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Web Image Re-ranking using Query Log Data and visual photo Quality Assessment

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ABSTRACT: Web-scale image search engines (e.g. Google Image Search, Bing Image Search) mostly rely on surrounding text properties. It is challenging for them to interpret users' search intention only by query keywords and this leads to ambiguous and noisy search results which are far from satisfactory.

It is important to use visual information in order to solve the locution in text-based image retrieval. Content-based image retrieval uses visual features to calculate image similarity. Relevance feedback was widely used to learn visual similarity metrics to capture users' search intention. However, it required more users' effort to select multiple relevant and irrelevant image examples and often needs online training. For a web-scale commercial system, users' activity has to be restricted to the minimum with no online training.

In this paper we are proposing a new approach making use of the Query Log data, which provides valuable co-occurrence cognition of keywords, for keyword expansion. One disadvantage of the current system is that sometimes duplicate images show up as similar images to the query improved by including duplicate detection in this work. And also further improve the quality of re-ranked images by combining this approach with photo quality assessment algorithm to re-rank images not only by content similarity but also by the visual quality of the images.

I. INTRODUCTION

Numerous commercial Internet scale image search engines exploit only keywords as queries. Users type query keywords in the desire of finding a definite type of images. The search engine gives thousands of images ranked by the keywords draw from the encompassing text. It is well known that text-based image search experiences from the locution of query keywords. The keywords rendered by users lean to be short.

They cannot depict the content of images exactly. The search results are clam ant and consist of images with quite various linguistics meanings. Figure 1 shows the top ranked images from Bing image search using "apple" as query. They belong to different categories, such as "green apple", "red apple", "apple logo", and "i phone", because of the locution of the word "apple". The locution issue happens for several reasons.

First of all query keywords' significant may be richer than users' beliefs. For example, the meanings of the word "apple" include apple fruit, apple computer, and apple iPod. Second, the user may not have enough cognition on the textual description of reference images. For example, if users do not know "gloomy bear" as the name of a cartoon character and they have to input "bear" as query to search images of "gloomy bear". Lastly and most significantly, in many cases it is difficult for users to describe the visual content of target images using keywords veraciously.

Fig:1 A keyword "apple" based image.

CONTENT-BASED image retrieval (CBIR) systems are commonly based on the description of images by low-level (colors, gray shades, textures), and middle-level (contours, regions, shapes) features. A retrieval algorithm matches these statements with a user query according to some similarity metric. The strength of a CBIR system depends on the choice of the set of visual features and on the choice of the metric that models the user's knowledge of similarity

The image 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 excavation of images are re-ranked by the search engines based on the query. By asking the user to select a peculiar image from the pool, the unexpanded images are re-ranked based on the user selected image. To avoid the locutions in the re-ranked process and to achieve an impressive and efficient re-ranking process we introduce a Bag Based Re-ranking approach. It performs

1) Automatic annotation process by K-means algorithm which split the positive and negative bag that contains relevant and irrelevant images respectively.

2) GMI-SVM process which perform bag based re ranking effectively.

3) Execute user log operation for individual user log in.

A major challenge is that the similarities of visual features do not well related with images' semantic meanings which understand users' search design. On

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the other hand, learning a comprehensive visual semantic space to qualify highly different images from the web is difficult and inefficient.

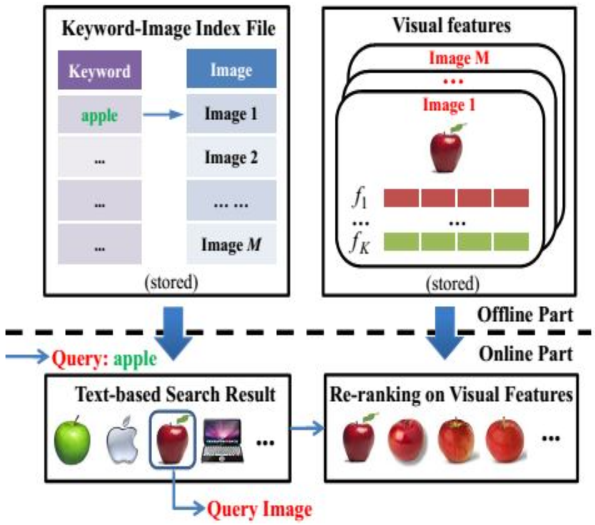

Fig:2 Framework for conventional re-ranking image.

