© 2015 IJEDR | Volume 3, Issue 2 | ISSN: 2321-9939

Web Image Re-ranking Using Semantic Signatures

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***Abstract* - Image re-ranking is one of the most effective technique to improve the results of web-based image search. This technique is adopted by current commercial search engines such as Bing & Google. In this paper we propose a novel image re-ranking framework with two stages , offline and online stage. In the offline stage, different semantic spaces for different query keywords are automatically learned and the visual features of images are 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 specified by the query keyword. The proposed system significantly improves both the accuracy and efficiency of image re-ranking by making use of query-specific semantic signatures.**

Index Terms- **Image retrieval, Semantic signatures, Query specific**

I. INTRODUCTION

Existing web image search engines mostly use keywords as queries and rely on surrounding text to search images. But these search engines suffer from the ambiguity of query key-words, as it is hard for users to accurately describe the visual content of target images using only keywords. For example, using "apple" as a query keyword, the retrieved images belong to different categories, such as "red apple," "apple logo," and "apple laptop". This ambiguity can be solved by using, content-based image retrieval [5], [1] with relevance feedback [8], [6], [2]. It requires users to select multiple relevant and irrelevant image examples, from which visual similarity metrics are learned through online training. Images are re-ranked based on the learned visual similarities. However, for web-scale commercial systems, users' feedback has to be limited to the minimum without online training.

Online image re-ranking [4], [3], [7], which limits users' effort to just one-click feedback, is an effective way to improve search results. Major web image search engines have adopted this strategy. A pool of images relevant to the query keyword is retrieved, based on the query keyword input given by the user, by the search engine according to a stored word-image index file. The user is then asked to select 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 word- image index file and visual features of images are pre-computed offline and stored. A major challenge in this method is that, without online training, the similarities of low-level visual features may not well correlate with images' high-level semantic meanings which interpret users' search intention.

II. SYSTEM ANALYSIS

A. Existing Image Re-ranking Framework

Most of the existing search engines perform image retrieval based on query keywords specified by the user and depend on the surrounding text to search for images. But this approach suffers from the ambiguity of keywords, as the user cannot accurately describe his intention using just the keywords. To solve this problem, content-based image retrieval with relevance feedback is widely used. This requires the user to select multiple relevant and irrelevant image examples. From these image examples, visual similarity metrics are learned via online training. Images are re-ranked based on the learned visual similarities. The existing image re-ranking framework is as depicted in fig.1.

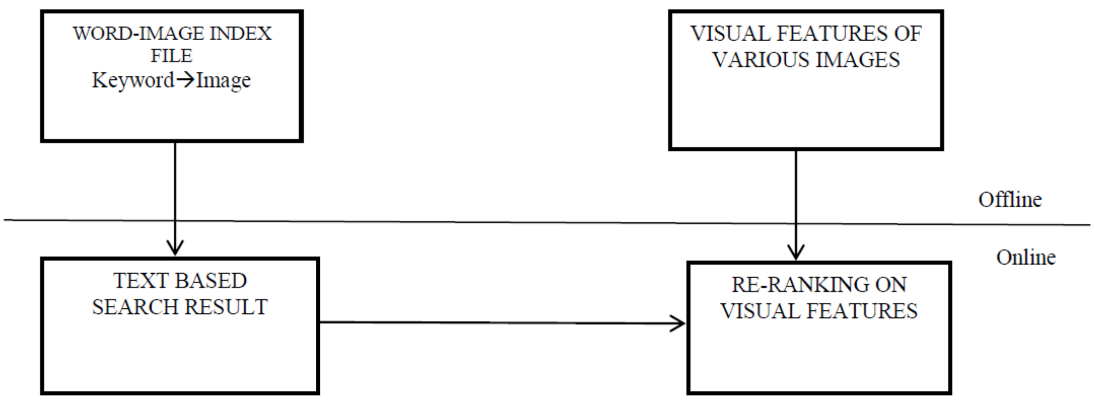

Fig 1 Existing Image Re-ranking Framework

As soon as the user inputs a query keyword, images relevant to the query keyword are retrieved by the search engines according to the stored word-image index file. The user is asked to select an image from the image pool, reflecting his search intention. The remaining images in the pool are re-ranked based on their visual similarities with the query image. The word-image index file and the visual features of the images are pre-computed and stored offline.

