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Re-Ranking of Web Image Search Using Relevance Preserving Ranking Techniques

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Abstract: **Searching images in web is become common in nowadays. An image search re-ranking is getting filtered search results as per user needs. It is achieved by mining the image's visual contents. Different techniques can be adopted for web image searching. But the current image search techniques have some deficiencies .So in order to improve re-ranking two techniques are used. They are feature extraction and ranking function design. Hyper sphere based relevance preserving algorithm is used for feature extraction. H-Rank is the ranking function used here. Reverse KNN algorithm is used for reviewing the One Click HRPP to understand exact search of user. OC-HRPP and H-Rank together form new method for image search re-ranking. A feature selection module Principle Component Analysis (PCA) is added here. It gives efficient and accurate result in less response time. So performance is improved.**

Keywords: **Feature extraction, Ranking function, Image search re-ranking, Text based image search, PCA.**

I. INTRODUCTION

Numerous search engines are available in nowadays such as Bing, google, cydral, yahoo, AltaVista, Ask etc. Lots of images are there on the internet. Image search can be fulfilled by these search engines. User express his/her need in search engines, and related images are displayed as output. For improving the search results two methods are used they are image annotation and web image search re-ranking. There are two types of image retrievals Content Based Image Retrieval (CBIR) and a Text Based Image Retrieval (TBIR).

A. Content Based Image Retrieval (CBIR)

In content based image retrieval (CBIR) we can extract the visual features, such as color, texture and shape of images and that can be extracted automatically. And detect the similarity between images by distances in the features. Implementation is easy and retrieval is fast here. Appropriate feature representation and a similarity measure for ranking pictures, given a query, are essential here. Most of the Content based image retrieval systems performs feature extraction as a preprocessing step. Figure 1, shows the procedure of CBIR. Features may include both text-based features such as key words, annotations and visual features like color, texture, shape, faces.

B. Text Based Image Retrieval (TBIR)

It is more effective in document and for image search. As shown in figure 2, input given is user's text query. These text-based queries can be formulated as free-text and it can be compared to such text descriptors as description, subjects, title and/or the text surrounding an embedded image, using the text retrieval techniques. The main problem of web image search is the mismatch between the image content and the web page text.

II. IMAGE SEARCH RERANKING

Image search re-ranking is rectification of the search results by employing visual characteristics of images to reorder the initial search results. The retrieved search result may include noisy images. It decreases efficiency of image search. So we have to rank the search results. This reordering helps to satisfy user's search experience in both accuracy and response time. The current image search re-ranking has two important steps, they are feature extraction and ranking function. It increases the image retrieval performance. This ranking function design is the main challenge in image search re-ranking. So it became an interested area of research. It can be classified into different area. That are classification based method, learning to rank based method and the graph based method. In classification based method, it first train the classifier with a training data which is get from initial search results. Then it reorders the result by the relevance scores. This methods takes the ranking as a classification problem. So the performance is poor as compared with rest techniques. In graph based methods, it implemented by a Bayesian perspective or random walk. Here re-ranking implement as random walk. Here the nodes represent the result of initial search. The stationary probability of this random walk is used for the computation of final re-ranking scores. But main limitation of this method is graph construction and ranking computation is expensive. So it limits its application to the large data sets. In learning to rank method, it utilize two popular learning to rank approaches. Here a content aware ranking model is used. By using this both textual and visual information are fetched in ranking learning process. But main limitation of this method is it require more training data to train a model, and it is not practical for re-ranking of real images.

III. RELEVANCE PRESERVING PROJECTION AND RANKING FOR WEB ISR

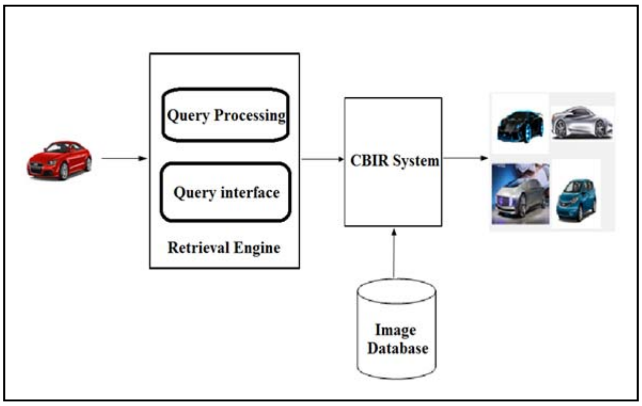

Figure 1: Content Based Image Retrieval (CBIR): search pictures as pictures.

