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Image Search Reranking

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Abstract—Image search reranking (ISR) has been implemented in order to get a refined image search as per the user needs. ISR fails to capture user expectation and needs for the search of a particular text query. In order to improve this reranking with user interactions or active ranking is highly demanded to improve the image search performance. Use of visual information can be used to solve text-based image retrieval. Among the papers referred for literature survey the techniques that can be implemented are, reverse K Nearest Neighbor (KNN), Hypersphere-based Relevance Preserving Projection (HRPP) and ranking function Hypersphere-based rank (H-rank) and K means clustering. HRPP is used to sort the images into various categories and sort. Reverse KNN is used in order to review On- Click Hypersphere based Relevance Preserving Projection (OC-HRPP) to know the exact search of the user. H-rank technique uses Euclidean distance formula and gives us all user relevant refined image result.

Index Terms—Image search reranking, feature extraction, clustering, text- based image search.

1 Introduction

WEB image search are mostly use text-based image search retrieval technique with reranking, in order to get user defined image search. Image search are done using various currently acessible image search engine tools. Some of the accessible image search engines are bing, google, cydral, yahoo, TinEye, corbis etc. Image mining are mainly used for extracting patterns, implicit knowledge, image data relationship or data that are not found in the images from databases and collections of images.

Image search engine usually works as shown in Fig 1.1, we firstly we enter a query and query related web page is downloaded as per user query match. Then the images are extracted from the page downloaded and stored in the database. Secondly, extract features of each image in the data set and then display the collected images that match user entered query. Thirdly, we re-rank images based on the features extracted and then collect relevant images among the whole available set.

Consider an example, a user provides a query to the search engine by typing a query keyword such as "sunflower" as shown in Fig. 1.2, then the search engine will have images that are relevant and irrelevant images among the display list. Some of the images displayed are not related to expected user expectation. The images displayed contain various search results such as sunflower of various colours and shapes of flowers that are related to it. But the user wants a images of pink sunflower. After applying techniques of feature extraction we can obtain images that have same images based on user colour, texture and shapes available in that dataset. By this implementation of techniques should give a good end result that is what a user expects.

Text-based image retrieval is more effective in document search and then for image search. Using text based image retrieval has various problems, which disuse the visual contents of the image and mismatch of images and related text. Image search reranking can be used to improve the overcome the failures in text based image retrieval. With content based image retrieval (CBIR) extraction of the visual features, such as color, texture and shape of images which are extracted automatically.

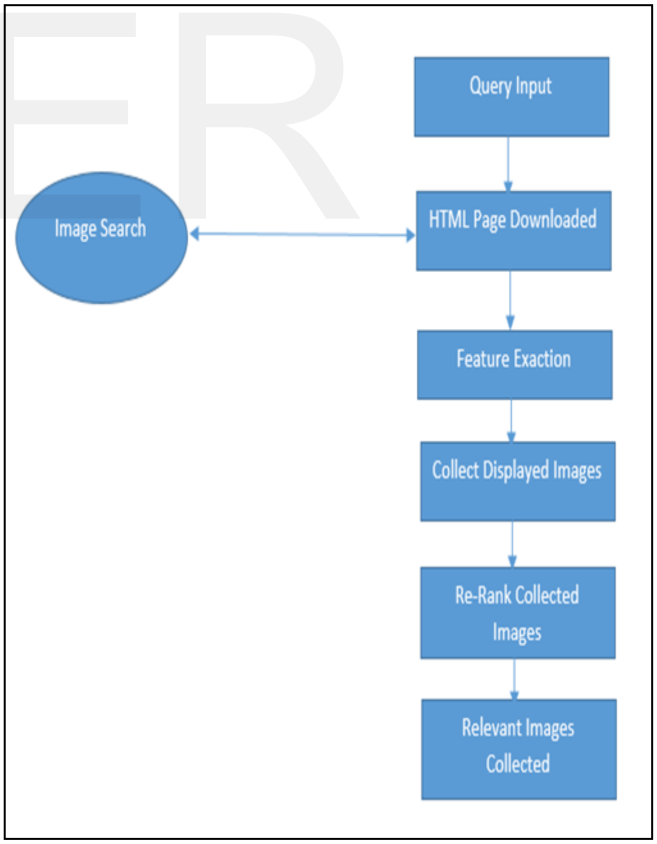

Fig. 1.1. Overall Diagram

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Fig 1.2. Result of user entered query "apple"

Fig 1.3 Relevant and irrelevant images of query as expected.

