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CBIR and SBIR System Based on the Free Hand Shake Sketch

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Abstract: Over the past few years, current Web search engines have become the dominant tool for accessing information online. As social networks are growing in terms of the number of users, the user may be lost or unable to find useful information. The large-scale user-generated meta-data not only facilitate users in sharing and organizing multimedia content. Personalized search serves as one of such examples where the web search experience is improved by generating the returned list according to the modified user search intents. Social elements could avoid this disorientation like the social annotations (tags) which become more and more popular and contribute to avoid the disorientation of the user. The social annotations and propose a novel framework simultaneously considering the user and query relevance to learn to personalized image search. The content based image retrieval (CBIR) is one of the most popular, rising research areas of the digital image processing. Images are manually annotated with keywords and then retrieved using text-based search methods. This paper aims to introduce the problems and challenges concerned with the design and the creation of CBIR systems that are based on a free hand sketch. With the help of the existing methods that can handle the informational gap between a sketch and a colored image and making an opportunity for the efficient search hereby. Descriptor is constructed after such special sequence of preprocessing steps that the transformed full color image and the sketch can be compared. The SBIR technology can be used in several applications such as digital libraries, photo sharing sites, and crime prevention. A possible application is matching a forensic sketch to a gallery of mug shot images.

I. INTRODUCTION

The user is the main entity in any social networks. As the social networks are growing in terms of number of users, the user may be lost or unable to find useful information. Before the spreading of information technology a huge number of data had to be managed, processed and stored. Social elements could avoid this disorientation like the social annotations (tags) which become more and more popular and contribute to avoid the disorientation of the user. Keyword-based search has been the most popular search paradigm in today’s search market.

We find a component which represents the tag assigned by a user in a specific resource. This component is usually represented as 3D matrix and treated as three bi-dimensional matrixes due to the complexity of the 3D matrix. Investigation has indicated its poor user experience - on Google search, for 52% of 20,000 queries. This is due to two reasons:

- Queries are in general short and nonspecific
- Users may have different intentions for the same query

One solution to address these problems is *personalized search. Here* user-specific information is considered to distinguish the exact intentions of the user queries and re-rank the list results. Compared with non-personalized search the rank of a document in the result list is decided not only by the query, but by the preference of user. Toy example for non-personalized and personalized image search results as shown in the fig.1

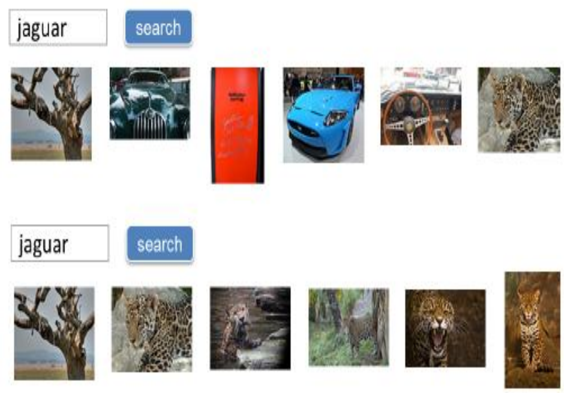

Fig. 1. Toy example for non-personalized (top) and personalized (bottom) search results for the query "jaguar"

The non-personalized search returned results only based on the query relevance and displays jaguar car images as well as wild cat on the top. Most of the existing work follow this scheme and decompose personalized search into two steps:

a. Computing the non-personalized relevance score between the query and the document
b. Computing the personalized score by estimating the user's preference over the document

The growing of data storages and revolution of internet had changed the world. Efficiency of searching in information set is a very important point of view. We cannot apply dynamic methods in the case of texts we can search flexibly using keywords. Two questions can come up:

a. Who yields the keywords?
b. Image can be well represented by keywords

The human is able to recall visual information more easily using for example the shape of an object. Since the human is visual type and follow this approach also at the categorizing. At this moment unfortunately there are not frequently used retrieval systems that retrieve images using the non-textual information of a sample image. Our purpose is to develop a content based image retrieval system that can retrieve using sketches in frequently used databases. Using a sketch based system can be very important and efficient in many areas of the life. The CBIR systems have a big significance in the criminal investigation. Another possible application area of sketch based information retrieval is the searching of analog circuit graphs from a big database. The Sketch-based image retrieval (SBIR) was introduced in QBIC and Visual SEEK systems. The images were divided into grids, colors and the texture features were determined in these grids.

