Performance Enhancements using Query Specific Semantic Signatures on Web Image Re-Ranking

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Abstract--- **Re-ranking of images has provided an efficient solution for the user to get the intended image. Nowadays, several search engines like Bing, Google, Ask are available to provide a pool of images. Then, the user selects a needed image, and then the remaining images are re-ranked. The proposed work introduces Query-Specific Semantic Signatures, which has offline and online part, in offline it learn semantic space of all textual information and in online images are re-ranked based on the semantic signatures.**

Keywords—

I. INTRODUCTION

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science discipline too.

Image processing basically includes the following three steps: Importing the image with optical scanner or by digital photography.Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.Output is the last stage in which result can be altered image or report that is based on image analysis. The purpose of image processing is divided into 5 groups. They are:

- Visualization - Observe the objects that are not visible.
- Image sharpening and restoration - To create a better image
- Image retrieval - Seek for the image of interest.
- Measurement of pattern – Measures various objects in an image.
- Image Recognition – Distinguish the objects in an image.

The two types of methods used for Image Processing are Analog and Digital Image Processing. Analog or visual techniques of image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. The image processing is not just confined to area that has to be studied but on knowledge of analyst to display the images.

Association is another important tool in image processing through visual techniques. So analysts apply a combination of personal knowledge and collateral data to image processing. Digital Processing techniques help in manipulation of the digital images by using computers. As raw data from imaging sensors from satellite platform contains deficiencies. The three general phases that all types of data have to undergo while using digital technique are Pre- processing, enhancement and display, information extraction.

The Characteristics of Image Processing includes, Before going to processing an image, it is converted into a digital form. Digitization includes sampling of image and quantization of sampled values. After converting the image into bit information, processing is performed. This processing technique may be Image enhancement, Image restoration, and Image compression.

A. Image enhancement

It refers to accentuation, or sharpening, of image features such as boundaries, or contrast to make a graphic display more useful for display & analysis. This process does not increase the inherent information content in data. It includes gray level & contrast manipulation, noise reduction, edge crispening and sharpening, filtering, interpolation and magnification, pseudo coloring, and so on.

B. Image restoration

It is concerned with filtering the observed image to minimize the effect of degradations. Effectiveness of image restoration depends on the extent and accuracy of the knowledge of degradation process as well as on filter design. Image restoration differs from image enhancement in that the latter is concerned with more extraction or accentuation of image features.

C. Image compression

It is concerned with minimizing the number of bits required to represent an image. Application of compression are in broadcast TV, remote sensing via satellite, military communication via aircraft, radar, teleconferencing, facsimile transmission, for educational & business documents, medical images that arise in computer tomography, magnetic resonance imaging and digital radiology, motion, pictures, satellite images, weather maps, geological surveys and so on.

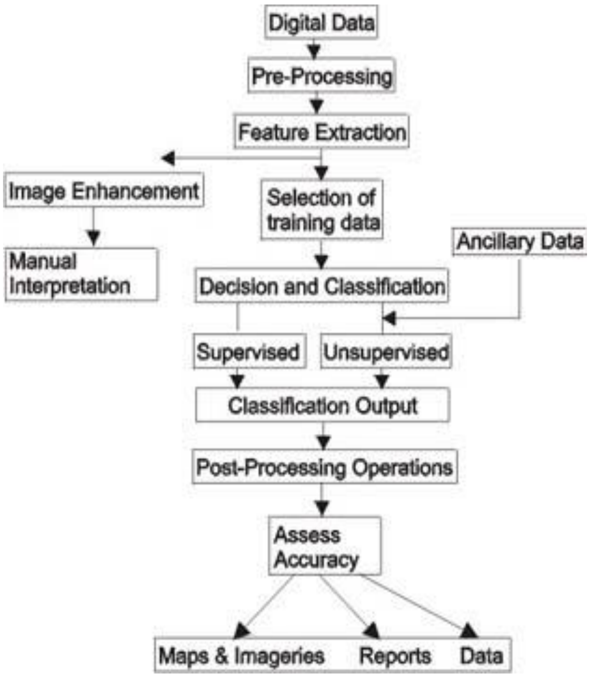

Fig. 1.Working Diagram of Image Processing

II. RELATED WORK

We have witnessed great interest and a wealth of promise in content-based image retrieval as an emerging technology. In this article, we survey almost 300 key theoretical and empirical contributions in the current decade related to image retrieval and automatic image annotation, and in the process discuss the spawning of related subfields. We also discuss significant challenges involved in the adaptation of existing image retrieval techniques to build systems that can be useful in the real world. In retrospect of what has been achieved so far, we also conjecture what the future may hold for image retrieval research.