Similarity between images can be detected by distances in the features and it is easy to implement and is faster means of retrieval. But CBIR there are some disadvantages that is manual annotation is not correct and is impossible for large database. As a picture is worth thousand words so identification and analysis of images along with is query text becomes impossible.

2 Related works

.In section I, brief description about image search reranking was discussed as per various techniques being used from the very beginning of the image mining. In order to get accurate results we have made a literature survey on various techniques that are used so far. Some of them are discussed below:-

Intent search of images done by capturing user intention for one click internet image search [1] uses visual feature design to check the similarity in images. Visual features being used are Gift, SIFT, Daubechies Wavelet, ColorSpatialet, Edge Orientation Histogram etc. Adaptive weight schema technique is done using query categorization and feature fusion.. In keyword expansion most images similar to the query are found on bases of visual similarity metric where textual word description are extracted and ranked using term frequency-inverse document frequency. Only advantage is it intention and try to enlarge image pool to include more relevant related images.

Query-specific semantic spaces are used to significantly captures user improve the effectiveness and productivity of online image re-ranking search. The visual features of searched images are proposed to relate semantic spaces and are learned through keyword expansions offline terms. The removed semantic signatures are 70 times shorter than the original visual features, while achieved 25-40 percent have relative improvement on reranking precisions over state-of-the-art methods.

To improve the learning approaches [2], query-specific distance functions allow to relate text-queries to share the learned distance functions being used. Query-specific based distance function improves ranking accuracy in certain query categories more than others, the ability to automatically select queries or query categories that are suitable for distance functions would be beneficially possible approach. It is to measure the disagreement between the co-click statistics and the visual similarity that are produced by using un-weighted Euclidean distance.

Image search which requires one-click user feedback [3], intention specific weight schema method was proposed to combine visual features and to compute visual similarity adaptive to query images. Without human feedback, textual and visual expansions were integrated to capture user intention. Expanded keywords were used to extend positive example images and also enlarge the image pool to include more relevant images. This method makes it possible for industrial scale image search results for both text and visual content. Proposed image reranking method consists of multiple steps, which can be improved separately or replaced by other techniques equivalently effective.

A multimodal hypergraph learning that is based on sparse coding method for the click prediction of images [4] were used to obtain sparse codes and can be used for image re-ranking by integrating them with a graph-based schema. We adopt a hypergraph in order to build a group of manifolds that try to explore the complementary characteristics of various features through a group of weights. Unlike graphs which have an edges between two vertices, when we connect a set of vertices by a hyper edge in a hypergraph. This helps to preserve the local smoothness of the constructed sparse codes. Then, a substitute optimization procedure is performed and the weights of different modalities and sparse codes are concurrently obtained using this optimization strategy. Finally, a voting strategy is used to predict the click from the corresponding sparse code.

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3 Proposed Methods for Image Search Reranking

As demonstrated in this document, the numbering for sections upper case Arabic numerals, then upper case Arabic numerals, separated by periods. Initial paragraphs after the section title are not indented. Only the initial, introductory paragraph has a drop cap.

3.1 Hypersphere Based Relevence Preserving Projection

With the idea of hypersphere in one- class classification, where initially searched images are distributed intrinsically in a hypersphere where relevant images are inside and irrelevant images are placed outside, in which relevant images are target data and irrelevant images are outlier.