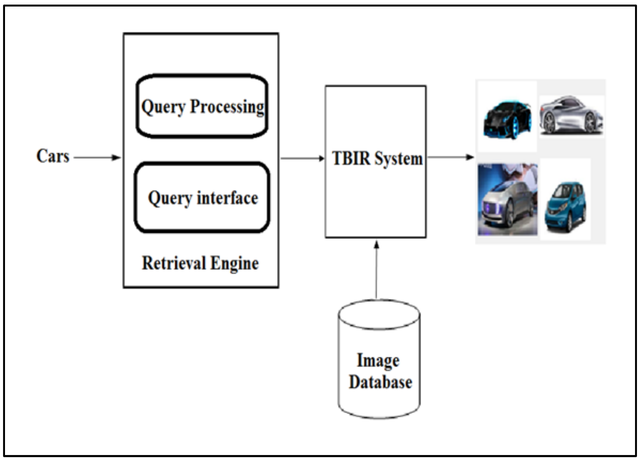

Figure 2: Text Based Image Retrieval (TBIR): search pictures as text queries.

Current image search re-ranking focus on mainly two aspects. They are feature extraction and ranking function. For image search re-ranking one of the main technique is Relevance Preserving Projection and Ranking. Here for feature extraction hyper sphere-based relevance preserving projection (HRPP) and for ranking hyper sphere based rank (H-Rank) is used. HRPP is a spectral embedding algorithm it transform an original high-dimensional feature space into an intrinsically low-dimensional hyper sphere space by preserving the relevance relationship among the images.

Ranking algorithm H-Rank is an effective ranking algorithm to sort the images by their distances to the hyper sphere center. To capture the user's intent with minimum human interaction, a reversed *k*-nearest neighbor (KNN) algorithm is proposed. It harvests enough pseudo relevant images by requiring that the user gives only one click on the initially searched images.

This HRPP method with reversed KNN is named one-click-based HRPP (OC-HRPP). The OC-HRPP algorithm and the H-Rank algorithm form a new ISR method, H-re-ranking.

IV. KEY IDEA OF RELEVANCE PRESERVING PROJECTION AND RANKING

The first step is image retrieval using the text query. Here the text query is given as the input. And the image which satisfy the query is retrieved. This retrieved result may include both the satisfactory and unsatisfactory images. The satisfactory or relevant examples match well with their queries, while unsatisfactory or irrelevant examples do not match with their queries. So this difference between different relevance degree groups may decrease the appropriate visual representations, and lowers the final ISR performance.

The next step is low level feature extraction. Here features of the retrieved result is extracted. HRPP is learns a feature embedding and it transform the original high-dimensional feature space into a low-dimensional hyper sphere space.

And the H-Rank algorithm ranks the initial searched images by calculating its distances to the hyper sphere center. We borrow the idea of hyper sphere and reorder the images with assumption that the relevant images are close to the hyper sphere center and the irrelevant images are far away from the center.

Next step is Relevant Image Selection Using KNN Algorithm. For capturing the interest of user with minimum interaction, we use a reversed KNN algorithm. So by this we obtain pseudo-relevant images by only one click by the user on the initially searched images. This HRPP method with reversed KNN is known as One-Click based HRPP (OC-HRPP).

The steps of this reversed KNN algorithm is:

1) First the user clicks on one of the relevant image which satisfies his/her interest from the initial search result. This image is then put into a relevant-image pool.

2) Then the nearest neighbor of this clicked images is chosen as a pseudo-relevant image from the top of the *N* initially searched images by the *k*-Nearest Neighbor (KNN) algorithm. And this image is also put into the relevant images pool. Now, there are two images in the pool.

3) By the minimum average distance between the images in the pool we find the next pseudo relevant image.

4) Repeat the step of 3) until the total image number in the pool reaches the predefined threshold *Tc*.

It can be observed that the most important idea in the proposed reversed KNN algorithm is Step 3), in which the image holding the minimum average distance with those in the pool is selected. Then the next step is OC HRPP Algorithm. The HRPP method with reversed KNN is known as One-Click based HRPP (OC-HRPP). It finds the low dimensional embedding of the data samples with the idea of one-classification and the spectral analysis. The input of the OCHRPP algorithm is online obtained training examples: $L=[x_1,\ldots,x_r,x_{r+1},\ldots,x_{r+h}]$ and the parameters are: reduced dimensionality d, labeled number r for the relevant examples, labeled number h for irrelevant examples. And the output is projection vectors $w=[w_1,\ldots,w_d]$ which belongs to R^{D+d} And the steps of OCHRPP algorithm is,

Step 1: compute the mean vector m as the hyper sphere center.