II. RELATED WORK

In recent years extensive efforts have been focusing on personalized search. According to the resources they leveraged, relevance feedback [4], explicit user profile [3], user history data, context information [6] are exploited. For the implementation there are two primary strategies, query refinement and result processing.

Query Refinement refers to the modification to the original query according to the user information. Query Refinement includes augmenting the query by other terms and changing the original weight of each query term. Kraft *et al.* [4] utilized the search context information collected from users' explicit feedback to enrich the query terms. In [25], proposed five generic techniques for providing expansion terms ranging from term and expression level analysis up to global co-occurrence statistics and external thesauri. Mapping the queries into user-specific topic spaces can be considered as implicit query refinement.

The Result Processing can be further classified into result filtering and re-ranking. It aims to filter irrelevant results that are not of interest to a particular user. Chirita *et al.* [3] conducted an early work by reranking the search results according to the cosine distance between each URL and user interest profiles constructed. Liu *et al.* [5] introduced a new method for visual search reranking called Crowd Reranking. Typical work is performed by Xu *et al.* [7], in which the overall ranking score is not only based on term similarity matching between the query and the documents but also topic similarity matching between the user's interests and the documents' topics. We build user-specific topics and calculate topic-sensitive user preference over images that differentiate our work from Xu [7] and Lu's [8].

III. EXISTING SYSTEM

We simultaneously consider the user and query dependence and present a novel framework to tackle the personalized image search problem. Collaborative tagging has become an increasingly popular means for sharing and organizing resources. It finally leading to a huge amount of user-generated annotations. Various researchers have investigated the applicability of social annotations to improve web search. Social annotations are employed for automatic evaluation of personalized search. We can directly estimate the users' preference under certain queries. We transfer the problem of personalized image search to users' annotation prediction. We build user-specific topic spaces to exploit the relations between queries and tags. The frame of the existing system is as shown in the fig.2. It contains two stages: offline model training stage and online personalized search response stage.

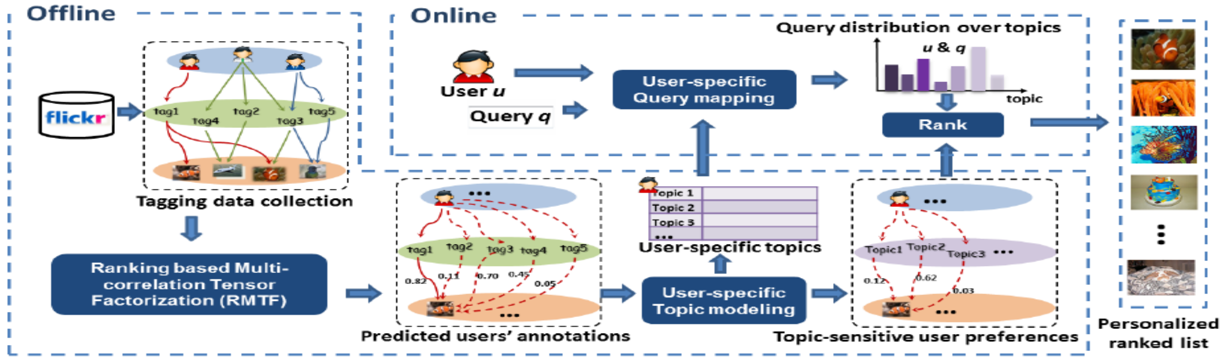

Fig. 2. The Existing system framework.