Image description is possibly the most critical factor for recovery performance, and usually includes a large number of momentous parameters. Increasing the dimension of the feature space, An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Given a textual query in conventional text based image retrieval (TBIR),applicable images are to be re ranked using visual features after the first text based image search.

II. RELATED WORK

Content-based image retrieval uses visual features to calculate image similarity. Relevance feedback [13, 16, and 14] was widely used to learn visual similarity metrics to capture users' search intention.

However, it required more users' effort to select multiple relevant and irrelevant image examples and often needs online training.
For a web-scale commercial system, users' feedback has to be limited to the minimum with no online training. Cui et al. [5, 4] proposed an image re-ranking approach which limited users' effort to just one-click feedback. Such simple image re-ranking approach has been adopted by popular web-scale image search engines such as Bing and Google recently, as the "find similar images" function.
The key component of image re-ranking is to compute the visual similarities between images. Many image features [8, 6, 2, and 10] have been developed in recent years. However, for different query images, low-level visual

To address this, Cu i ET AL. [5, 4] classified the query images into eight predefined intention categories and gave different feature weighting schemes to different types of query images. Still, it was tricky for only eight weighting schemes to cover the large diversity of all the web images. It was also potential for a query image to be classified to a wrong category.

The diagram of existing approach is shown in Figure.4 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 Mac Book", and "apple i Phone") are automatically selected considering both textual and visual information.
This set of keyword expansions defines the reference classes for the query keyword. To automatically acquire 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.
The re-ranking based on the semantic signature is shown clearly after retrieved the image with the histogram is and the keyword give for it was "laptop". Now the diagrammatic explanation for the re-ranking based on semantic signature will be shown in fig.3 (a)

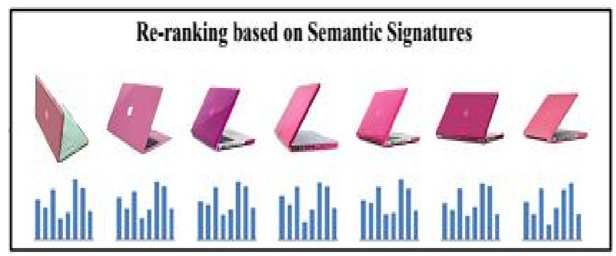

Fig: 3(a) Re-ranking based on semantic signatures with offline part.

The other before the re-ranking is the text based image search. By giving the text with a keyword we can get the result of such images which we need but in different pictures,Which will be shown in fig.3 (b)

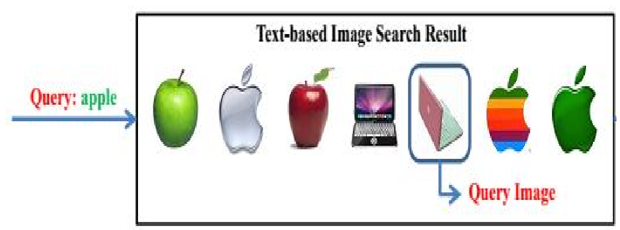

Fig: 3(b) Text-based image search result with query image.