B. Proposed System

We propose a semantic web-based search engine which is also called as Intelligent Semantic Web-based Search Engine. It learns different semantic spaces for different query keywords individually and automatically. These query specific semantic spaces can more accurately describe the images to be re-ranked, as they have excluded other unlimited number of irrelevant concepts that serve only as noise and deteriorate the re-ranking performance on both accuracy and computational cost. The visual and textual features of the images are projected into their related semantic spaces to obtain semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures.

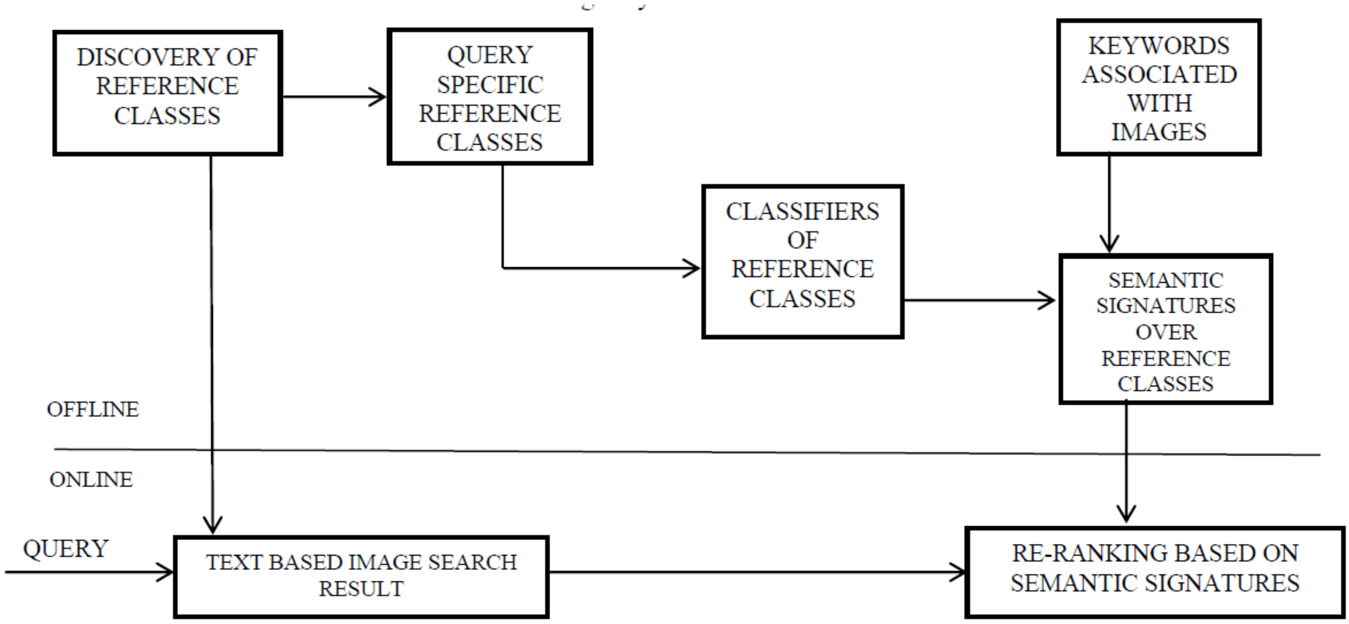

Fig 2 System Overview

The semantic spaces of query keyword can be described by using just 20-30 concepts. Thus semantic signatures are very short and hence image re-ranking becomes extremely efficient. Due to the large number of keywords and dynamic variations of the web, the semantic spaces of query keywords are learned automatically through keyword expansions. There are certain criteria that must be considered in search scenarios. We expect the top ranked images to be in the same semantic category as that of the query image. If the search intention is to find a target image, then the images that are visually similar to the query image are expected to have higher ranks. Query specific semantic signatures make image matching more consistent with visual perception. Fig.2 shows the overview of our approach.