Typically a weighting parameter will be optimized to balance the two scores or the learnt user preference is used to re-rank the query relevance-based original list. Three types of data including users in the offline stage, images and tags as well as their ternary interrelations and intra-relations are first collected. We then perform users' annotation prediction. Since the photo sharing websites utilize a different tagging mechanism that repetitive tags are not allowed for unique images.

To alleviate the sparsity and noisy problem, we present a novel method named *Ranking based Multi-correlation Tensor Factorization* (RMTF) to better leverage the observed tagging data for users' annotation prediction. We can straightly utilize the predicted user annotations for personalized image search. If a user has a high probability to assign the tag *t* to an image then the image should be ranked higher when the user issues query *t.* This formulation has two problems:

- It is unreasonable to assign the query to a single tag in the tag vocabulary
- There are variations in individual user's tagging patterns and vocabularies

We perform *User-specific Topic modeling* to build the semantic topics for each user to address the above problems. The user's annotation for an image is viewed as *document*. User's annotations for all the images constitute the *corpus*. The individual tag to the image is *word*.

The user's topic distribution per image can be considered as his/her preference over the image on the learned user-specific topic space. After the offline stage two outcomes are stored in the system. At the stage of the offline the user-specific topics and topic-sensitive user preferences.

Whereas in the online stage, when a user *u* submits a query *q*, we first map the query *q* to user *u*-specific topics. Query distribution is then sent to the rank module and employed as the weight on topics to calculate the user *u*'s topic sensitive preferences over the images. Judgmentally, the images are ranked according to the calculated user's preference that simultaneously considers the query and user information.

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IV. PROPOSED SYSTEM

The components and their communications are introduced and the functionality of subsystems and the algorithms are shown.

The Purpose of the System:

Our goal is to develop a content-based associative search engine that databases are available for anyone looking back to freehand drawing. Even though the measure of research in sketch-based image retrieval increases there is no widely used SBIR system.

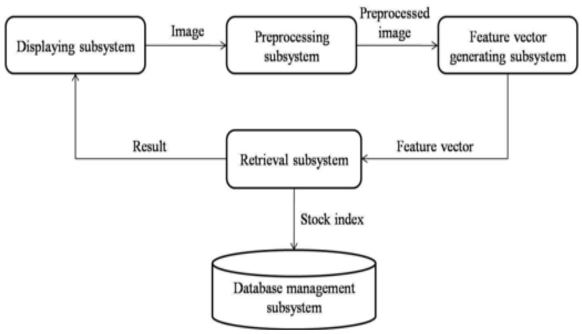

Fig. 3. The global structure of the proposed system.

The global structure of the proposed system is as shown in the fig.3 consist of the processing subsystem, retrieval subsystem, feature vector generation subsystem, db management subsystem.

The retrieval results are grouped by color for better clarity. Most important task is to bridge the information gap between the drawing and the picture that is helped by own preprocessing transformation process. System the iteration of the utilization process is possible by the current results looking again, which increase in the prediction.

The Global Structure of Our System:

The system building blocks include a preprocessing subsystem that eliminates the problems caused by the diversity of images. The feature vector generating subsystem our image can be represented by numbers considering a given property. DB management subsystem provides an interface between the database and the program. Based on the feature vectors and the sample image the retrieval subsystem provides the response list for the user using the displaying subsystem (GUI). The content-based retrieval as a process can be divided into two main phases:

- *Database construction phase*
  The data of preprocessed images is stored in the form of feature vectors
- *Retrieval process*
  The on-line unit of the program

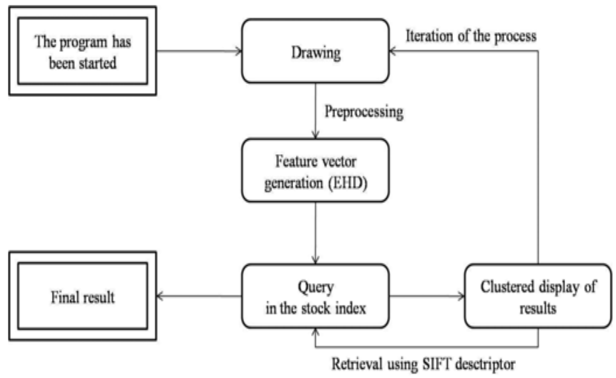

Fig. 4. The data flow model of the system from the user's point of view

The Preprocessing Subsystem:

The system was designed for databases containing relatively simple images even in such cases large differences can occur among images in file size or resolution. As shown in the fig.5 some images may be noisier, the extent and direction of illumination may vary and so the feature vectors cannot be effectively compared.