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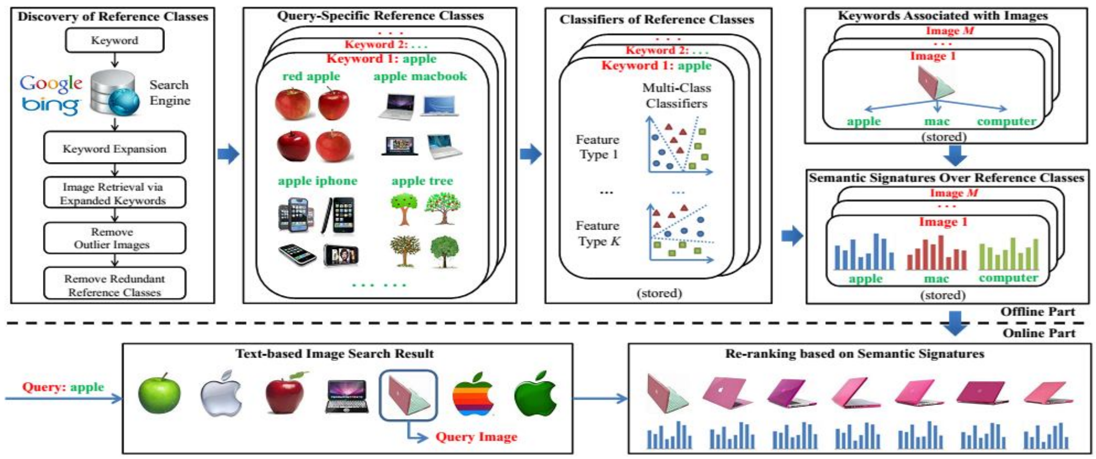

Fig:4.complete mechanism for the content based image retrieval semantic signatures with offline.

("Red apple") are much less diverse than those acquired by the original keyword ("apple"). After automatically removing deviations, the recovered top images are used as the training examples of the reference class. Some reference classes (such as "apple laptop" and "apple Mac Book") have similar semantic meanings and their training sets are visually similar. To improve the efficiency of online image re-ranking, excess reference classes are removed.

III. PROPOSED METHOD

In order to solve the locution, additional cognition has to be used to acquiring users' search purpose. One Method is text-based keyword enlargement, so description of the query more detailed. Subsist linguistically-related methods find either synonyms or other linguistic-related words from synonym finder, or find words frequently concurrent with the query keywords.

In this paper we are proposing a new approach making use of the query log data, which provides valuable co-occurrence information of keywords, for keyword expansion the key problem to be solved in this paper is how to gaining control user intention from this single-click query image. Four steps are suggest as follows.

(1)**Adaptive similarity**. We design a set of visual features to depict different characteristic of images. How to combine different features to calculate the similarities between the query image and other images is an important problem. In this paper, an Adaptive Similarity is proposed, prompt by the idea that a user constantly has particular purpose when submitting a query image. For example, if the user refers an image with a big face in the middle, most likely he/she wants images with related faces and using face-related features is more appropriate. In our approach, the query image is foremost into one of the standard adaptive weight.

(2)**Keyword expansion**. Query keywords input by users tend to be short and some important keywords may be missed because of users' lack of knowledge on the textual description of target images. In our Method, query keywords are enlarged to acquiring users' search intention, getting from the visual message of query images, which are not considered in conventional keyword expansion approaches. A word wise proposed as an expansion of the query, if a clump of images are visually same to the query image and all obtain the same word w .The expanded keywords better capture users' search intention since the accuracy of both visual content and textual description is ensured .Many Internet scale image search methods are text-based and are limited by the fact that query keywords cannot describe image content accurately. Content-based image retrieval uses visual features to evaluate image similarity. Many visual features were developed for image search in recent years.

