Web Image Re-Ranking Using Query-Specific Semantic Signatures

Nikit chaudhary, Kiran malunjkar, Shubham mahale, Shivaji kardel, prof. Sunil jadhav

***Abstract*— Image re-ranking, as an effective way to improve the results of web based image search, has been adopted by current commercial search engines. Given a query keyword, a pool of images are first retrieved by the search engine based on textual information. By asking the user to select a query image from the pool, the remaining images are re-ranked based on their visual similarities with the query image. A major challenge is that the similarities of visual features do not well correlate with images' semantic meanings which interpret users' search intention. Experimental results show that 20% to 35% relative improvement has been achieved on re-ranking precisions compared with the state of-the-art methods.**

***Index Terms*— Re-ranking, Query semantic space, Text based search , Ranking protocol.**

I. INTRODUCTION

Web-scale image search engines mostly use keywords as queries and rely on surrounding text to search images. It is well known that they suffer from the ambiguity of query keywords.For example, using "apple" as query, the retrieved images belong to different categories, such as "red apple", "apple logo", and "apple laptop". Online image reranking has been shown to be an effective way to improve the image search results. Major internet image 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. RELATED TECHNOLOGY PRINCIPLE

A. Existing system

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 they usually 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 high recall rate. In early search engine that offered disambiguation to search terms.

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User intention identification plays an important role in the intelligent semantic search engine.

B. Proposed system

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. The xml page will be consisted of built-in and user defined tags. Here propose the intelligent semantic web based search engine. We use the power of xml meta-tags deployed on the web page to search the queried information. The xml page will be consisted of built-in and user defined tags. 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.

C. Re-ranking framework

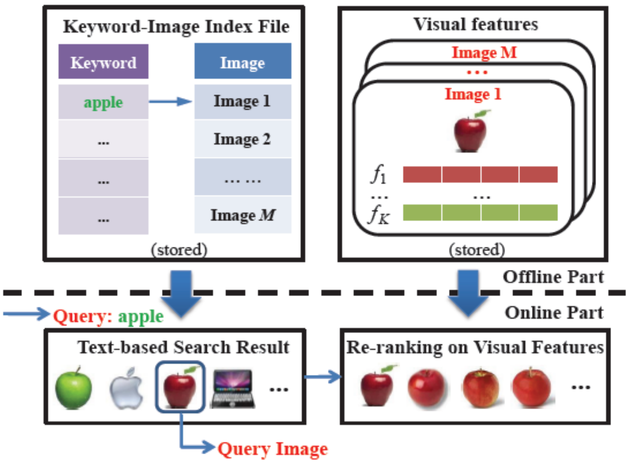

Figure 1. The conventional image re-ranking framework

Major internet image search engines have since adopted the re-ranking strategy.Its diagram is shown in Figure 1. Given a query keyword input by a user, according to a stored word-image index file, a pool of images relevant to the query keyword are retrieved by the search engine. By asking a user 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 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 lowlevel 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.

D. New image re-ranking framwork

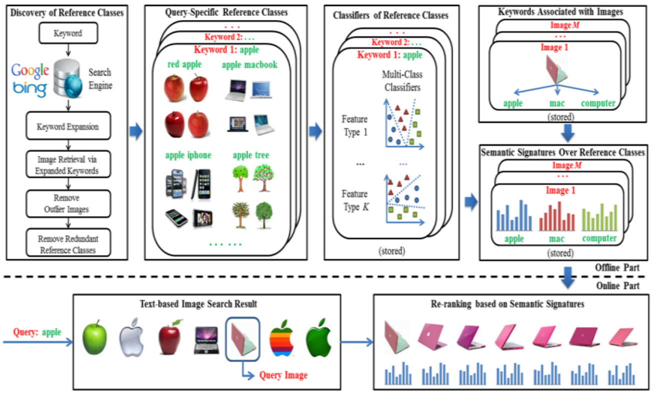

Figure 2: Diagram of our new image re-ranking framework

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. At the online stage, a pool of images are retrieved by the search engine according to the query keyword input by a user. Since all the images in the pool are relevant to the query keyword, they all have pre-computed semantic signatures in the semantic space of the query keyword. Once theuser chooses a query image, all the images are re-ranked by comparing similarities of the semantic signatures.