At the offline stage, the following computations take place.

1. **Discovery Of Reference Classes**

The discovery of reference classes is done through keyword expansions. When a query keyword is given, a set of images are retrieved based on the given query. From this set of images, words required for the keyword expansion are extracted. Using the keyword combinations the images are retrieved. For example, the query keyword is “apple”, a set of most relevant keyword expansions such as “red apple”, “apple MacBook”, “apple logo” are selected using both textual as well as visual information.

2. **Query Specific Reference Classes**

The set of keyword expansions defines the reference classes for the query keyword. Some reference classes such as “apple laptop” and “apple MacBook” have similar semantic meanings and their training image sets are also visually similar. In order to improve the efficiency of online re-ranking, such redundant reference classes are removed using binary Support Vector Machine (SVM).

3. **Classifiers Of Reference Classes**

The multiclass SVM is trained to classify more than one reference classes based on their feature vectors. The multiclass SVM is trained using the visual features of the image. Six categories of technique are adapted for the classification of features such as texture, shape, color of the image. They include “color spatiality” which describes the spatial arrangement of color in an image. GIST is used for texture extraction. “Wavelet” characterizes the texture feature of the image. "Attention guided color signature" facilitates color composition of the image. "Histogram of oriented gradients" is used for image edge detection and describes shape information of the image.

4. Keyword Associated With Images

According to the word image index file, an image is associated with multiple keywords which have different semantic spaces. Thus it may have different semantic signatures. The query keyword input by the user decides which semantic signature to choose. If any one of the associated keyword is given as query, the concerned image will be retrieved and re-ranked.

5. Semantic Signature Over Reference Classes

Semantic signature of reference classes can be computed and stored offline. For each query keyword, its reference classes form the basis of its semantic space. The semantic signature of an image is extracted by computing the similarities between the image and the reference classes of the query keyword using the trained multiclass classifier . If there are k-types of features, such as color, texture, shape of an image, we can combine them together to train a single classifier, which extracts one semantic signature for an image. We can also train separate classifier for each type of features. Then the K classifiers based on different types of features extract K semantic signatures, which are combined at the later stage of image matching.

At the online stage,

1. User Query

First the user inputs a query keyword with the intention of finding desired image.

2. Image Retrieval Based On Textual Query

Once the user inputs a query, the search engine retrieves a pool of images based on the query keyword. The user can then select a query image from the pool which accurately depicts his search intention.

3. Re-Ranking Using Semantic Signatures

Once the user clicks on preferred image, remaining images in the database are re-ranked by comparing their semantic signatures with that of the query image.

Compared to the image re-ranking shown in Fig.1, our approach is much more efficient at the online stage. This is because the main online computational cost is on comparing visual features. In our approach we use semantic signatures whose lengths are much shorter than those of the low-level features. Also it does not require online training as required by pseudo relevance feedback. It also provides much better re-ranking accuracy, since offline training of the classifiers of reference classes captures the mapping between visual features and semantic meanings. However, in order to achieve significant improvement of online efficiency and accuracy, our approach does need extra offline computation and storage, which come from collecting the training examples and reference classes, training the classifiers of reference classes and computing the semantic signatures.

III. CONCLUSION

Here we propose a novel framework, which uses 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 which are automatically learned through keyword expansions offline. The extracted semantic signatures achieve 25-40 percent relative improvement on re- ranking precisions over state-of-the-art methods.

IV. REFERENCES

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