Traditional methods of image retrieval require that meta-data is associated with the image, commonly known as keywords. These methods power many World Wide Web search engines and accomplish reasonable amounts of search accuracy. Though some content based image retrieval (CBIR) systems use both semantic and primitive attributes to match search criteria, history has proven that it is difficult to extract linguistic information from a 2D image. In this research, activity theory is used as a base to demonstrate how semantic information can be retrieved from objects identified in an image. Using an image segmentation technique by The Berkeley Digital Library Project (Blob world), and combining it with object-to-community relationships, a high-level understanding of the image can be demonstrated.

Relevance feedback schemes based on support vector machines (SVM) have been widely used in content-based image retrieval (CBIR). However, the performance of SVM-based relevance feedback is often poor when the number of labeled positive feedback samples is small. This is mainly due to three reasons: 1) an SVM classifier is unstable on a small-sized training set, 2) SVM's optimal hyper plane may be biased when the positive feedback samples are much less than the negative feedback samples, and 3) over fitting happens because the number of feature dimensions is much higher than the size of the training set. In this paper, we develop a mechanism to overcome these problems. To address the first two problems, we propose an asymmetric bagging-based SVM (AB-SVM). For the third problem, we combine the random subspace method and SVM for relevance feedback, which is named random subspace SVM (RS-SVM). Finally, by integrating AB-SVM and RS-SVM, an asymmetric bagging and random subspace SVM (ABRS-SVM) is built to solve these three problems and further improve the relevance feedback performance.

Web image search using text queries has received considerable attention. However, current state-of-the-art approaches require training models for every new query, and are therefore unsuitable for real-world web search applications. The key contribution of this paper is to introduce generic classifiers that are based on query-relative features which can be used for new queries without additional training. They combine textual features, based on the occurrence of query terms in web pages and image meta-data, and visual histogram representations of images. The second contribution of the paper is a new database for the evaluation of web image search algorithms. It includes 71478 images returned by a web search engine for 353 different search queries, along with their meta-data and ground-truth annotations. Using this data set, we compared the image ranking performance of our model with that of the search engine, and with an approach that learns a separate classifier for each query. Our generic models that use query-relative features improve significantly over the raw search engine ranking, and also outperform the query-specific models.

III. EXPERIMENTAL ARCHITECTURE

WEB-SCALE image search engines mostly use keywords as queries and rely on surrounding text to search images. They suffer from the ambiguity of query keywords, because it is hard for users to accurately describe the visual content of target images only using keywords. For example, using “apple” as a query keyword, the retrieved images belong to different categories (also called concepts in this paper), such as “red apple,” “apple logo,” and “apple laptop.”

This is the most common form of text search on the Web. Most search engines do their text query and retrieval using keywords. The keywords based searches theyusually provide results from blogs or other discussion boards. The user cannot have a satisfaction with these results due to lack of trusts on blogs etc.low precision and highrecall rate. In early search engine that offered disambiguation to search terms. User intention identification plays an important role in the intelligent semantic search engine.

In this paper, a novel framework is proposed for web image re-ranking is shown in the figure 2. Instead of manually defining a universal concept dictionary, it learns different semantic spaces for different query keywords individually and automatically. The semantic space related to the images to be re-ranked can be significantly narrowed down by the query keyword provided by the user. For example, if the query keyword is “apple,” the concepts of “mountain” and “Paris” are irrelevant and should be excluded. Instead, the concepts of “computer” and “fruit” will be used as dimensions to learn the semantic space related to “apple.” The query-specific semantic spaces can more accurately model the images to be re-ranked, since they have excluded other potentially unlimited number of irrelevant concepts, which serve only as noise and deteriorate the re-ranking performance on both accuracy and computational cost. The visual and textual features of images are then projected into their related semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the semantic space of the query keyword. The semantic correlation between concepts is explored and incorporated when computing the similarity of semantic signatures.

We propose the semantic web based search engine which is also called as Intelligent Semantic Web Search Engines. We use the power of xml meta-tags deployed on the web page to search the queried information. We use the power of xml meta-tags deployed on the web page to search the queried information. The metadata information of the pages is extracted from this xml into rdf. our practical results showing that proposed approach taking very less time to answer the queries while providing more accurate information.