One of the major challenges of content-based image retrieval is to learn the visual similarities which will reflect the semantic connection of images. Some of features

- **Gist**. Gist [11] characterizes the holistic quality of an image, and also well for scenery images.
- **SIFT.** We adopt 128-dimension SIFT [13] to describe regions near Harris interest points. SIFT signifier are judged according to a codebook of 450 words.
- .**Daubechies Wavelet**. We use the second-order moments of wavelet coefficients in various frequency bands (DWave) to characterize the texture properties in the image [17].
- **Histogram of Gradient** (HoG). HoG [12] reflects distributions of edges over different parts of an image, and is especially works for images with robust long edges

Keyword Expansion Once the top k images most similar to the query image are found according to the visual same metric introduced in Sections 3.2 and 3.3, words from their textual signifiers are pulled out and ranked, using the term frequency inverse document frequency

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(tf-idf) method. The top m (m¼5in our experiments) words are keep back as candidates for query expansion.

The above semantics of images are to be taken which contains of Gist, Sift, Daubechies Wavelet, and Histogram of Gradient as shown above and now some similar word search is to be shown below with the word "palm tree".

Fig: the image containing the same word "palm tree" with varies in visual content.

The goal of the proposed framework is to capture user intention and is achieved in several steps. The user thought is first close to represent by dividing the query image into one of the coarse semantic categories and choosing a suitable weight schema according to that. The adaptive visual similarity extracted from the selected weight schema is used in all the below steps. Then correspond to the query keywords and the query image given by the user is further captured in two aspects: 1) finding more query keywords (called keyword expansion) describing user intention more accurately 2) and in the meanwhile finding a cluster of images (called visual query expansion) which are both visually and semantically correct with the query image. The keyword expansion rarely coincides with the query keywords and the visual expansion is visually similar to the query image. However, it is required that all the images in the cluster of visual query expansion contain the same keyword expansion.
Therefore, the keyword expansion and visual expansion support each other and are obtained simultaneously. In the later steps, the keyword expansion is used to expand the image pool to include more images relevant to user intention, and the visual query expansion is used to learn visual and textual similarity metrics which better reflect user intention
For our new approaches, two different ways of calculating semantic signatures as discussed in previous Section are analyzed.
Query-specific visual semantic space using single signatures (QSVSS-single). For an image, a common semantic signature is calculated from one SVM classifier and trained by collecting all types of visual features.
Query-specific visual semantic space using multiple signatures (QSVSS-Multiple). For an image, multiple semantic signatures are calculated from multiple SVM classifiers, each of which is trained on one type of visual features individually.

IV. CONCLUSION

Finally we propose that our approach significantly improves the performance of search engines by adding this feature, ranking images by using semantic features. And the work we proposed uses query log data to enhance the queries and keyword expansion.

REFERENCES

[1] F. Jing, C. Wang, Y. Yao, K. Deng, L. Zhang, and W. Ma, "Igroup: Web image search results clustering," inProc. ACM Multimedia, 2006.

[2] J. Cui, F. Wen, and X. Tang, "Real time google and live image search re-ranking," inProc. ACM Multimedia, 2008.

[3] ——, "Intentsearch: Interactive on-line image search re-ranking," in Proc. ACM Multimedia, 2008.

[4] "Bing image search, http://www.bing.com/images."

[5]Y. Jing and S. Baluja, "Pagerank for product image search," in Proc. Int'l Conf. World Wide Web, 2008.

[6] N. Ben-Haim, B. Babenko, and S. Belongie, "Improving web-based image search via content based clustering," inProc. Int'l Workshop on Semantic Learning Applications in Multimedia, 2006.

[7]R. Fergus, P. Perona, and A. Zisserman, "A visual category filter for google images," inProc. European Conf. Computer Vision, 2004.

[8] G. Park, Y. Baek, and H. Lee, "Majority based ranking approach in web image retrieval," in Proc. the 2nd International Conference on Image and Video Retrieval, 2003.

[9] W. H. Hsu, L. S. Kennedy, and S.-F. Chang, "Video search reranking via information bottleneck principle," in Proc. ACM Multimedia, 2006.

[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?

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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

[17] R. Datta, D. Joshi, and J. Z. Wang, "Image retrieval: Ideas, influences, and trends of the new age," ACM Computing Surveys,vol. 40, pp. 1–60, 2007.

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