E. Keyword expansion

For a keyword q, we automatically define its reference classes through finding a set of keyword expansions E(q) most relevant to q. To achieve this, a set of images S(q) are retrieved by the search engine using q as query based on textual information. Keyword expansions are found from the words extracted from the images in S(q)3. A keyword expansion e 2 Eq is expected to frequently appear in S(q). In order for reference classes to well capture the visual content of images, we require that there is a subset of images which all contain e and have similar visual content. Based on these considerations, keyword expansions are found in a search-and-rank way as follows.

For each image I belongs to S(q), all the images in S(q) are reranked according to their visual similarities to I.

III. SUMMERY OF TECHNOLOGY

A. EXPERIMENTAL RESULTS

The images for testing the performance of re-ranking and the images of reference classes can be collected at different time and from different search engines. Given a query keyword, 1000 images are retrieved from the whole web using certain search engine. As summarized in Table 1, we create three data sets to evaluate the performance of our approach in different scenarios. In data set I, 120; 000 testing images for re-ranking were collected from the Bing Image Search using 120 query keywords in July 2010. These query keywords cover diverse topics including animal, plant, food, place, people, event, object, scene, etc. The images of reference classes were also collected from the Bing Image Search around the same time. Data set II use the same testing images for re-ranking as in data set I. However, its images of reference classes were collected from the Google Image Search also in July 2010. In data set III, both testing images and images of reference classes were collected from the Bing Image Search but at different time (eleven months apart)5. All testing images for re-ranking are manually labeled, while images of reference classes, whose number is much larger, are not labeled.

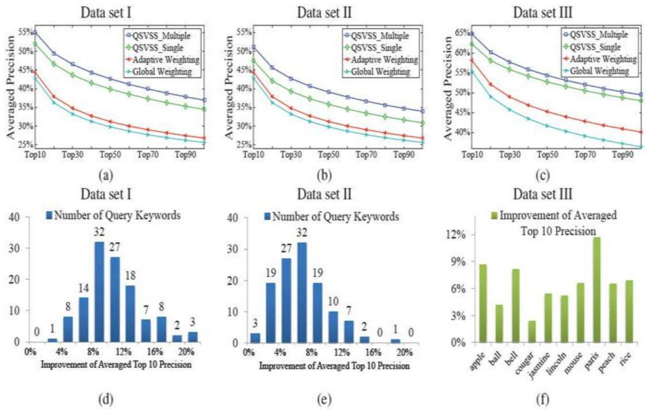

Figure 4: Comparison

B. ONLINE EFFICIENCY

The online computational cost of image re-ranking depends on the length of visual feature (if directly comparing visual features) or semantic signatures (if using our approach). In our experiments, the visual features have around 1; 700 dimensions, and the averaged number of reference classes per query is 25. Therefore the length of the single semantic signature (QSVSS Single) is 25 on average.Since six types of visual features are used, the length of the multiple semantic signatures (QSVSS Multiple) is 150. It takes 12ms to re-rank 1000 images matching the visual features, while QSVSS Multiple and QSVSS Single only need 1:14ms and 0:2ms respectively. Given the large improvement of precisions our approach has achieved, it also improves the efficiency by around 10 to 60 times compared with matching visual features

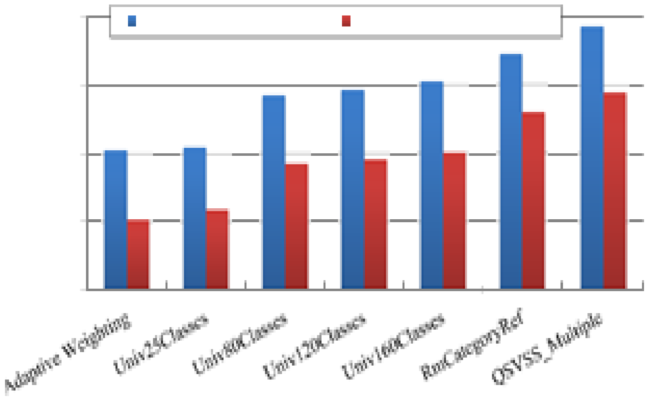

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Figure 4: Comparisons of averaged top m precisions of re-ranking images outside reference classes and using universal semantic space on data set.

