Internet Image Search Using Semantic Signature

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***Abstract*— The growth and broad accessibility of multimedia content on internet led to the research on activity in image search. Text-based image search and content based image search has less success as they ignore the user's intention for ranking images. Image re-ranking using semantic space rank the images according to users search intention. In this, first the images are retrieved based on the query keyword given by the user using textual information. Then ask a user to select query image , and images are re-ranked by comparing with the semantic signature of query image which are computed and stored offline. The thousands of visual feature dimensions are reduced to 25 dimensions as considering only the query keyword for semantic space. Hence, this method gives more accuracy and efficiency.**

Keywords-text-based,content based,query keyword, query image, semantic space, semantic signature.

I. INTRODUCTION

In the traditional text-based image search, the image re-ranking and image search are done using the textual information. The textual information is gathered from the query keyword given by the user. But it forms the ambiguity of query keyword, as visual contents cannot well describe by using text. For Example, giving "apple" as query keyword , the retrieved images belong to different categories as "apple logo", "apple mobile", "apple tree", "apple fruit" etc.

To avoid such ambiguity, content-based image retrieval is used. In this, search analyzes the contents of the image such as colors, shapes, structures etc. This is the iterative method and continuously requires users interaction for the feedback. As user gives feedback till the required image does not get hence it takes more time for image search

Hence another technique, traditional online image re-ranking comes forward. It limits the user interaction to just one click. In this technique, user needs to click on query image which closely match with the users required image in the image pool. Then rests of the images are matched according to visual features of query image. The diagram is given in fig. 1. Query keyword is given by user as input and images are retrieved relating to keyword-image index file which is stored offline. Then ask the user to select one query image from image result set. The remaining images from the result set are re-ranking according to visual similarities with query image. The keyword-image index

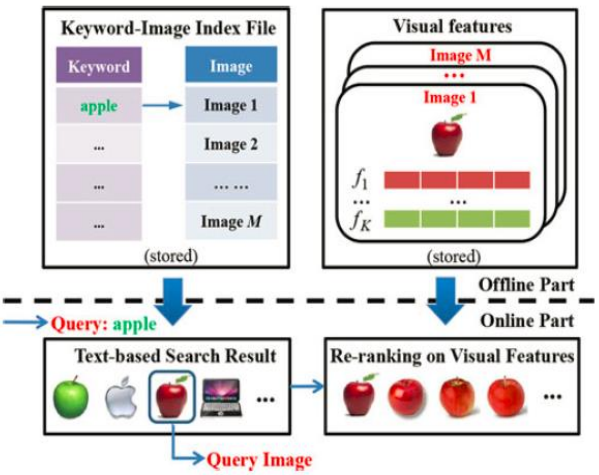

Fig. 1. Traditional online image re-ranking framework [5].

file and visual features of each image are stored offline. The visual features are like shape, color, texture etc. For every image their k types of visual features are already computed. The computational cost for this technique is to match visual features. Hence to get more efficiency, visual features need to be small in size.

But it also suffers from some limitations. The visual feature does not closely match to image semantic meaning which represents the users search intention. i.e. low level features may not match with the high level features. Also the low level features sometime inconsistent with the visual features. For example, the image of same object captured in different angles, different lighting or in different compression. Then it gives different perception. Hence their low level semantic meanings may change.

Also for single query keyword there are many concepts. As per the empirical study, the 120 keywords have 1500 concepts. To design such huge dictionary is difficult. Also the topic of web images is diverse. Hence it is feasible to generate such concepts dynamically.

To minimize this semantic gap, query specific semantic signatures used. In this technique, match the visual features

of query image into their semantic spaces which are obtained from keyword expansion and get the semantic signature for each image.

II. LITERATURE SURVEY

Initially the work is done on image re-ranking using text information. D. Grangier [1] gives a discriminative model that use text queries for retrieval of images. In this model learning procedure is given to optimize the ranking performance. Low-level visual features are different for different query image. Hence Cui et al [2] [3] classified the query image into eight different categories and gives different weighting schemes to those features.

