based Image Retrieval is a methodology that allows a user to extract an image based on a query from the database. Here, in this work, K Nearest Neighbor (KNN) classifier is used with Jaccard coefficient to find the relevant images. With the use of Jaccard Coefficient the result found are far better than the previous work. The earliest use of the term content-based image retrieval in the literature seems to have been by Kato [1]. In CBIR, images are indexed by their own visual contents such as color, texture, and shape. Visual contents are extracted from the images as automatically as possible [2]. Thus, CBIR systems have two main advantages over TBIR systems. First, they minimize the human effort. Second, due to reduced people intervention, subjectivity is also reduced. This feature makes CBIR systems more useful in many areas, such as search and browse large image collections.

Index Terms- CBIR,Image Content, Content Based Search.

1. INTRODUCTION

In a typical CBIR system (Figure 1.1), image low level features like color, texture, shape and spatial locations are represented in the form of a multidimensional feature vector. The feature vectors of images in the database form a feature database. The retrieval process is initiated when a user query the system using an example image or sketch of the object. The query image is converted into the internal representation of feature vector using the same feature extraction routine that was used for building the feature database. The similarity measure is employed to calculate the distance between the feature vectors of query image and those of the target images in the feature database. Finally, the retrieval is performed using an indexing scheme which facilitates the efficient searching of the image database. Recently, user's relevance feedback is also incorporated to further improve the retrieval process in order to produce perceptually and semantically more meaningful retrieval results. In this, we discuss these fundamental techniques for content-based image retrieval.

Applications of CBIR Detailed applications for CBIR technology can be found in [3]. Some of them are listed below:

Web searching: A large number of digital images are accessed by the Internet users. CBIR systems can help the

• users to effectively and what they are looking for. Medical diagnosis: A large number of medical images have been stored by hospitals. Thus, CBIR systems can

• be used to aid diagnosis by identifying similar past cases. Journalism and advertising: Articles, photographs, videos of the newspapers, journals or televisions are queried

•By using CBIR systems. Military: Databases of all images in military applications; such as remotely sensed data, weapons, aircrafts,

• automatic target recognition, etc. Intellectual properties: Most of the companies have their own trademark image. Whenever a new trademark

• image is to be registered, it must be compared with existing marks to eliminate duplications. Crime prevention: After a serious crime, law enforcement agencies search their archives for visual evidence.

• Such archives include photographs, fingerprints, tyre treads, shoeprints, and etc. of the past occasions. Thus, a CBIR system may help those agencies in finding related evidence.

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Characteristics of Image Queries CBIR systems can be evaluated according to the queries they handle. The queries are classified into three levels [4, 5]. Queries of the level 1 consist of primitive features such as color, texture, shape, or location of certain image elements. Queries of the level 2 and level 3 are composed of logical and abstract attributes, respectively. Logical features require some degree of logical inference about the identity of the objects depicted in the image, whereas abstract attributes involve a significant amount of high-level reasoning about the meaning and purpose of the objects depicted. Example queries for each level are listed below.

Level 1 -Retrieve images that look like (or similar) to `this' image".(This type of queries are also called query by example). -Retrieve images with blue rectangle at the top of the image" -Retrieve images that contain yellow squares"

Level 2 -Retrieve images of a woman" -Retrieve images of the Eiffel tower"

Level 3 -Retrieve images depicting suffering" -Retrieve images of Turkish folk dancing" When interpreting and executing the queries of Level 1, a CBIR system uses features, which are both objective and directly derivable from the images themselves. Unlike Level 2 and 3, there is no ne ed to refer any external knowledge base. Some researchers prefer to use the terms lower-level approaches for Level 1 and higher-level approaches for Level 2 and 3 [6], while the others call Level 2 and 3 together as semantic image retrieval [3]. Most of the higher level queries require automatic object recognition and classification, which are still among the unsolved problems in computer vision and image understanding literature [7]. Moreover, the queries of Level 2 and 3 cannot be interpreted and executed, unless underlying primitive (low-level) features are sufficient, effective, and accurate. The major problem in CBIR systems is that the lack of a direct link between the high-level human concepts of images and the low-level features used by the CBIR systems. This fact is called the semantic gap problem. The available CBIR systems, whether commercial or experimental, operate at Level 1 [8]. More specifically, most of the CBIR researches, including this dissertation, have been focused on \query by example". In query by example, the user does not have any particular target in mind, but selects an image or draws a sketch and asks to retrieve similar images. Thus, the basic operation is ordering a portion of image database with respect to a similarity metric [9].

