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A Review on Web Image Retrieval Techniques

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***Abstract*—In today's era search engines are used everywhere, as it is source to retrieve efficient result related to query. Web based image search engines frequently uses keywords as queries to search images. These search engines entails complexity due to the ambiguity of query keywords, since it is hard for users to properly illustrate the visual content of target images by only using keywords. For example, if query keyword is mouse, then result may contain mouse animal, Mickey Mouse, wireless mouse, or optical mouse etc. To overcome this problem search engines uses re-ranking. Image Re-Ranking is the process which reorganizes the result by considering different features of image. A main challenge in the research of image re-ranking is that the similarities of visual features do not correlate semantic meanings of images that understand users' search aim. This paper represents an extensive survey of feature extraction; image searching and re-ranking for different queries is carried out.**

***Keywords*— image search engine, keyword, image re-ranking, semantic signatures**

I. Introduction

Image re-ranking [1] [2] [3] improves the result of web based image search. Image Re-Ranking is the process of which reorganizes the result by considering different features of image. For a given query keyword, search engine re-ranks the cluster of images based on the query. In conventional re-ranking framework user is promoted to select query image from a group of images ranking is performed on the user selected image.

In recent years ranking is performed on One-click feedback [3] [4] method that is used to improve search results. This approach has been adopted by main web image search engines. Its diagram is shown in Fig. 1. For a user given query keyword input, a pool of images which are relevant to the given query keyword is retrieved by the search engine. The retrieval has been done with respect to a stored word-image index file. To accomplish high effectiveness, the visual feature vectors need to be short and their matching should be done faster.

This paper is organized in three sections first section presents various techniques of feature extraction, as features of image plays important role while retrieving similar images. Second section presents strategies used for image searching. Third section presents techniques used for re-ranking.

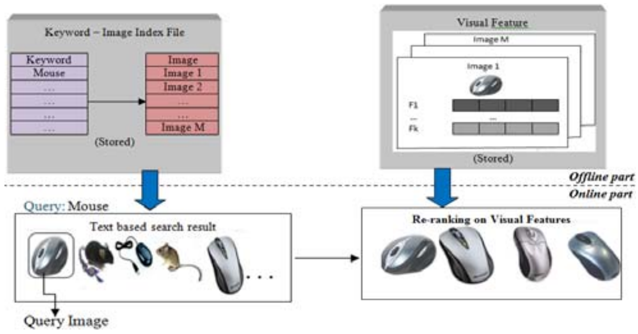

Fig. 1 Standard image re-ranking framework sample

II. Feature Extraction Strategies

A. *Face Recognition*

In [5] Qi Yin presented a new model, called "Associate-Predict" (AP) model, to overcome issues related to finding similar faces. The associate-predict representation is built on an extra standard uniqueness of dataset, in which each identity contains multiple images with large intra-personal variation. By considering two faces under significantly different settings (e.g., non-frontal and frontal), first "associate" one input face with alike identities from the generic identity date set. The appearance of one input face under setting of another input face can be predicated from the associated faces. The two prediction methods "appearance-prediction" and "likelihood-prediction" are proposed in literature.

TABLE I
TYPES OF PREDICATE MODEL

Sr. no.	Predicate model	Approach
1.	Appearance-prediction	Face descriptors [6] are used to find "nearest" generic identity of any component of an image with component of dataset images.
2.	Likelihood-prediction	Classifier [7] is trained using positive and negative samples.

By leveraging an extra dataset and the "associate-predict" model, the intrapersonal variation can be effectively handled. Final model can substantially improve the performance of most existing face recognition methods.

B. Object recognition

In [8] Antonio Torralba presented an object recognition technique and also predicted the location of the object. The goal is to spot known locations (e.g., workplace 610, meeting room 941, Main Street), to sort out new environments (office, passage, road) and to use that information to give appropriate priors for object recognition (e.g., tables are more likely in an office than a street). This paper considered a low-dimensional global image representation that provides relevant information for place recognition and categorization, and show how such contextual information introduces strong priors that simplify object recognition. The algorithm has been included into a mobile system that provides real-time feedback to the user.