To overcome the limitations of text-based search, A. Kovashka, D. Parikh, and K. Grauman [4], gives a WhittleSearch technique. This is content based image retrieval and also need user's continuous interaction to get accurate result. In this paper author used the hybrid approach. In that user gives continuous feedback that which are relevant image and which are irrelevant. Every time user gives feedback about the retrieved images until his required image does not appear in the result. This method requires large time to get required image.

D.Parikh and K. Grauman [6] gives the concept of Relative Attribute. In this paper it gives the ranking function to represent the strength of attribute in an image with respect to other image. Lu et al. [8] gives the method for detection of outlier images in image set using Deep Contexts and refine the image result.

Krapac et al. and M. allan [9] gives the generic classifier. This classifier is based on query-relative features and used for new query keyword without any online training. This method combines the image meta-data and textual information. In this paper new database is also generate for image retrival.

Y. Kuo, W. Cheng [10] gives method for discovery of semantic features. In this paper gives a general framework which integrates both textual and visual information. Construct graph of images by visual and textual information respectively. Then automatically propagate and select the informative semantic features across the visual and textual Graphs.

To hashed the semantic signature, A. Andoni and P. Indyk [11] gives near optimal hashing algorithms. In this paper hashing based algorithm is given which is LSH (Locality-Sensitive-Hashing) for the case where objects are points and points live in a d-dimensional space under some distance function. This problem has major importance in several areas; such as data compression, data mining, information retrieval, pattern recognition, image and video databases, machine learning, statistics and data analysis.

III. PROPOSED WORK

The framework for image search and re-ranking using semantic signature is divided into two parts as shown in Fig. 2. One is online and other is offline. In the offline part some classes are computed and stored.

At the first, take query keyword as input and automatically generate the reference classes. To get the reference classes search the images based on text first. Then consider top ranked images and most frequently appeared words for keyword expansion.

A) Keyword Expansion

For each image I ε A(q), all the images in A(q) are ranked by considering their visual similarity with I. Among the D re-ranked images, the T most frequent words are found. As $W_1=\{w_1^1, w_1^2, \text{--------}, w_1^D\}$ and are sorted according to frequency of words in the D images. If a word w is present in the top ranked images then their ranking score is $r_1(w)$ otherwise 0.

$$r_I(w) = \begin{cases} T - j & w = w_I^j \\ 0 & w \notin W_I. \end{cases} \quad (7)$$

B) Training Images for Reference classes

To get the training images for reference classes, combine each keyword expansion with query keyword and retrieve images from search engine and top k images are considered. The images retrieved by this new keyword are less diverse than the original keyword. Then remove outlier images and the resultant images are used as training images for reference class.

For every query keyword, its reference classes forms the basis for semantic space. After getting the reference classes, classify those classes into multi-class classifier using textual and visual features. The multi-class classifiers are trained from the reference classes. These multi-class classifiers are computed and stored offline. If there are k types of visual and textual features then one can create separate classifier for every feature or can combine all the features and then make single classifier. To get the semantic signature, the image is compared with the classifier. So a image can have single semantic signature or may have different k types of semantic signatures for each feature. Afterwards, combine those all semantic signature. The semantic signatures are small in size, but to improve the efficiency of ranking method we can make them more compact using hashing .

As per the word-image index file, single image may be associated with many query keywords. So an image may have different semantic spaces and the different semantic signatures. Hence which semantic space to choose is depending upon the query keyword that is given by user. So all these semantic spaces need to be computed offline and stored.