The performance of a CBIR system is measured by precision, which is the number of relevant images retrieved relative to the total number of retrieved images and recall, which is the number of relevant images retrieved, relative to the total number of relevant images in the database.

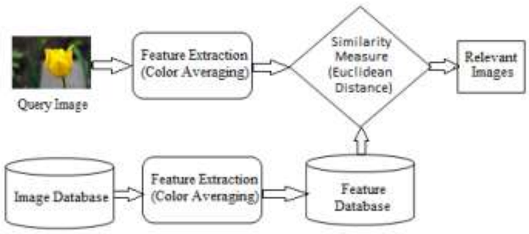

Figure 1: Image retrieval system based on color averaging.

II. RELATED WORK

[2]Content-based retrieval is ultimately dependent on the features used for the annotation of data and its efficiency is dependent on the invariance and robust properties. The Polar Fourier Transform (PFT) is similar to the Discrete Fourier Transform in two dimensions but uses transform parameters radius and angle rather than the Cartesian co-ordinates. To improve implications for content based retrieval of natural images where there will be a significantly higher number of textures [6]Local radial symmetry is to identify regions of interest within a scene. A facial feature detector and as a generic region of interest detector the new transform is seen to offer equal or superior performance to contemporary techniques. The method has been demonstrated on a series of face images and other scenes, and compared against a number of contemporary techniques from the literature. Equal or superior performance on the images tested while offering significant savings in both the computation required and the complexity of the implementation. [5]The refining process is formulated as an optimization framework based on the consistency between "visual similarity" and "semantic similarity" in social images. An image retagging scheme that aims at improving the quality of the tags associated with social images in terms of content relevance.

Our work is related to works on privacy setting configuration in social sites, recommendation systems, and privacy analysis of online images.

Privacy Setting Configuration

Several recent works have studied how to automate the task of privacy settings (e.g. [7], [16]). Bonneau et al. [7] proposed the concept of privacy suites which recommend to users a suite of privacy settings that “expert” users or other trusted friends have already set, so that normal users can either directly choose a setting or only need to do minor modification. Similarly, Danezis [8] proposed a machine-learning based approach to automatically extract privacysettings from the social context within which the data is produced. Parallel to the work of Danezis, Adu-Oppong et al. [16] develop privacy settings based on a concept of “Social Circles” which consist of clusters of friends formed by partitioning users’ friend lists. Ravichandran et al. [13] studied how to predict a user’s privacy preferences for location-based data (i.e., share her location or not) based on location and time of day. Fang et al. proposed a privacy wizard to help users grant privileges to their friends. The wizard asks users to first assign privacy labels to selected friends, and then uses this as input to construct a classifier which classifies friends based on their profiles and automatically assign privacy labels to the unlabeled friends. More recently, Klemperer et al. studied whether the keywords and captions with which users tag their photos can be used to help users more intuitively create and maintain access-control policies. Their findings are inline with our approach: tags created for organizational purposes can be repurposed to help create reasonably accurate access-control rules. The aforementioned approaches focus on deriving policy settings for only traits, so they mainly consider social context such as one’s friend list. While interesting, they may not be sufficient to address challenges brought by image files for which privacy may vary substantially not just because of social context but also due to the actual image content. As far as images, authors in [12] have presented an expressive language for images uploaded in social sites. This work is complementary to ours as we do not deal with policy expressiveness, but rely on common forms policy specification for our predictive algorithm. In addition, there is a large body of work on image content analysis, for classification and interpretation retrieval are some examples), and photo ranking also in the context of online photo sharing sites, such as Flickr Of these works, Zerr’s work is probably the closest to ours. Zerr explores privacy aware image classification using a mixed set of features, both content and meta-data. This is however a binary classification (private vs. public), so the classification task is very different than ours. Also, the authors do not deal with the issue of coldstart problem.

The CBIR-social employs a multi-criteria inference mechanism that generates representative policies by leveraging key information related to the user’s social context and his general attitude toward privacy. As mentioned earlier, CBIRsocial will be invoked by the CBIR in two scenarios. One is when the user is a newbie of a site, and does not have enough images stored for the CBIR to infer meaningful and customized policies. The other is when the system notices significant changes of privacy trend in the user’s social circle, which may be of interest for the user to possibly adjust his/her privacy settings accordingly. In what follows, we first present the types of social context considered by CBIR Social, and then present the policy recommendation process.

III.PROPOSED SYSTEM

The term "content" in the context of CBIR might refer to colors, shapes, textures, or any other information that can be derived from the image itself. In the existing approach, a new content based image retrieval approach based on the database classification using Support Vector Machine (SVM) and color string coding feature selection was presented. By the use of database classification, performance of the content based image retrieval can be enhanced as compared with normal CBIR. With the large dataset, SVM approach is not perfect as it search on the whole dataset and results are not good in terms of precision, recall, time complexity.