TABLE II
TYPES OF FEATURES FOR OBJECT RECOGNITION

Sr. No	Type of Feature	Technique	Approach
1.	Local Feature	Trainable System[15]	Object classes described in terms of orientation, multiscale intensity differences between adjacent regions.
		Multidimensional Receptive Field Histogram[16]	Appearances of objects are represented by joint statistics of local neighborhood operators.
2.	Global Feature	Capture global image properties, while keeping some spatial information. Consider mean value of magnitude of local features averaged over large spatial regions.[8]	

C. Image Object Retrieval and Tag Refinement

In [9] Yin-Hsi Kuo presented solution to the problems of object retrieval by leveraging both the image contents and associated textual information. Authors focused on graphs among images to get relevant semantic feature. The framework automatically discovers relevant semantic features by propagation and selection in textual and visual image graphs. This framework can be directly applied to various applications such as image object retrieval, tag refinement and keyword based image search.

Object retrieval adapts:

- SIFT (Scale-invariant feature Transform)[17] descriptor to capture local information. SIFT descriptors are quantized to visual words, such as indexing techniques well developed in the text domain can be directly applied. The learned visual words vocabulary will directly affect the image object retrieval performance.
- BoW(Bag of Words)[18] model to conduct object matching. The traditional BoW model adapts k-means clustering to generate the vocabulary.

III. IMAGE SEARCHING STRATEGIES

A. Support Vector Machines-Based Relevance Feedback in Image Retrieval

In [10] Dacheng Tao, presented new algorithms to get Relevance feedback schemes based on support vector machines (SVM). These relevance feedbacks have been widely used in content-based image retrieval (CBIR). But, if the number of labeled positive samples is small then the performance of SVM-based relevance feedback is often poor. To advance the SVM performance, this work uses bagging and a random subspace method which shows extra efficiency than conventional classifier.

TABLE III
FACTORS AFFECTING THE PERFORMANCE OF RETRIEVAL

Sr. No	Factors affecting performance	Solution
1.	A small-sized training set.	An asymmetric bagging-based SVM(AB-SVM).
2.	The positive feedback samples	An asymmetric bagging-based SVM(AB-SVM).
3.	The number of feature dimensions is much higher than the size of the training set.	Random Subspace SVM (RS-SVM)

B. Query relative classifiers

In [11] Josip Krapac presented standard classifiers that are based on query-relative features which can be used for new queries without additional training.
Contribution of this paper is as follows:

- Combining textual features, based on the occurrence of query terms in web pages and image meta-data, and visual histogram representations of images.
- A new database for the evaluation of web image search algorithms.

It includes 71478 images returned by a web search engine for 353 different search queries, along with their meta-data and ground-truth remarks. Dataset can be used to evaluate the performance of proposed system with search engine.

C. One Click Internet Image Search

In [3] Xiaoou Tang presented new technique to overcome the impact of ambiguous results generated by search engines due to text based searching approach. To solve the ambiguity in text based image retrieval, visual information is taken into consideration. It only requires the user to click on one query image with minimum effort and images from a pool retrieved by text-based search are re-ranked based on both visual and textual content. Our key contribution is to capture the users' search intention from this one-click query image. Experimental evaluation shows that this approach significantly improves the precision of top-ranked images and also the user experience.

IV. IMAGE RE-RANKING STRATEGIES

A. *Supervised Re-ranking for Web Image Search*

In [13] Linjun Yang presented Visual search re-ranking to induce higher text-based image search with the assistance from visual content analysis. The unattended character of the re-ranking model makes it expertise from troubles, to optimally resolve the role of sight over totally different application situations. In this paper the "learning-to-re-rank" model is employed, that derives the re-ranking operate in a very supervised fashion from the human-labeled training data. Query-independent re-ranking models are going to be learned for all queries exploitation query-dependent re-ranking options. In this paper, eleven light-weight re-ranking features are planned to work out the connectedness between the visual and matter queries of images.