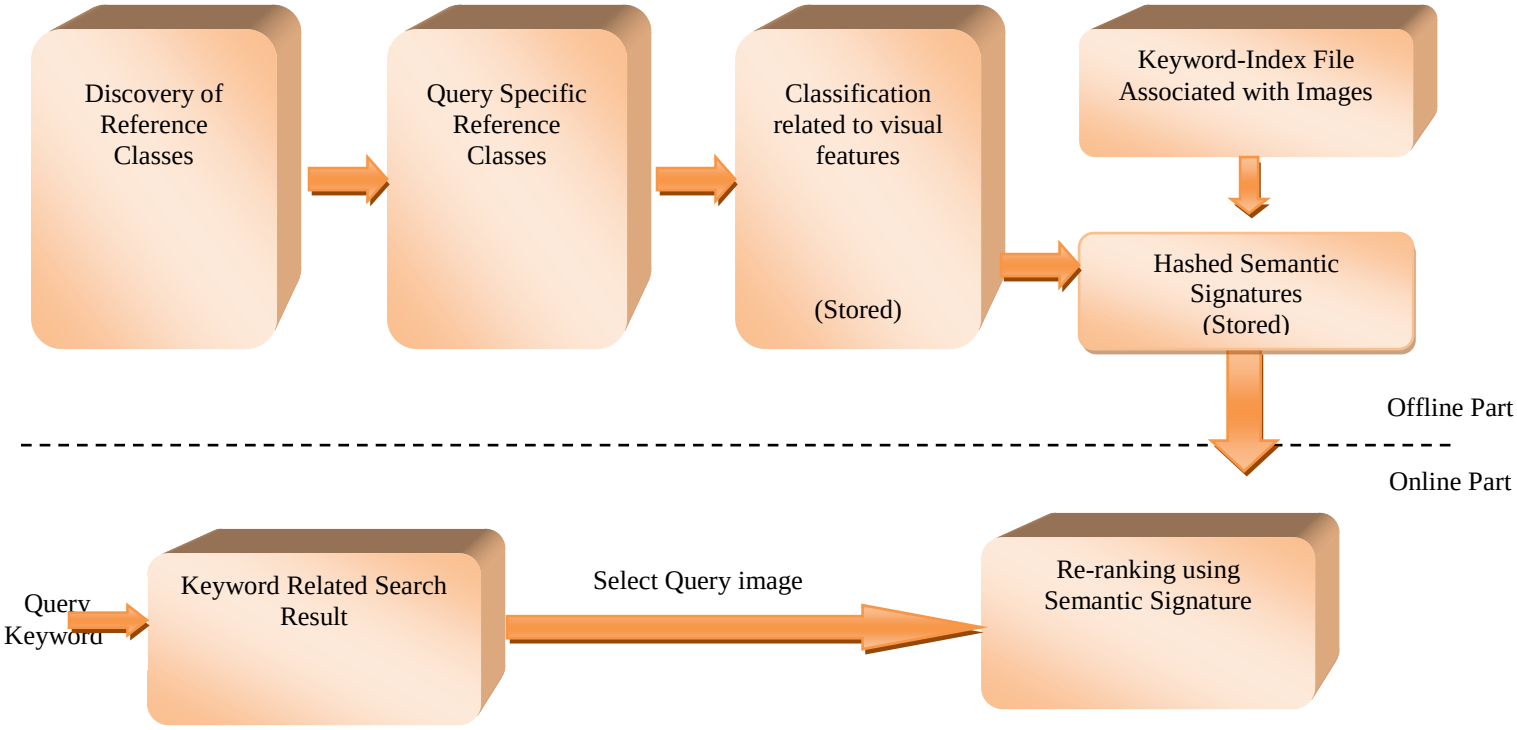

Fig- 2 Framework of Internet Image Search using Semantic Signature

At the online side, user first gives query keyword as input and set of images are retrieved according to textual information. As all these images are associated with word-image index file, so their semantic signatures are already calculated and stored. Then ask the user to select one query image that closely match with his required image. Then semantic signatures are user find closely match images and re-rank the set of images accordingly.

CONCLUSION

In this paper, image re-ranking framework is discussed, that uses the semantic signature for image re-ranking. Using semantic signature for image re-ranking reduce the semantic gap between image visual features and users search intention. The reference classes generate from the keyword expansion hence the retrieved images are less than actual image result. Hence it gives more accurate and efficient result. Also hashed the semantic signatures to do more compact and improve the matching efficiency. As the semantic signatures are stored, the computational cost contains the time required to compare the images with semantic signature and re-rank the result set.

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