Image Re-Ranking Process Using Query System

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***Abstract*— For all type of question we are answer using only with text, if the answer is enriched with multimedia content like images, video then the user will understand the answer easily. For searching the multimedia answer we are using the Google search engine as a tool so the answer will get from web data we need to analyze and re-rank the search results. A major challenge is that the similarities of visual features do not well correlate with images' semantic meanings which interpret users' search intention. Recently people proposed to match images in a semantic space which used attributes or reference classes closely related to the semantic meanings of images as basis. However, learning a universal visual semantic space to characterize highly diverse images from the web is difficult and inefficient. In this Project, we propose a novel image re-ranking framework, which automatically offline learns different semantic spaces for different query keywords. 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 query-specific semantic signatures significantly improve both the accuracy and efficiency of image re-ranking.**

I. INTRODUCTION

The traditional search engine works by taking query as input, if any image contains that query keyword in its surrounding text then that image is retrieved as result. If image contains irrelevant surrounding information and if that keyword is found into that information then this image is also displayed even it is not related with user intention.

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 reran king has been shown to be an effective way to improve the image search results. 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.

In current years, the large amount scale storing of images the need to have an efficient method of image searching and retrieval has more increased. Raw of the image searching systems present today are text-based, in which images are parallel annotated by text keywords and when we query by a keyword, instead of looking into the collection of the image, in this system same as the query to the keywords present in the large database.

For Selecting query images this application also requires the user to input a query keyword. But it consider that images returned by initial text-only. The search have a Query-specific semantic signature can be applied to image re-ranking without dominant topic and images belonging to that topic should have higher ranks.

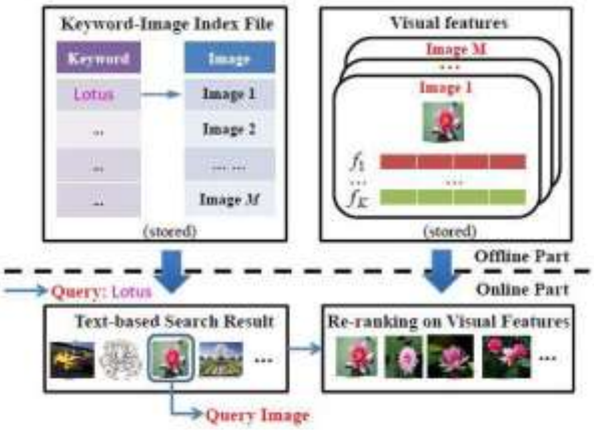


Figure 1. Image re-ranking framework

diagram is shown in Fig. 1. Given a text keyword as input by the user, a large amount of images related to the text keyword is retrieved by the search engine according to a stored word-image in index file. Usually the size is fixed for the returned image pool.

II. RELATED WORK

The aim of the image search is to retrieve the relevant image with respect to user query from a large image database. So identifying the accurate image with user intention is the most Challenging task.

The key component of image re-ranking is to compute the visual similarities between images. Many image features have been developed in recent years. However, for different query images, low-level visual features that are effective for one image category may not work well for another. To address this, Cui et al.[5] classified the query images into eight predefined intention categories and gave different feature weighting schemes to different types of query images. However, it was difficult for only eight weighting schemes to cover the large diversity of all the web images. It was also likely for a query image to be classified to a wrong category.

Recently, for general image recognition and matching, there have been a number of works on using predefined concepts or attributes as image signature. The mapped visual features to a universal concept dictionary. We used predefined attributes with semantic meanings to detect novel object classes. Some approaches transferred knowledge between object classes by measuring the similarities between novel object classes and known object classes (called reference classes). All these concepts/attributes/reference-classes were universally applied to all the images and their training data was manually selected. They are more suitable for offline databases with lower diversity (such as animal databases and face databases) such that object classes better share similarities.

The user provides a query image and all the images related to query image is obtained. This can be done by taking into consideration the visual features of query image with all related images having same visual features. It is similar but unnecessary or irrelevant images are also re-ranked. Thus it does not fulfil the user requirement. In which system of image-based content retrieval and automatic image annotation are becoming more and more relevant to the ways in which large database of digital media are stored and accessed. Significance comment: a power tool for interactive content-based image retrieval. Content based image re-ranking retrieving for general-purpose image databases is a highly challenging issue because of the big size of the database, the difficulty in understanding images, both by people and computers, in technical environment the difficulty of formulating a query and evaluating the issue of results accurately. It gives results properly of query and issue. A number of image search engines Content based image re-ranking retrieving have been developed.

