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Web Image Re-ranking Using Semantic Signature

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***Abstract:** Image re-ranking, as an effective way to improve the results of online image search, has been adopted by traditional search engines. Given a query, a pool of images are first fetch by the search engine based on textual information. By asking the user to select a query image from the data, the remaining images are re-ranked based on their visual similarities with the selected image. A major problem is that the similarities of visual features do not correlate with images semantic meanings which shows users search intention. On the other hand, learning a universal visual semantic space to characterize images from the web is difficult. In this paper, we propose image re-ranking framework, which automatically offline learns semantic spaces for different query's. The visual features of images are shows into their related semantic spaces to get semantic signatures. At the online part, images are re-ranked by comparing their semantic signatures obtained from the semantic space specified by the query. The new approach significantly improves both the accuracy and efficiency of image re-ranking. Experimental results show that 20 - 30 percentage improvement has been achieved on re-ranking precisions compared with the traditional methods.*

***Keywords:** Image Search, Content based image search, Image Re-ranking, Annotation based Image Search.*

I. INTRODUCTION

Online image search engines mostly use keywords as queries and search images. It is well known that the ambiguity of query keywords. For example, using "apple" as query, the fetched images belong to different categories, such as "red apple", "apple logo", and "apple laptop". Online image re-ranking is an effective way to improve the image search results. Many internet image search engines have used the re-ranking strategy .Given a query input by a user, a pool of images relevant to the query keyword are retrieved by the search engine. By asking a user to pick a query image, which reflects the user's search intention, from the pool, the remaining images in the pool are re-ranked based on their visual similarities with the query image. The visual features of images are pre computed offline and stored by the search engine. The main online computational cost of image re-ranking is on comparing visual features. In order to achieve high efficiency, the visual feature vectors need to be short and their matching needs to be fast. Another major challenge is that the similarities of low-level visual features may not well correlate with images 'high-level semantic meanings which interpret users' search intention. To narrow down this semantic gap, for offline image recognition and retrieval, there have been a number of studies to map visual features to a set of predefined concepts or attributes as semantic signature However, these approaches are only applicable to closed image sets of relatively small sizes. They are not suitable for online web- based image re-ranking. According to our empirical study, images retrieved by 120 query keywords alone include more than 1500 concepts. Therefore, it is difficult and inefficient to design a huge concept dictionary to characterize highly diverse web images.

II. Literature Survey

In the literature survey we are going to discuss recent methods over the concepts of CBIR and ABIR approaches: First five methods are presented over CBIR systems by various authors are listed below.

Chin-Chin Lai et.al .[4] have proposed an interactive genetic algorithm (IGA) to reduce the gap between the retrieval results and the users expectation .They have used Colour attributes like the mean value, standard deviation, and image bitmap .They have also used texture features like the entropy based on the gray level co-occurrence matrix and the edge histogram . They compared this methods with others approaches and achieved better results.

Meenakshi Madugunki et.al. [5] Have published a paper on detailed classification of CBIR Systems. They have used the Global colour histogram, Local Colour histogram, HSV method for extracting the colour feature and matched the result by using Euclidean distance, Canberra distance and city block distance. They have also used DWT for Tex-ture Feature extraction and compared the result obtained by using different features.

Gwenole Quellec et.al. [6] Have presented a novel method to adapt a multidimensional wavelet filter bank to any specific problem .They have applied this method for content based image retrieval. The performances of the adapted wavelet filter bank over the no adapted wavelet filter bank are higher for every database.

Nhu-Van Nguyen et.al. [7] Have proposed Clustering and Image Mining Technique for fast Retrieval of Images. The main objective of the image mining is to remove the data loss and extracting the meaningful information to the human expected needs.

The clustering-repeat gives good result when the number of examples of feedback is small.

A.Kannan et.al.[8]have proposed Clustering and Image Mining Technique for fast retrieval of Images. The main objective of the image mining is to remove the data loss and extracting the meaningful information to the human expected needs. The images are clustered based on RGB Components, Texture values and Fuzzy C mean algorithm. Entropy is used to compare the images with some threshold constraints.

In this paper [9] Hua Yuan et.al.have presented a new statistical model-based image feature extraction method in the wavelet domain and a novel Kullback divergence-based similarity measure. The GMM and GGMM are presented to help extract new image features. Compared with conventional norm-based distances (City-block or Euclidean), the Kullback divergence is more appropriate and efficient in the similarity measure and achieved a higher retrieval rate with the same level of computational complexity in a CBIR system.