Step 2: compute the similarities S_{ij} between two examples with the labeled relevant data.

Step 3: Compute the matrices D,Q,P and the corresponding Laplacian matrix by L=P-Q.

Step 4: Perform the eigenvalue decomposition and construct D×d embedding matrix W.

And the next step is H-Rank algorithm. Figure 3, gives the frame work of H-Re-ranking method. It has four stages: 1) image feature extraction, 2) images labeling, 3) feature embedding with the proposed OC-HRPP algorithm, 4) image search re-ranking with the proposed H-Rank algorithm.

Here first user makes a query for his/her needs. And then it is submitted to a web image search engine. An initial search result based on the text query is returned to the user. This result is unsatisfactory because of the presence of some noisy and irrelevant images. It decreases the searching efficiency. To increase the performance of image retrieval, H-Re-ranking method can be adopted. Here first the low-level original features are extracted.

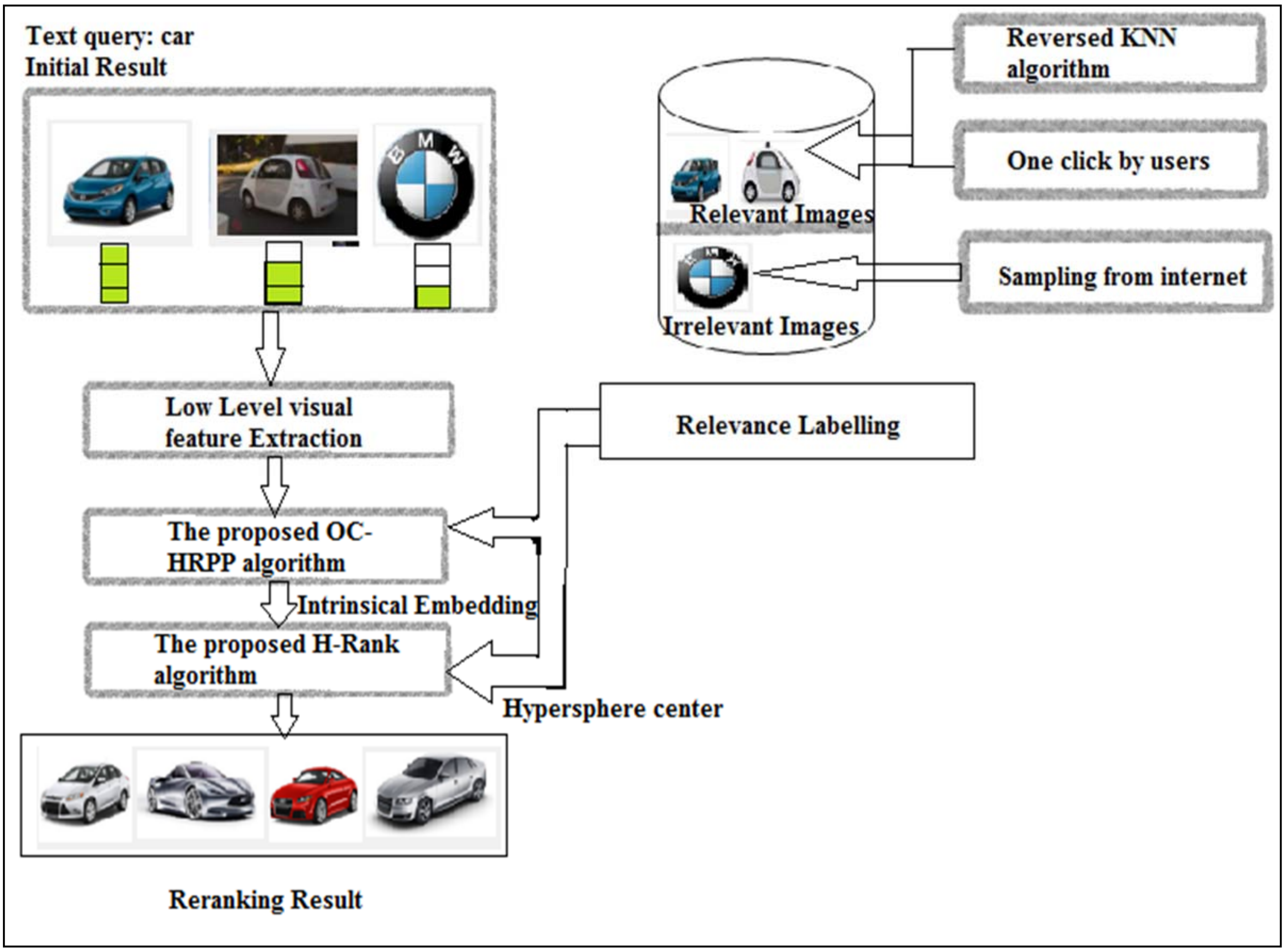

Figure 3: Framework of H-Re-ranking method

Then some of the relevant and irrelevant images are labeled. It can be done manually or automatically. It is used for the implementation of the proposed One-Click-based HRPP and H-Rank algorithm. Then the features that are intrinsically embedded, is obtained with the proposed OC-HRPP algorithm. In this algorithm the images are transformed into a hyper sphere space. At last the retrieved images are reordered with the H-Rank algorithm by calculating the distance to the hyper sphere center.

V. RECENT TECHNIQUES OF IMAGE SEARCH RERANKING

In image search re-ranking the text based search first generate the ranked list and the retrieved visual features will re-rank the initial search result. There are so many image search re-ranking techniques are available.

A. Active re-ranking for web image search

The ISR methods may fail to retrieve the user's intention when the given query term is ambiguous. So the re-ranking with user interactions, known as active re-ranking is very effective. It improves the web image search results. One of the main problem in active re-ranking is how to find the user's intention. For this structural information based sample selection strategy is used. It minimize the labeling efforts of the users. A local global discriminative dimension reduction algorithm is used to localize the wish based on the visual features of users. It transfer the local geometry and the discriminative information from the labeled images to the whole image database.

Consider the example shown in figure 4, the query is apple. An initial text based search result for apple is generated. This result is not satisfactory because of the presence of both fruit and company logo as the top results. It is because of the ambiguity of the text query. Without the involvement of user, removal of ambiguity is impossible.

In active re-ranking first pick the four images based on an active sample selection strategy. Then the user mark them according tom his/her intention. Suppose the user marks the fruit apple as relevant query and other images such as company logo as irrelevant query then fruit apple is the user’s intention.