Visual Query Expansion

So far we only have one positive image example which is the query image. The goal of visual query expansion is to obtain multiple positive example images to learn a visual similarity metric which is more robust and more specific to the query image. An example in Fig. 2 explains the motivation. The query keyword is “Paris” and the query image is an image of “Eiffel tower.” The image re-ranking result based on visual similarities without visual expansion is shown in Fig. 9 and there are many irrelevant images among the top-ranked images. This is because the visual similarity metric learned from one query example image is not robust enough. By adding more positive examples to learn a more robust similarity metric, such irrelevant images can be filtered out. In a traditional way, adding additional positive examples was typically done through relevance feedback, which required more users’ labelling burden. We aim at developing an image re-ranking method, which only requires one click on the query image and thus positive examples have to be obtained automatically. The cluster of images chosen has the closest visual distance to the query example and have consistent semantic meanings. Thus, they are used as additional positive examples for visual query expansion. We adopt the one-class SVM to refine the visual similarity.

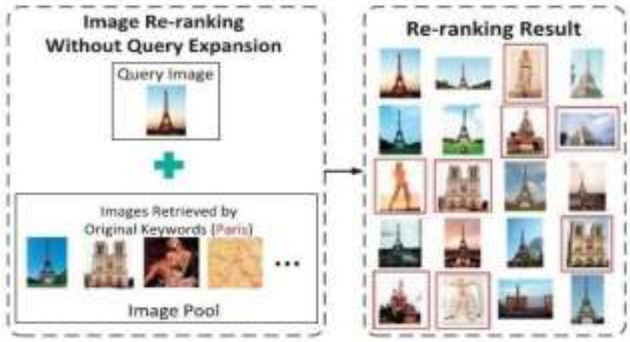


Fig 2. Image re-ranking based on visual similarity

Accurately, there are only a small number of relevant images with the same semantic meanings as the query image in the image pool. This can significantly degrade the ranking performance. In Section C, we re-rank the top N retrieved images by the original keyword query based on their visual similarities to the query image. We remove the N/2 images with the lowest ranks from the image pool. Using the expanded keywords as query, the top N/2 retrieved images are added to the image pool. We believe that there are more relevant images in the image pool with the help of expanded query keywords. The re-ranking result by extending image pool and positive example images is shown in Fig. 3, which is significantly improved compared with Fig. 2

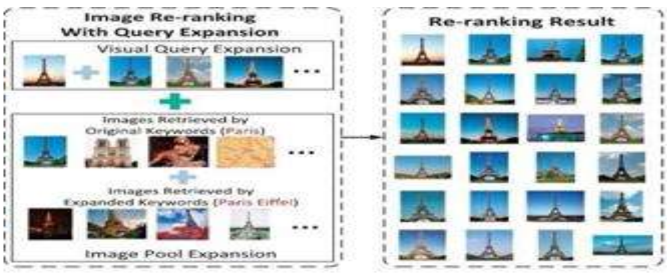


Fig3.image re-ranking by extending the image pool and positive exampie images

III. Existing System

Although text-based search techniques show their effectiveness in the data searching, they are complicated when applied to the image search. The two main problems

are occurs in this system. One is the inequality between images and their associated text-based information, resulting into not necessary images display in searching results.
The other problem is that the text-based information is not effective to represent the similar characteristics of the images. The same query words may describe to images that are functionally different. Recently aseveral of image are re-ranking methods has been proposed to unfairly the usage of the visual information for referring the text-based searching result. The query term is confusing. The information is not effective to imply the user's intention.

Disadvantage of existing system:

- Some images are in high dimensions and efficiency is not satisfied if they are directly matched.
- In the already existing system User intention is not considering.
- When the query term is unclear, re-ranking methods usually fail to capture the user's intention
- Due to the mismatching between images and their associated textual information text-based search techniques are problematic when applied to the image search.