We take online training examples and then name it as array set label L=[$x_{1\ldots}$,x_r ,x_{r+1},…,…x_{r+k}] , reduced dimensionality d, labeled number r for relevant examples and labeled number h for irrelevant examples. Relevant examples are clustered based on the closeness to the hypersphere, which is user search expectation. We use the mean vector m of the labeled relevant examples as the hypersphere center for simplicity i.e :

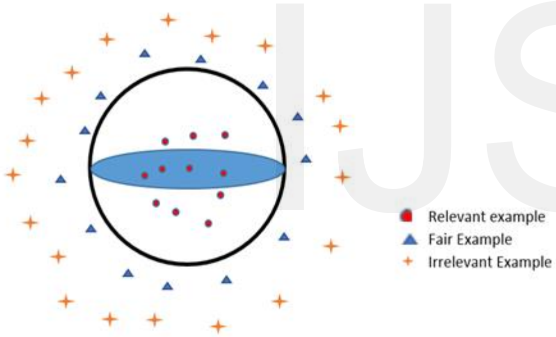

Fig. 3 Hypersphere based sorting of relevant and irrelevant images

$$m = \frac{1}{r}\sum_{i=1}^{r} y_i = \frac{1}{r} w^T \sum_{i=1}^{r} x_i \qquad (1)$$

Objective function is given as :

$$J_R = min_w \sum_{i=1}^{r} ||y_i - m||^2 \qquad (2)$$

Graph Laplacian function regularize [9][10] we have :

$$J_W = min_w \sum_{i,j=1}^{r} S_{ij} ||y_i - y_j||^2 \qquad (3)$$

where $S_{ij} = e^{\frac{-||x_i - x_j||^2}{2\sigma^2}}$,

measures similarity between x_i and x_j , whereas σ is scaling parameter

To sort irrelevant images away we use the objective function:

$$J_I = min_w \sum_{i=r+1}^{r+h} ||y_i - m||^2 \qquad (4)$$

Equation (4) helps us to enlarge the distance between irrelevant images from the hypersphere. Final objective function of HRPP algorithm is maximizing to :

$$J = J_I - J_R - J_W \qquad (5)$$

With constraint:

$$w^T w = 1 \qquad (6)$$

Compute Laplacian method $L = P - Q$, where :

$$P_{ij} = \begin{cases} (2r^2 S_{ij} + r + h)/r^2 & 1 \le i,j \le r \\ -2/r & r+1 \le i \le r+h, 1 \le j \le r \\ 0 & otherwise \end{cases} \qquad (7)$$

$$Q_{ij} = \begin{cases} 1 + 2D_{ii} & 1 < i,j < r \\ -1 & r+1 \le i \le r+h, 1 \le j \le r \end{cases} \qquad (8)$$

$$D_{ii} = \sum_{j=1}^{r} S_{ij} \qquad (9)$$

By using Lagrangian multiplier we can resolve eigen decomposition,

$$XWX^T w_i = \lambda_i w_i \qquad (10)$$

where **w**$_i$ is the generalized eigenvector of **XLX**^{T} and λi is the corresponding eigenvalue.

3.2 Reverse KNN algorithm

It is mainly used to understand the user intentions from user clicks. The HRPP algorithm with Reverse K Nearest Neighbor(KNN) is called On-Click based HRPP(OC-HRPP).

The first step is to make the user click on image so that we can sort the images based on users interest and by which we can make relevant user pool of images. Secondly, nearest neighbors of the images are chosen as pseudo relevant images from from the top N images searched by KNN and put in relevant image pool. Thirdly, we find the remaining pseudo relevant images from the pool that are relevant by calculating minimum average distance between the images in the relevant pool and remaining top N images. Fourthly, continue the third procedure till all images in the procedure reach a thresholdT_c.

As we had seen that we categorize images into relevant and irrelevant based on their distance measurement in the hypersphere and this data can be ranked based on their distance. Euclidian distance is adopted in H- Rank algorithm.

$$D_i = ||y_i - a|| = ||W^T x_i - a|| , \; i = 1, \ldots, n \qquad (11)$$

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where a is hypersphere center and smaller the D_i better the accuracy as it matches user expectation.ie : $D_i < D_j \Rightarrow y_j > y_i$ Hypersphere center a is obtained by support vector data description(SVDD).