The intention, i.e., the fruit apple, a discriminative sub manifold should be distinguish the relevant images from irrelevant images. To localize the visual characteristics of the intention of user a dimension reduction step is used. Based on the intention of user, including both the labeling information and the learned discriminative sub manifold, the re-ranking is done.

B. Web image re-ranking by bag-based

In web image re ranking by bag based approach, we propose a new bag-based re-ranking framework shown in figure 5, for large-scale TBIR. Here we first cluster the relevant images by using both textual and visual features.

Each cluster is known as bags .The images in the bag is known as "instances". This problem is a Multi-Instance (MI) learning problem. For identifying the ambiguities on the instance labels positive and negative bags are set.

GMI improve retrieval performance. For bag annotations a bag ranking method is used to rank all the bags according to the defined bag ranking score. In this optimized top ranked bags have the similar relevant images. And it is used as pseudo positive training bags, while pseudo negative bags have irrelevant queries. The positive and negative bags are clustered according o the theory of Generalized Multi called as bag based image re-ranking.

In GMI learning method of bag based framework, weak bag annotation process automatically finds the positive and negative bags for the classifiers. Firstly it , introduce an instance ranking score is defined by the similarity between the textual query and the important images. Averaging this instance ranking scores of the instances in this bag is obtain with the help of ranking score of each bag. Finally, rank all bags with the bag ranking score.

C. Web image re-ranking using query-specific semantic signatures

First user gives a query keyword, then a pool of images are retrieved based on this text query. The user select a query image from the pool, so that the remaining images are re-ranked based on their visual similarities with the query image. Procedure for web image re-ranking using query specific semantic signatures is described in figure 6.The main challenge here is that the similarities of visual features may not well similar with the semantic meanings of image. It has mainly two parts: offline part and online part. In the offline part, it finds the different semantic spaces for different keyword queries. These semantic signatures are get based on projecting the visual feature of images to the semantic spaces indicated by the query keyword. In the online part, it compare the semantic signatures which is acquired from the semantic space and images are re-ranked. The query-specific semantic signatures increases the accuracy and effectiveness of image re-ranking.

D. Click prediction for web image re-ranking hyper graph base sparse coding

Nowadays the user click information is used in image search re-ranking. It is because the clicks have been shown to more accurately describe the relevance of retrieved images to search queries. But it has a deficiency. The main problem the lack of the data clicked. Because only a small number of web images have actually been clicked by the users. So we solve this problem by predicting the image clicks.A new model multimodal hyper graph learning-based sparse coding method shown in figure 7, is used for image click prediction, and then apply the obtained click data to the re-ranking of images. Here we adopt the technique of a hyper graph to build a group of manifolds.