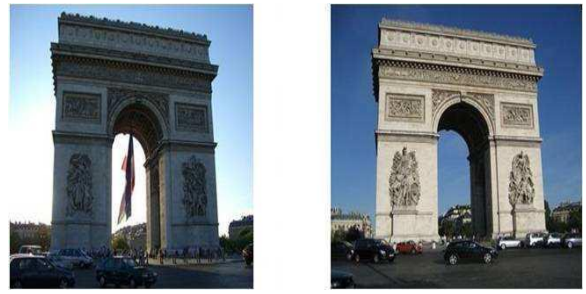

Fig. 5. The retrieval has to be robust in contrast of illumination and difference of point of view.

The input of the preprocessing subsystem is one image and the output is the respective processed result set as shown in the fig.6. The main problem during preprocessing of the color images of real situations is that the background containing several textures and changes generate unnecessary and variable-length edges. It gives very valuable results, if a textured object of little color stands in a homogenous background.

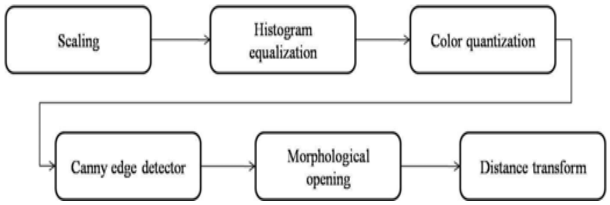

Fig. 6. The steps of preprocessing

The Feature Vector Preparation Subsystem:
Basically three different methods were used, namely:

- Edge histogram descriptor (EHD) [9]
- Histogram of oriented gradients (HOG) [10]
- Scale invariant feature transform (SIFT) [11]

Our system works with databases containing simple images. Even some cases that must be handled. If the description method does not provide perfect error handling, that is expected to be robust to the image rotation, scaling and translation. Another problem was encountered during the development and testing. An information gap arises between retrieved sketch and color images of database. In contrast at a binary edge image only implicit content and explicit location of pixels can be known.

The Retrieval Subsystem:
The retrieval can start when the feature vectors are ready. For the retrieval the distance based search was used with Minkowski distance and the classification-based retrieval.

The Database Management Subsystem:
The images and their descriptors are stored and the necessary mechanism for subsequent processing is provided. The database management subsystem consists of three parts:

a. The storage module
b. The retrieval module
c. The data manipulation module

The storage module provides information and the associated feature vectors are uploaded to the database. Some of the list is attached to the associated features like size, format and file name. The information related to the preparation is gathered as the maker's name, image title, and creation date, so on. We may need more information of color depth, vertical and horizontal resolution, image dimension, resolution, so we take care of their storage. The data is stored in a global and not scattered place in the hard disk.

The Displaying Subsystem:
Drawing surface is provided because drawings are the basis of the retrieval where they can be produced. A database is needed for search that also must be set before the search. The methods in our system cannot work without parameters and therefore an opportunity is provided to set these as well. Number of results to show in the user interface is an important aspect. This number depends on the resolution of the monitor and forasmuch the large resolution monitors are widely used. So this number can move between 20 and 40.

V. EXPERIMENTAL RESULTS

Data sets:
The system was tested with more than one sample database to obtain a more extensive description of its positive and negative properties. All objects have been taken from 14 different orientations with 450×450 resolution. This database is most often used in computer and psychology studies. Some of the images are sown in the fig.7.