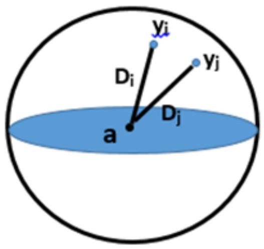

Fig 4: Images close to center 'a' are the images that are of more accurate images Upto user expectation

Consider we have given vector set of relevant and pseudo- relevant images $\{y_1, \ldots, y_r\}$, where r is total number of relevant and pseudo-relevant images, $y_i \in R^d$ where d is dimentional feature space.
We use objective function :

$$min_{R,a} R^2 + C \sum_{i=1}^{N} \xi_i \qquad (12)$$

with constraints ,

$$||y_i - a||^2 \leq R^2 + \xi_i \,, \quad i=1, \ldots, r \qquad (13)$$

where the slack variables $\xi i \geq 0$ with constraints, are used to measure the distance to the boundary and the parameter C gives the trade-off between the number of outliers and the volume of the hyperrsphere..

Lagranges multiplier is used to obtain dual problem :

$$min_{\alpha,} \sum_{i,j} \alpha_i \alpha_j (x_i . x_j) - \sum_i \alpha_i (x_i . x_i) \qquad (14)$$

with constraints,

$$0 \leq \alpha_i \leq C \;\; and \;\; \sum_i \alpha_i = 1 \qquad (15)$$

with constraint, solving the dual optimization problem yields Lagrange Multipliers αi .

3.3 K-Means Clustering

It is used obtain dual probllem to obtain very accurate clustering of images, by differentiating it by calculating the features extracted from the images and then try to match to values of similarity in them.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} ||x_i^{(j)} - c_j||^2 \qquad (16)$$

Where $||x_i^{(j)} - c_j||^2$ is a selected as a distance measured between a data point $x_i^{(j)}$ and the cluster center c_j, is a signal of the distance of the n different data points from their respective cluster centers.

4 Experimnetal Results

In this section we are going to demonstrate how we use all these four techniques together for image search reranking. We firstly have a collection of image data sets all of same size. Then we try to search images in database and name each images and update it in the database, besides the update it is extracting various features of the image like haar features, color extraction, wavelet, texture of the image and canny edge detection. Once a few set of images are updated we can give a text based query to search. Once we enter a query it will display images based on the entered query. Using reverse KNN technique we will click an image of user expectation. It will display images of similarity based on rank using the calculated feature extracted similarity.

Consider an example, we type query say bus, after that it will display mages of bus to the user, user will click on red bus. After clicking the images it will display images in ranking as per the best match results of red bus. But analysis of this images can be done as follows, we can display it in three different sections best match, confusion assessment and excluded images As shown in Fig. 5, we can see that images of best match are displayed graphically.

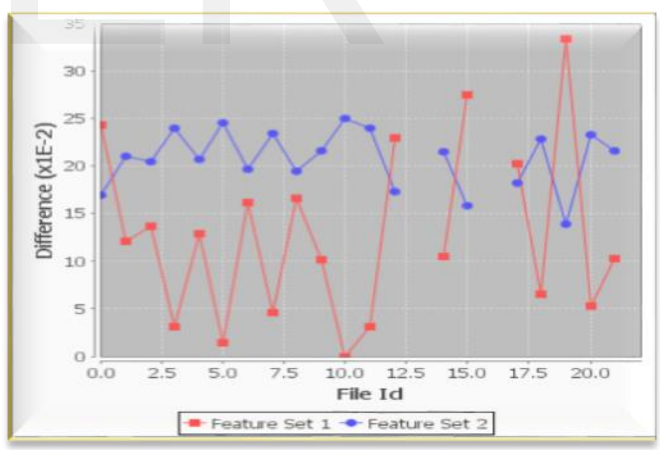

Fig 5: Best Search Result Analysis after H-Ranking

As shown in Fig. 6, confusion assessment will show images of features that matches somewhat as per the user intentions but not exact .In Fig. 7 it shows, images that are not all of any match.

Clustering of images are also shown based on their similarity which matches the various clustering levels. They check based on each individual value and then sort it accordingly.

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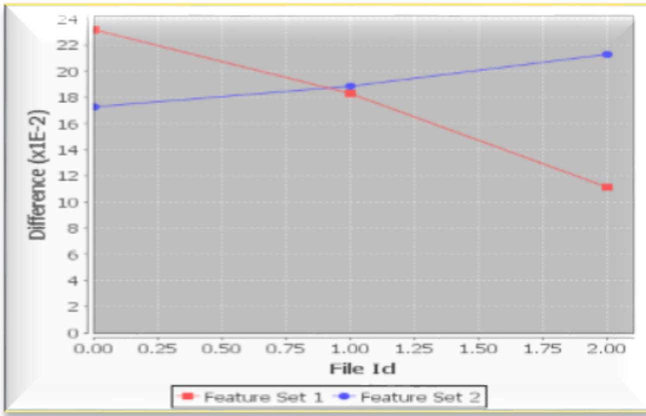

Fig 6: Confusion assessment Result of image set

We can experiment on various results by giving search based on different image size and understand the differences of feature extraction.