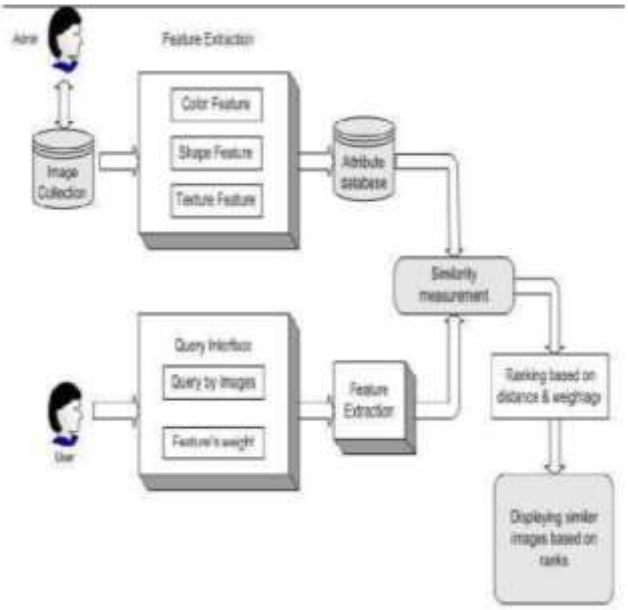
IV. PROPOSED SYSTEM

The main objective is to extend text based Question and Answers to multimedia Question and Answers. Thus the enrich textual answer with media is grabbed. We use stemming and partial-match retrieval algorithm for getting the best solution. The query-specific semantic spaces can more accurately model the images to be re-ranked, since they have excluded other potentially unlimited number of irrelevant concepts, which serve only as noise and deteriorate the re-ranking performance on both accuracy and computational cost. Different query images, the effective low-level visual features are different. Therefore, queries classified query images into eight predefined intention categories and gave different feature weighting schemes to different types of query images.
Offline system consists of database images retrieval approach proposed System. And online system consist query and re-ranking on visual feature The semantic space related to the images to be re-ranked can be significantly narrowed down by the query keyword provided as a input by the user. Consider the example, if the query keyword is used "apple", the like concepts of "semantic images" and "Paris image" are not likely to be similar and can be unseen. as an alternative, the similar concepts of this keyword is used for "computers" and "fruit" will be used to learn the visual semantic space interconnected to "apple" keyword. Practically results showing that proposed approach taking very less time to answer of this queries while providing more accurate and efficient information of this given query.

A) K-means Algorithm:

Input

- k: the number of clusters
- D: a dataset containing *n* Elements
- Output: a set of *k* clusters
- Method



(1) at random select *k* elements from *D* as the first cluster mean value
(2) repeat
(3) allocate each element to the cluster whose mean the element is *closest* to
(4) single time all of the elements are allocated to clusters, find the *real* cluster mean

V. CONCLUSION

In this paper, we have concluded that web based search Image approach effectively retrieves images. We have also discussed the conventional web based image search techniques. The reviewed image re-ranking framework overcomes the shortcomings of the previous methods and also significantly improves both the accuracy and efficiency of the re-ranking process. We propose an 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 rejected into their related visual semantic spaces automatically learned through keyword expansions at the offline stage. The extracted semantic signatures can be 80 times shorter than the original visual feature on average, while achieve 25%-45% relative improvement on re-ranking precisions over state-of the- art methods.

REFERENCES

[1] E. Bart and S. Ullman. Single-example learning of novel classes using 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] Click Internet Image Search, IEEE Transactions on Pattern Analysis And Machine Intelligence, Vol.34,pp No.1342-1353,July 2012.
[7] Y. Kuo, W. Cheng, H. Lin, and W. Hsu, Unsupervised semantic feature discovery for image object retrieval and tag refinement, IEEE Trans on Multimedia, vol.14, pp.10791090, 2012.
[8] A. Kovashka, D. Parikh, and K. Grauman, Whittle search: Image search with relative attribute feedback, in Proc.CVPR, 2012.
[9] V. Jain and M. Varma, Learning to re-rank: Query-dependent image reranking using click data, in Proc. WWW, pp.345-348, 2011.
[10] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In Proc. CVPR, 2005.
[11] C. Lampert, H. Nickisch, and S. Harmeling. Learning to detectunseen object classes by between-class attribute transfer. In Proc. CVPR, 2005.
[12] D. Lowe. Distinctive image features from scale-invariant keypoints. Int'l Journal of Computer Vision, 2004.
[13] 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.
[14] J. Philbin, M. Isard, J. Sivic, and A. Zisserman. Descriptor Learning for Efficient Retrieval. In Proc. ECCV, 2010.

Selected Paper from International Conference on Computing (NECICC-2k15)