Zhang Xu-bo et.al. [10] Have published a paper on improved K-means clustering and relevance feedback to re-rank the search result in order to remedy the rank inversion problem in content based image retrieval. Experimental results show that the re-ranking algorithm achieves a more rational ranking of retrieval results and it is superior to Reranking via partial Grouping method.

III. System Application

The diagram of our approach is shown in Figure 2. At the offline stage, the reference classes (which represent different semantic concepts) of query keywords are automatically discovered. For a query keyword (e.g. apple), a set of most relevant keyword expansions (such as red apple, apple MacBook, and apple iPhone) are automatically selected considering both textual and visual information. This set of keyword expansions defines the reference classes for the query keyword. In order to automatically obtain the training examples of a reference class, the keyword expansion (e.g. red apple) is used to retrieve images by the search engine. Images retrieved by the keyword expansion (red apple) are much less diverse than those retrieved by the original keyword (apple). After automatically removing outliers, the retrieved top images are used as the training examples of the reference class. Some reference classes (such as apple laptop and apple MacBook) have similar semantic meanings and their training sets are visually similar. In order to improve the efficiency of online image re-ranking, redundant reference classes are removed.

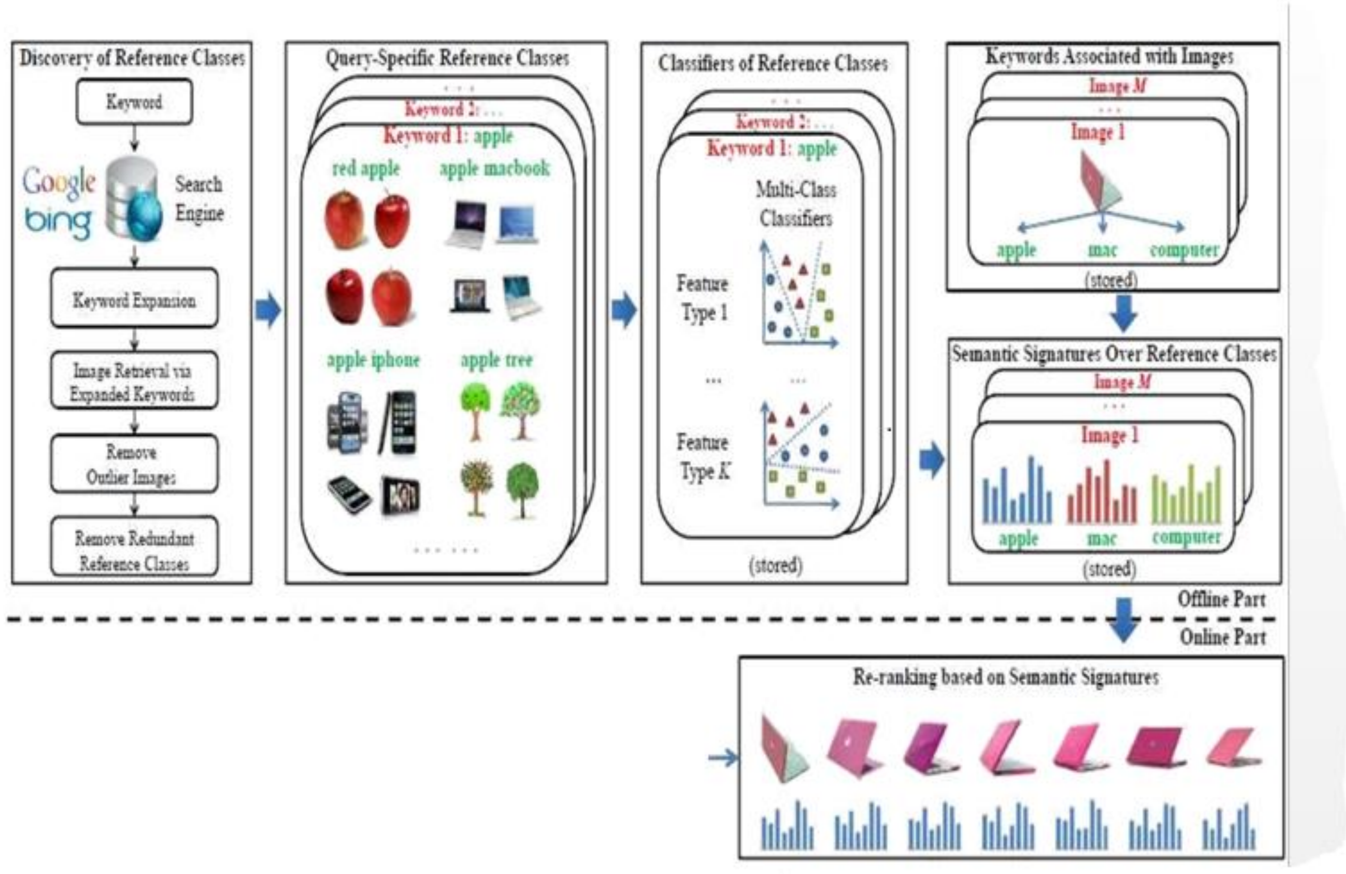


Fig.1. Proposed Image Re-ranking Framework

IV. METHODOLOGY

At offline stage we train all the images regarding keywords used in dataset. For training image following steps are used

1. Reference Image Download: for image training all the reference images regarding keyword are download.
2. Image Feature Extraction: All available reference images are collected and extract the feature i.e. image Color feature and image shape feature are extracted.