It explore the similarity of different features through a group of weights. A hyper graph has an edge between two vertices, a hyper edge connects a set of vertices, and it helps to conserve the smoothness of the generated sparse codes. Then we get the optimization procedure and the weights of different modalities and the sparse codes. Finally a voting strategy is there. It explains the predicted click as a binary event i.e. a click occurred or no click is occurred, from the images' corresponding sparse codes.

E. Comparison of recent image search re-ranking techniques

In active re-ranking the methodologies used are Collecting labeling information from user to obtain specified semantic space. And to localize the visual characteristics of the user intentions in space. Its advantages are It reduce user labeling efforts. And it satisfies the user's intention. It learn the user's intention more extensively and completely. Approaches used are S Info Based Sample Selection and LGD reduction Algorithm.

In web image re-ranking by bag based the methodologies used are Partition images into clusters using textual and visual features. And generalized multi instance (GMI) framework. It treats each cluster as Bag and images as instances. Its advantages are Textual and visual features are efficiently extracted. And it is effective to address the ambiguities Approaches used are MI, GMI, Weak bag Annotation, Clustering Algorithm.

In web image re-ranking using query specific semantic signatures the methodologies used are offline, learns different semantic spaces for different query keyword. At online, images re-ranked by comparing the semantic signatures obtained from semantic space specified by the query keyword. Its advantages it improve accuracy and efficiency. At online stage, efficient computational cost. At offline stage, accuracy at the cost of storage. Approaches used here are Query specific semantic signature. And Visual/textual features at online and offline stage.

In Click prediction for web image re-ranking hyper graph base sparse coding the methodologies used are MHGSC for image click prediction, re-ranking images. Hyper graph and hyper edges preserve the local smoothness of the constructed sparse codes. Optimization is performed. Voting strategies used to describe the predicted clicks. Graph based schema. Its advantages are it Optimize web image re-ranking. Improved and fast web image re-ranking. Highly satisfies the user intention. Minimize reconstruction errors. Approaches used here are MHGSC, Early and late fusion, Optimize Voting strategy.

In Relevance preserving projection and Ranking for web image search re-ranking, the methodologies used are image retrieval using text query, low level feature extraction, relevant image selection using KNN algorithm, OC-HRPP algorithm, H-rank algorithm.

Modification to this relevance preserving projection and re-ranking makes the system more perfect. Advantages of this modified system are here extraction of image's feature is most important. So we change some features to get better and accurate result. It have a feature selection module that select some of the main features. Here we are using feature selection using PCA. It gives efficient and accurate result in less response time. So performance is improved [9].

VI. ENHANCEMENT TO THE SYSTEM

The main drawback of relevance preserving projection and ranking for web image search re-ranking is execution speed depends on length of features. Here feature length is 899. So when number of images increases feature dimension is also increases. So running time increases as an effect execution speed decreases. The next problem is semantic gap directly depends on low level features.

An image search re-ranking (ISR) technique is the refinement of text-based search results by mining visual content of the images. For minimizing limitations we introduce some modifications to it. Since it relay on content based image retrieval, the extraction of image's feature is most important. So we change some of the features to get better and accurate result. Here we include a feature selection module that select some of the main features. So we introduce feature selection using PCA. It gives efficient and accurate result in less response time.

So performance is improved. After the low level feature extraction, we add feature selection using PCA. Figure 8 shows the performance improvement of both existing and enhanced technique.

VII. CONCLUSION

Image search is very common in nowadays. So searching images on web is tremendously increased. For better and effective searching experience web image search re-ranking is introduced. When a user gives a query to the system many search results are generated. But these search results are unsatisfactory. Because it may include both relevant and irrelevant images.

It decreases user search experience. So for improving search experience an image re-ranking is used. Many techniques are used for the web image search re-ranking. They are relevance preserving projection and ranking for web image search, Active re-ranking for web image search, Web image re-ranking by bag-based, Web image re-ranking using query-specific semantic signatures, Click prediction for web image re-ranking hyper graph base sparse coding. It effectively improves user search experience.

In relevance preserving re-ranking technique feature extraction and ranking function are used. The HRPP algorithm transforms the original visual features space into an intrinsically low-dimensional space. The H-Rank algorithm sorts the images with their distances to the hyper sphere center. Here it capture the user's intent by requiring that the user gives only one click on the initially searched images. It makes the H-Re-ranking method have a strong practical significance. The feature selection module Principle Component Analysis (PCA) improves the performance of the system.

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