B. *Real Time Google and Live Image Search Re-ranking*

In [14] Jingyu Cui presented real time searching. Generally search engines rely almost purely on surrounding text features. Text based searching leads to ambiguity and noisy results. This paper uses adaptive visual similarity to re-rank the text based search results. Initially query image is sort out into one of several predefined target category, and a precise similarity measure is used inside each category to combine image features for re-ranking based on the query image.

C. *Bayesian Visual Re-ranking*

In [23] Xinmie Tian.et.al presented Bayesian visual re-ranking that model the visual and textual information from the probabilistic viewpoint and makes visual re-ranking as an optimization system in the Bayesian framework. In this scheme, the textual information is replicated as probability, to duplicate the divergence between text-based search results and re-ranked results that is described as ranking distance. The visual information is replicated as a conditional previous, to purpose the ranking score uniformity among visually similar examples that is thought as visual consistency. Bayesian visual re-ranking technique obtains the best re-ranking consequences by increasing visual uniformity whereas decreasing distance of ranking. A novel pair-wise technique is employed that computes the ranking distance with reference to the divergence in terms of pair-wise directions.

TABLE IV
COMPARATIVE ANALYSIS OF PAPERS USING COMMON CATEGORIES FOR IMAGE RETRIEVAL

Sr. No.	Paper	Category	Algorithms Used	Reference	Dataset	Performance measure
1.	Real Time Google and Live Image Search Re-Ranking	Feature Extraction	1. Gist 2. Daubechies Wavelet 3. SIFT 4. Multi- layer rotation invariant EOH[22] 5. HoG 6. Facial Feature[23]	[1]	1. Google image search 2. Microsoft live image search	Precision and recall are Calculated using text and intent search
		Image Searching	1. Adaptive weighting similarity			
		Image Re-ranking	1. Online image search re-ranking algorithm			
2.	Learning to Re-Rank: Query-Dependent Image Re-Ranking Using Click Data	Feature Extraction	1. Query-independent static features 2. Textual features 3. Image features	[19]	1. Bing Image Search	Ranking improvement of about 13% over the Bing image search engine
		Image Searching	1. SVM			
		Image Re-ranking	1. Gaussian Process regression			
3.	Intent Search: Capturing User Intention for One-Click Internet Image Search	Feature Extraction	1. Attention Guided Color Signature 2. Color Spatialet (CSpa) 3. Multilayer Rotation Invariant (EOH).[22] 4. Facial Feature[23]	[3]	1. Bing Image Search	Precision of initial Re-ranking using adaptive weight is improved from 32.9 to 51.9 percent.
		Image Searching	1. Adaptive similarity			
		Image Re-ranking	1. ExtBoth (V + T) 2. Image re-ranking by transmedia distances 3. Image re-ranking by the pseudo-relevance feedback			
4.	Web Image Re-Ranking Using Query-Specific Semantic Signatures	Feature Extraction	1. Integrated visual and textual features	[21]	1. Bing Image Search	25-40 percent relative improvement on re-ranking precisions
		Image Searching	1. QSVSS(single) 2. QSVSS(multiple)			
		Image Re-ranking	1. Semantic spaces 2. Re-Ranking Without Query Images			

V. CONCLUSION

This paper presents survey on various methods used for feature extraction, image searching and re-ranking of web-scale images. All surveyed methods are considerably well-organized in image retrieval process and ranking of images. Retrieval performance can be measured using retrieval accuracy and computational time. This paper surveyed to for performance measure of each method in all aspects

REFERENCES

[1] J. Cui, F. Wen, and X. Tang, "Real Time Google and Live Image Search Re-Ranking," Proc. 16th ACM Int'l Conf. Multimedia, 2008.