The visual features of images are projected into their related semantic spaces automatically learned through keyword expansions offline.

Our experiments show that the semantic space of a query keyword can be described by just 20-30 concepts (also referred as “reference classes”).

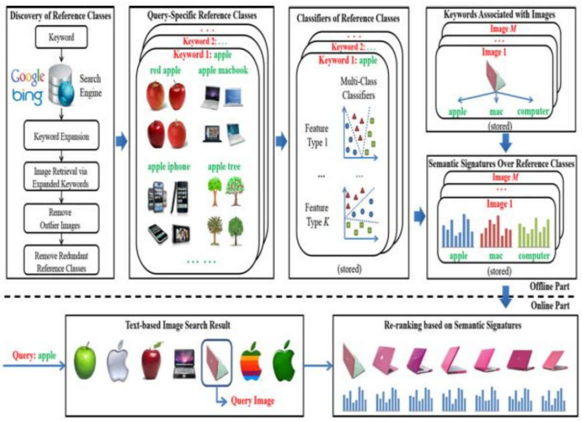

Fig. 2. System architecture

Therefore the semantic signatures are very short and online image re-ranking becomes extremely efficient. Because of the large number of keywords and the dynamic variations of the web, the semantic spaces of query keywords are automatically learned through keyword expansion.

Query-specific semantic signatures effectively reduce the gap between low-level visual features and semantic. Query-specific semantic signatures are also effective on image re-ranking without query images being selected. Collecting information from users to obtain the specified semantic space.

Localizing the visual characteristics of the user’s intention in this specific semantic space is achieved.

1) Re-Ranking accuracy

The labelers were unaware of what reference classes have been discovered by our system. The number of image categories is also different than the number of reference classes. Each image was labeled by at least three labellers and its label was decided by voting.

2) Re-Ranking Images outside Reference Class

If the category of a query image corresponds to a reference class, we deliberately delete this reference class and use the remaining reference classes to train classifiers and to compute semantic signatures when comparing this query image with other images.

3) Incorporating Semantic Correlations

The re-ranking precisions for all types of semantic signatures on the three data sets. Notably, QSVSS SingleCorr achieves around 10 percent relative improvement com-pared with QSVSS Single, reaching the performance of QSVSS multiple despite its signature is six times shorter.

4) Re-Ranking with Semantic Based

It assumes that images returned by initial text-only search have a dominant topic and images belonging to that topic should have higher ranks. Our query-specific semantic signature is effective in this application since it can improve the similarity measurement of images. In this experiment QSVSS Multiple is used to compute similarities. Thus, the above Graph shows that the, after re-ranking Apple-fruit has high voting than the apple iphone, apple logo.

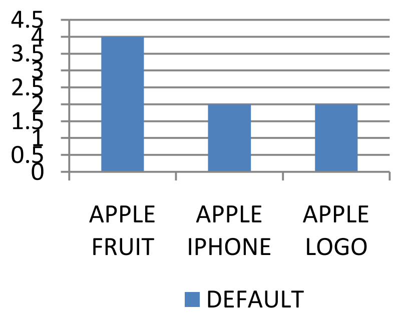

Fig. 3 Graph Analysis

IV. CONCLUSION

We propose a novel framework, which learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image re-ranking. The visual features of images are projected into their related semantic spaces automatically learned through keyword expansions offline. The extracted semantic signatures can be 70 times shorter than the original visual features, while achieve 25-40 percent relative improvement on re-ranking precisions over state-of-the-art methods. In the future work, our framework can be improved along several directions. Finding the keyword expansions used to define reference classes can incorporate other metadata and log data besides the textual and visual features. For example, the co-occurrence information of keywords in user queries is useful and can be obtained in log data. In order to update the reference classes over time in an efficient way, how to adopt incremental learning under our framework needs to be further investigated. Although the semantic signatures are already small, it is possible to make them more compact and to further enhance their matching efficiency using other technologies such as hashing.

As a future enhancement we propose the problem of solving the ambiguity. This solution is the future enhancement where the contribution of providing more accuracy to the proposed system by enhancing using ambiguity resolving problem. Ambiguity is, Middle vision is the stage in visual processing that combines all the basic features in the scene into distinct, recognizable object groups.

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