C. RE-RANKING IMAGES OUTSIDE THE REFERENCE CLASS

It is interesting to know whether the learned queryspecific semantic spaces are effective for query imageswhich are outside the reference classes. To answer this question, if the category of an query image corresponds to a reference class, we deliberately delete this reference class and use the remaining reference classes to train SVM classifiers and to compute semantic signatures when comparing this query image with other images. We repeat this for every image and calculate the average top m precision. Multiple semantic signatures (QSVSS Multiple) are used. The results are shown in It still greatly outperforms the approaches of directly comparing visual features. This result can be explained from two aspects Many negative examples (images belonging to different categories than the query image) are well modeled by the reference classes and are therefore pushed backward on the ranking list.

IV. CONCLUSION

We propose a novel image re-ranking framework, which learns query-specific semantic spaces to significantly improve the effectiveness and efficiency of online image reranking. The visual features of images are projected into their related visual semantic spaces automatically learned through keyword expansions at the offline stage. The extracted semantic signatures can be 70 times shorter than the original visual feature on average, while achieve 20%35% relative improvement on re-ranking precisions over state-ofthe-art methods.

V. FUTURE WORK

In future, we can work on improving the quality of re-ranked images, we intent to combine this work with photo quality assessment work in to re-rank images not only by content similarity but also by the visual quality of the images. Also, this framework can be further improved by making use of the query log data, which provides valuable co-occurrence information of keywords, for keyword expansion.

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REFERENCES

[1] E. Bart and S. Ullman. Single-example learning of novel classesusing representation by similarity. In Proc. BMVC, 2005.
[2] Y. Cao, C. Wang, Z. Li, L. Zhang, and L. Zhang. Spatial-bag-offeatures. In Proc. CVPR, 2010.
[3] G. Cauwenberghs and T. Poggio. Incremental and decremental support vector machine learning. In Proc. NIPS, 2001.
[4] J. Cui, F. Wen, and X. Tang. Intentsearch: Interactive on-line image search re-ranking. In Proc. ACM Multimedia. ACM, 2008.
[5] J. Cui, F. Wen, and X. Tang. Real time google and live image search re-ranking. In Proc. ACM Multimedia, 2008.
[6] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In Proc. CVPR, 2005.
[7] C. Lampert, H. Nickisch, and S. Harmeling. Learning to detect unseen object classes by between-class attribute transfer. In Proc. CVPR, 2005.
[8] D. Lowe. Distinctive image features from scale-invariant keypoints. Int'l Journal of Computer Vision, 2004.
[9] B. Luo, X. Wang, and X. Tang. A world wide web based image search engine using text and image content features. In Proceedings of the SPIE Electronic Imaging, 2003.
[10] J. Philbin, M. Isard, J. Sivic, and A. Zisserman. Descriptor Learning for Efficient Retrieval. In Proc. ECCV, 2010.
[11] N. Rasiwasia, P. J. Moreno, and N. Vasconcelos. Bridging the gap: Query by semantic example. IEEE Trans. on Multimedia, 2007.
[12] M. Rohrbach, M. Stark, G. Szarvas, I. Gurevych, and B. Schiele.What helps wherevand why? semantic relatedness for knowledge transfer. In Proc. CVPR, 2010.
[13] Y. Rui, T. S. Huang, M. Ortega, and S. Mehrotra. Relevance feedback: a power tool for interactive content-based image retrieval. IEEE Trans. on Circuits and Systems for Video Technology, 1998.
[14] D. Tao, X. Tang, X. Li, and X. Wu. Asymmetric bagging and random subspace for support vector machines-based relevance feedback in image retrieval. IEEE Trans. on Pattern Analysis and Machine Intelligence, 2006.
[15] Q. Yin, X. Tang, and J. Sun. An associate-predict model for face recognition. In Proc. CVPR, 2011.
[16] X. S. Zhou and T. S. Huang. Relevance feedback in image retrieval: A comprehensive review. Multimedia Systems, 2003.

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