[2] J. Cui, F. Wen, and X. Tang, "Intent Search: Interactive on-Line Image Search Re-Ranking," Proc. 16th ACM Int'l Conf. Multimedia, 2008.

[3] X. Tang, K. Liu, J. Cui, F. Wen, and X. Wang, "Intent Search: Capturing User Intention for One-Click Internet Image Search," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 34, no. 7, pp. 1342-1353, July 2012.

[4] X.S. Zhou and T.S. Huang, "Relevance Feedback in Image Retrieval: A Comprehensive Review," Multimedia Systems, vol. 8, pp. 536-544, 2003.

[5] Q. Yin, X. Tang, and J. Sun, "An Associate-Predict Model for Face Recognition," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2011.

[6] Z. Cao, Q. Yin, J. Sun, and X. Tang. Face recognition with Learning-based Descriptor. In Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2010.

[7] N. Peter, P. Joao, and J. David. Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection. IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(7), 1997.

[8] A. Torralba, K. Murphy, W. Freeman, and M. Rubin, "Context-Based Vision System for Place and Object Recognition," Proc. Ninth IEEE Int'l Conf. Computer Vision (ICCV), 2003.

[9] Y. Kuo, W. Cheng, H. Lin, and W. Hsu, "Unsupervised Semantic Feature Discovery for Image Object Retrieval and Tag Refinement," IEEE Trans. Multimedia, vol. 14, no. 4, pp. 1079-1090, Aug. 2012.

[10] 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. Pattern Analysis and Machine Intelligence, vol. 28, no. 7, pp. 1088-1099, July 2006.

[11] J. Krapac, M. Allan, J. Verbeek, and F. Jurie, "Improving Web Image Search Results Using Query-Relative Classifiers," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2010.

[12] J. Lu, J. Zhou, J. Wang, X. Hua, and S. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2012.

[13] L. Yang and A. Hanjalic, "Supervised Reranking for Web Image Search," Proc. ACM Int'l Conf. Multimedia, 2010.

[14] J. Cui, F. Wen, and X. Tang, "Real Time Google and Live Image Search Re-Ranking," Proc. 16th ACM Int'l Conf. Multimedia, 2008.

[15] C. Papageorgiou and T. Poggio. A trainable system for object detection. Intl. J. Computer Vision, 38(1):15–33, 2000.

[16] B. Schiele and J. L. Crowley. Recognition without correspondence using multidimensional receptive field histograms. Intl. J. Computer Vision, 36(1):31–50, 2000.

[17] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," Int. J. Comput. Vis., vol. 60, no. 2, pp. 91–110, 2004.

[18] J. Sivic and A. Zisserman, "Video Google: A text retrieval approach to object matching in videos," in Proc. IEEE Int. Conf. Comput. Vis., 2003, vol. 2, pp. 1470–1477.

[19] Vidit Jain, Manik Varma, " Learningto Re-Rank: Query-Dependent Image Re-Ranking Using Click Data," Proc. International conference of WWW,2011, pp 277-286

[20] Xiaogang Wang, Shi Qiu, Ke Liu, and Xiaoou Tang, Web Image Re-Ranking Using Query-Specific Semantic Signatures, IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 36, No. 4, April 2014.

[21] W. Freeman and M. Roth, "Orientation Histograms for Hand Gesture Recognition," Proc. Int'l Workshop Automatic Face and Gesture Recognition, 1995.

[22] R. Xiao, H. Zhu, H. Sun, and X. Tang, "Dynamic Cascades for Face Detection," Proc. Int'l Conf. Computer Vision, 2007.

[23] X. Tian, L. Yang, J. Wang, X. Wu, and X. Hua, "Bayesian Visual Re-ranking," IEEE Trans. Multimedia, vol. 13, no. 4, pp. 639-652, Aug. 2011.