Objectives Following are the objectives of proposed work: To study the existing Model.

- To improve the existing model using improvement in classified database
- To improve the values of Precision, Recall value and F-measure and Time Complexity

Planning or Work We propose a new approach named “A New Approach for Content Based Image Retrieval Using KNN”. The proposed work is used to improve the results carried out in the previous work. Our approach works in the following three steps: 1. Database Classification a. The learning process b. Classification using KNN c. Similarity Measure using Jaccard similarity coefficient 2. Feature Extraction 3. Similarity Measures

IV. SECURITY EVALUATION

The policy prediction algorithm provides a predicted policy of a newly uploaded image to the user for his/her reference. More importantly, the predicted policy will reflect the possible changes of a user’s privacy concerns.

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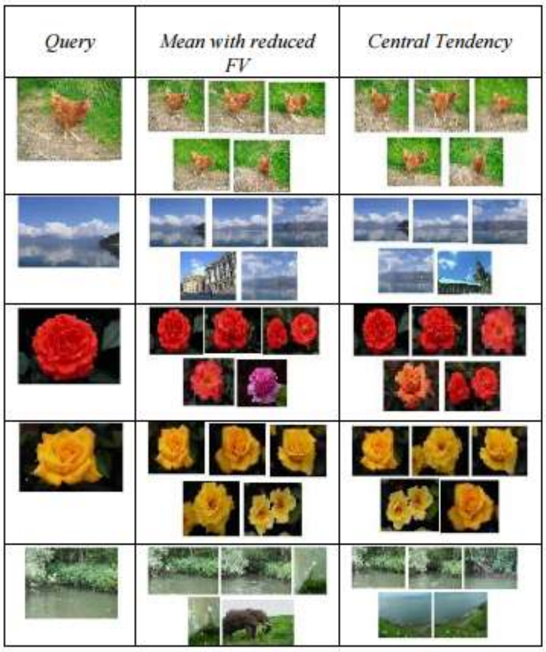
The prediction process consists of three main phases: (i) policy normalization; (ii) policy mining; and (iii) policy prediction. The policy normalization is a simple decomposition process to convert a user policy into a set of atomic rules in which the data (D) component is a single-element set. An example of policy normalization is shown below. Example 2: Consider policy P in Example 1. Suppose that the album "vacation album" contains k images, namely img1 .jpg, img2 .jpg, ..., imgk.jpg. P is normalized into the following set of atomic rules:



Policy Mining

We propose a hierarchical mining approach for policy mining. Our approach leverages association rule mining techniques to discover popular patterns in policies. Policy mining is carried out within the same category of the new image because images in the same category are more likely under the similar level of privacy protection. The basic idea of the hierarchical mining is to follow a natural order in which a user defines a policy. Given an image, a user usually first decides who can access the image, then thinks about what specific access rights (e.g., view only or download) should be given, and finally refine the access conditions such as setting the expiration date. Correspondingly, the hierarchical mining first look for popular subjects defined by the user, then look for popular actions in the policies containing the popular subjects, and finally for popular conditions in the policies containing both popular subjects and conditions.

Policy Prediction

The policy mining phase may generate several candidate policies while the goal of our system is to return the most promising one to the user. Thus, we present an approach to choose the best candidate policy that follows the user's privacy tendency. To model the user's privacy tendency, we define a notion of strictness level. The strictness level is a quantitative metric that describes how "strict" a policy is. In particular, a strictness level L is an integer with minimum value in zero, wherein the lower the value, the higher the strictness level.