   a) For image feature extraction we used RGB algorithm.

RGB algorithm:

Step1: Convert Image from RGB to HSV color space

Step2: Using HSV values, convert pixel values to C1 to C54

Step3: For each Image count C1 to C54 to calculate 54 color histogram.

Step4: Apply K-means algorithm.

Step5: Calculate Recall and Precision.

   b) For image shape feature extraction we used SURF framework to improve the object recognition system. Using this algorithm, it can generate a set of feature pairs between the query image and each individual database image. For object recognition task, SURF algorithm is used because of its powerful attributes. The images in the test set are compared to all images in the reference set by matching their respective interest points. The object shown on the reference image with the highest number of matches with respect to the test image is chosen as the recognized object.

SURF algorithm:

It is used to feature generate feature vector, feature direction, feature matching and object recognition

Steps for SURF descriptor:

i) Initially it finds interest points in image by using Hessian matrix.

ii) Then find out major interest point in scale space by using the non-maximal suppression on points.

iii) To find the direction of feature uses the Harr transform.

iv) In last stage it generate the feature vector.

3. Image Clustering: after image feature extraction all the redundant classes are find out, remove the redundancy and cluster all remaining images. For image clustering we used K-Means algorithm.

At online stage we enter a query keyword and rank the images using following steps,

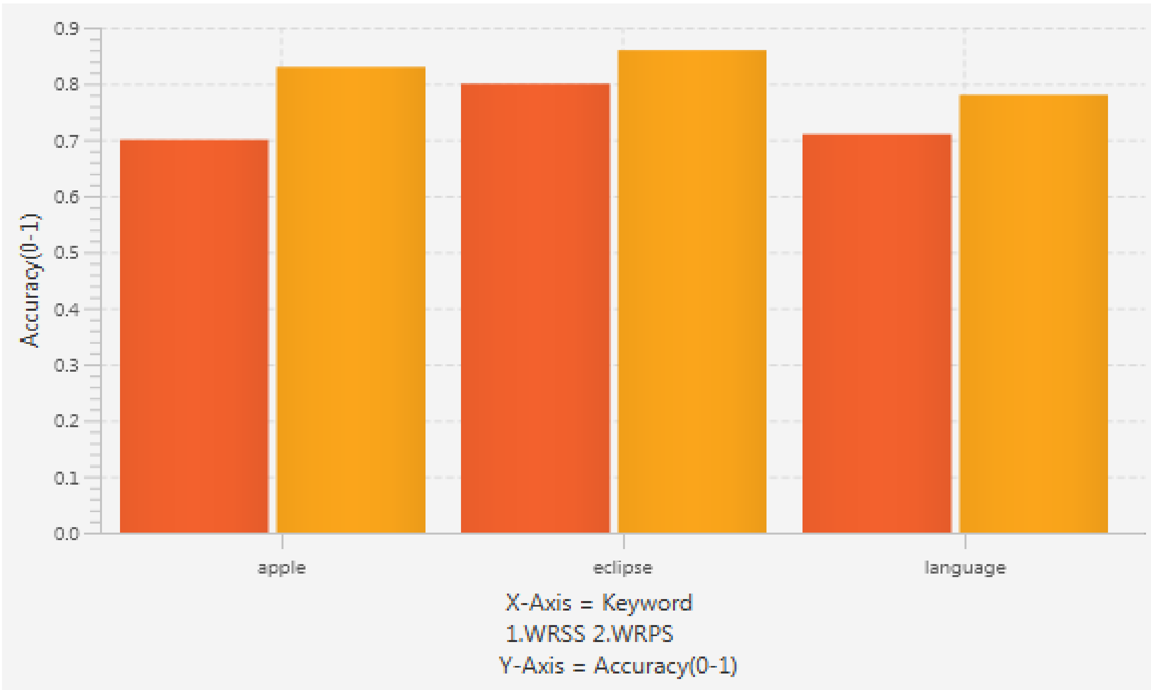
1. Google image search: Using google API we search the images regarding query keyword and download all the images.
2. Image ranking: for image ranking we used KNN algorithm.
3. Image personalization: for personalize image ranking we used web blog mining.