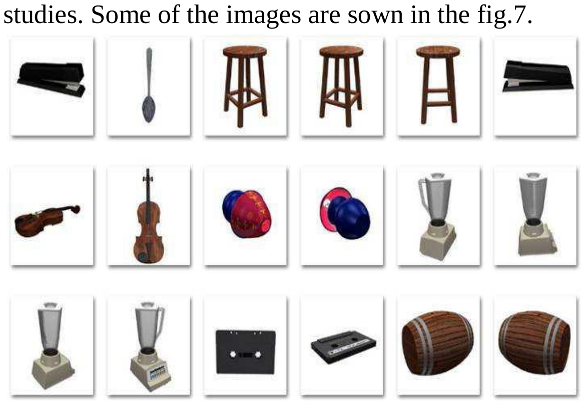

Fig. 7. Some sample images of the Microsoft Research Cambridge Object Recognition Image Database.

Another test database was the Flickr 160. It was used before for measuring of a dictionary-based retrieval system. 160 pieces of general-themed pictures have sorted from the photo sharing website called Flickr. Images can be classified into 5 classes based on their shape. Since the test results are documented and the retrieved sketches are also available. Some images of Flickr 160 database can be seen in Fig. 8.

Testing Aspects and Used Metrics:

We can evaluate the effectiveness of the system forming methods and compare the different applied methods. Let be a test database containing N pieces images and P length retrieval list from which Q pieces matter as relevant results. Z denotes the number of expected relevant hits. With these information following metrics is calculated:

$$precision = \frac{relevant\ hits(Q)}{all\ hits(P)}$$

The precision gives information about the relative effectiveness of the system:

$$recall = \frac{relevant\ hits(Q)}{exception\ hits(Z)}$$

The recall gives information about the absolute accuracy of the system. The impact of multi-level retrieval to the efficiency of retrieval is measured that confirms the importance of multi-level search. The ROC curves plot the true and false positive hit rate. As shown in the fig.11 the Object Databank database was used by EHD the provided precision and recall values can be seen using different block size values and in Fig. 9 using different threshold values.

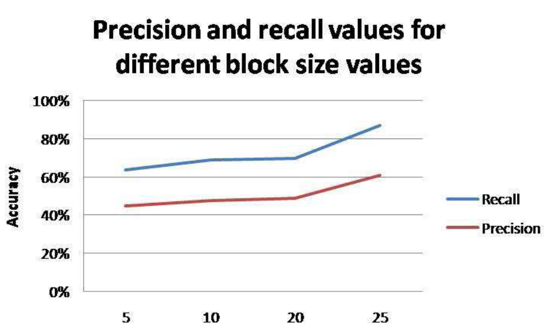

Fig. 8. Effect of block size change using EHD method. Threshold is constant 2.

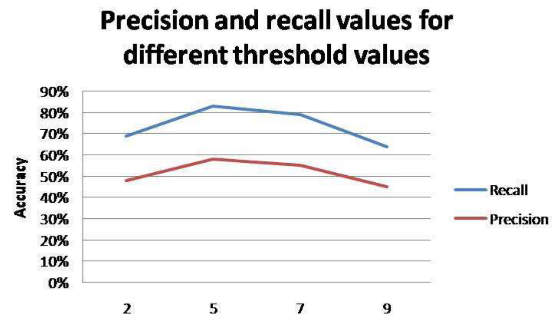

Fig. 9. Effect of threshold value change using EHD method. Block size is constant 10.

VI. CONCLUSION

Two main aspects were taken into account. Retrieval process has to be unconventional and highly interactive. Robustness of the method is essential in some degree of noise that might also be in case of simple images. Drawn image without modification cannot be compared with color image, or its edge representation. The simple smoothing and edge detection based method was improved that had a similar importance as the previous step. At the tests the effectiveness of EHD and the dynamically parameterized HOG implementation was compared. In our experience the HOG in more cases was much better than the EHD based retrieval. Using the SIFT-based multi-level solution the search result list is refined. The categorization of retrieval response a bigger decision possibility was given to the user on that way.

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