V.RESULTS

We observe that users with similar background tend to have similar privacy concerns, as seen in previous research studies and also confirmed by our collected data. This observation inspires us to develop a social context modeling algorithm that can capture the common social elements of users and identify communities formed by the users with similar privacy concerns. The identified communities who have a rich set of images can then serve as the base of subsequent policy recommendation. The social context modeling algorithm consists of two major steps. The first step is to identify and formalize potentially important factors that may be informative of one's privacy settings. The second step is to group users based on the identified factors. First, we model each user's social context as a list of attributes: {sc1, sc2, ..., scn}, where sci denote a social context attribute, and n is the total number of distinct attributes in the social networking site. These social context attributes are extracted from users' profiles. Besides basic elements in users' profiles, many social sites also allow users to group their contacts based on relationships (e.g., friends, family members). If such grouping functionality is available, we will consider its influence on privacy settings too. In a social site, some users may only have their family members as contacts, while some users may have contacts including different kinds of people that they met offline or on the Internet. The distribution of contacts may shed light on the user's behavior of privacy settings. We assume that users who mainly share images among family members may not want to disclose personal information publicly, while users having a large group of friends may be willing to share more images with a larger audience [19]. Formally, we model the ratio of each type of relationship among all contacts of a user as social connection. Let R1, ..., Rn denote the n types of relationships observed among all users. Let NuRi denote the number of user U's contacts belonging to relationship type Ri. The connection distribution (denoted as Conn) is represented as below: For example, suppose that there are four types of relationships being used by users in the system: R1="family", R2="colleague", R3="friend", R4="others". Bob has 20 contacts, among which he has 10 family members, 5 colleagues, and 5 friends. His social connection is represented as { 10/20 , 5/ 20 , 5/ 20 , 0/ 20}. It is worth noting that, the number of social context attributes may grow when more rich information is collected by social networking sites in the future, and our algorithm is dynamic and capable of dealing with any number of attributes being considered. The second step is to identify groups of users who have similar social context and privacy preference. Regarding social context, it rarely happens that users share the same values of all social context attributes. More common cases are that a group of users have common values for a subset of social context attributes. Such subset can be different for different groups of users, which makes the user grouping a challenging task. We illustrate the scenario using the following example. For simplicity of illustration, we take a smaller set of attributes to be considered.

In this first round of tests, we used the two datasets collected through our survey to evaluate the accuracy of our recommended policies. CBIR Our first experiment compares CBIR with alternative prediction approaches. In particular, we use a straw man solution as the baseline approach, whereby we sample at random a small set of image settings from the same user and use them to determine a baseline setting (by counting the most frequent items). The baseline settings are applied to all images of the users. Further, we compare the CBIR with two variants of itself, in order to evaluate the contribution of each component in the CBIR made for privacy prediction. The first variant uses only content-based image classification followed by our policy mining algorithm, denoted as "Content Mining". CBIR Social In the second round of experiments, we analyze the performance of the CBIR-Social component using the first set of data collection. For each user, we use the CBIR-Social to predict policies and compare it with three other alternative approaches :(i) prediction based on only similarity of privacy strictness levels; (ii) prediction based on Cosine similarity; (iii) prediction based on Pearson similarity. In particular, the first base-line approach does not consider social contexts but bases recommendation only on social groups that have similar privacy strictness level for same type of images. The second approach adopts Cosine similarity to measure the similarity of the social contexts between the new user and all the existing users, and then finds the top two users with the highest similarity score as the candidate users. The images of the candidate users are then sent to the CBIR for the policy prediction. The approach using the Pearson similarity requires an additional assumption that the new user should have already provided privacy preferences (levels) for several image categories other than the one waiting for the recommendation. These user specified privacy preferences are then treated as the "rating" in the Pearson similarity formula. The data we use for this assumption is the response to three privacy-related questions users provide on their pre-session survey during data collection (the questions are adapted from the wellknown privacy-index measures from Westin). Accordingly, we use the Pearson similarity to find the candidate users who are similar to this new user. The experimental results show that the policy prediction accuracy (full matching) of our CBIR-Social and the other three approaches are: CBIR-Social(88.6%), Strictness level similarity (86.4%), Cosine similarity(82.5%) and Pearson similarity (81.4%)..More importantly, the CBIRsocial is the most general approach and most efficient among the all. Although the prediction accuracy yielded by the approach using strictness level similarity is quite close to the CBIR-social, it requires the new user to provide preferred privacy level because it needs this information to look for existing users with similar strictness levels. The same assumption is required by the approach using the Pearson similarity too. The CBIR-social instead also works when the new user has no idea about what privacy level is appropriate. The CBIR-social considers social contexts thus can take care of such new users who did not provide preferred privacy level and need some guidance on their initial privacy settings. Moreover, in terms of efficiency, all the three comparison approaches need to scan all the existing users whereas the CBIR-Social just needs to check a subset of users attributed to the use of the inverted index

VI.CONCLUSION AND FUTURE

From above discussion we conclude that the with the use of Nearest Neighbor (KNN) Classification (to calculate the relevant images from Dataset) and Jaccard similarity coefficient (for calculating the distances and sorts them according to their relevancy) the proposed approach perform better than existing approach with reduced value of precision, recall, f-measure and improved time complexity value. There is no need to check the whole dataset as we have the concept of Test dataset and Train dataset, so the time to retrieve the image will be less. So it helps in reducing the time complexity

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