V. Result and Analysis

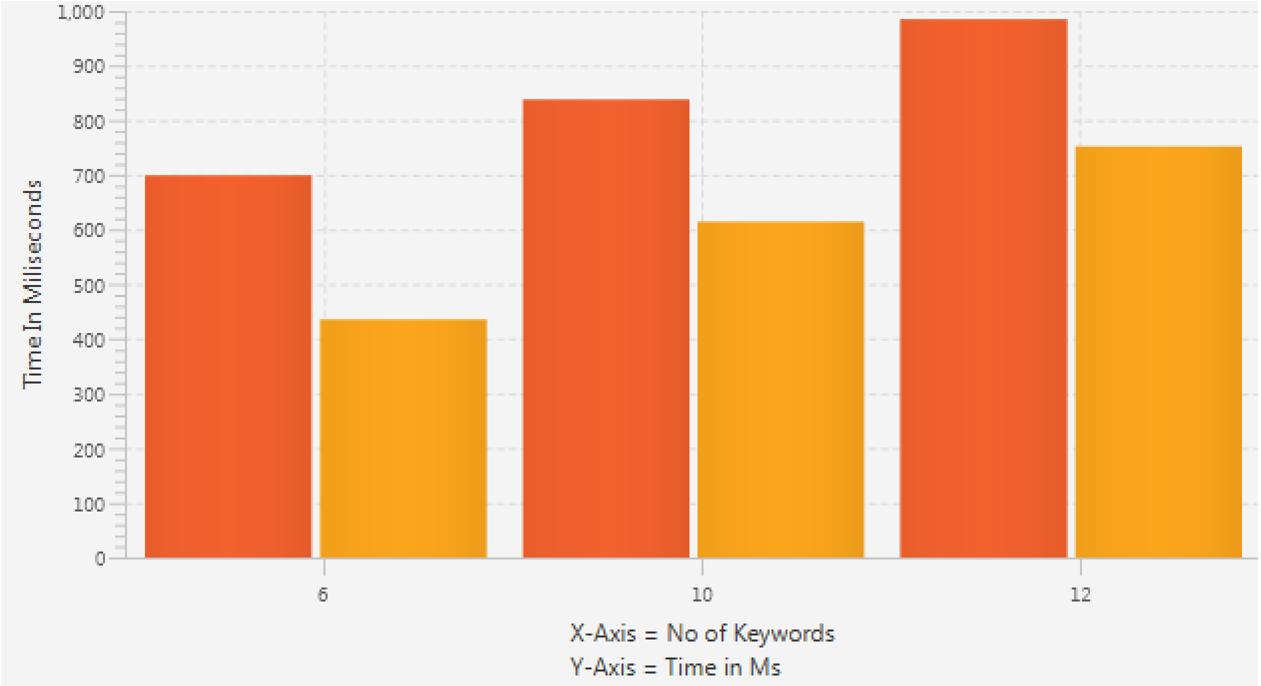
For testing we have collected 500 images associated with 10 keywords which have collected from Google Image Search. In this database we have many keywords such as mobile, language, city, laptop, flower, wallpaper, devices and people etc. and prepare a large number of keyword.

Data set	#Keywords	#Images	Collecting date	Search Engine
III	10	500	5th April 2017	Google

Result analysis with respect to Accuraacy:



Result analysis with respect to time:



VI. 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.

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