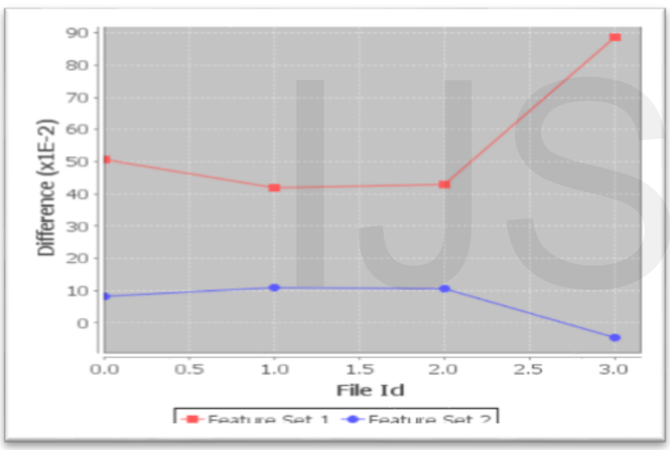

Fig 7: Excluded images that do not match user expectation

5 CONCLUSION

Image search by its visual content. It is used mainly to get a refined image search as per the satisfaction of the user using internet. Form this survey, we can understand what the different techniques that were used earlier are and what are the advantages and disadvantages of using such techniques that could refine the search image mined result. Among all the survey that was conducted, feature extraction and ranking of the images after sorting.

The future scope of the image search reranking is that we can apply it in application level by implementing it in a server which contains whole set of images and analyse the results

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REFERENCES

[1] Xinmei Tian, Dacheng Tao, Xian-Sheng Hua and Xiuqing Wu., "Active Re-ranking for Web Image Search " , IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 19, NO. 3, MARCH 2010

[2] Xiaogang Wang, Shi Qiu, Ke Liu, and Xiaoou," Web Image Re-Ranking Using Query-Specific Semantic Signatures", IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 36, NO. 4, APRIL 2014

[3] Yushi Jing, Michele Covell, David Tsai, and James M. Rehg ," Learning Query-Specific Distance Functions for Large-Scale Web Image Search," IEEE TRANSACTIONS ON MULTIMEDIA, VOL. 15, NO. 8, DECEMBER

[4] Xiaoou Tang, Ke Liu, Jingyu Cui, Fang Wen, and Xiaogang Wang," IntentSearch: Capturing User Intention for One-Click Internet Image Search," IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 34, NO. 7, JULY 2012 M.Spertta and S.Gach,"Personalizing Search Based on User Search Histories,"Proc.IEEE/WIC/ACM Int'l Conf.Web Intelligence,2005.

[5] Jun Yu, Yong Rui and Dacheng Tao," Click Prediction for Web Image Re-ranking Using Multimodal Sparse Coding", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 23, NO. 5, MAY 2014.

[6] B. Szanto, P. Pozsegovis, Z. Vamossy, Sz. Sergyan, "Sketch4Match- Content based Image Retrieval Using Sketches ",Jan. 2011

[7] Ashutosh Gupta, M. Gangadharappa.," Image Retrieval Based on Color, Shape and Texture",2015.

[8] Zhong Ji and Yanwei Pang," Relevance Preserving Projection and Ranking for Web Image Search Reranking," November 2015.

[9] M. Wang, H. Li, D. Tao, K. Lu, and X. Wu, "Multimodal graph-based reranking for Web image search," *IEEE Trans. Image Process.*, vol. 21 no. 11, pp. 4649–4661, Nov. 2012.

[10] X. Tian, L. Yang, J. Wang, X. Wu, and X.-S. Hua, "Bayesian visual reranking," *IEEE Trans. Multimedia*, vol. 13, no. 4, pp. 639–652, Aug.