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An Advanced Web Image Search Reranking using HRPP and Feature Selection

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ABSTRACT:Web Image Search Reranking (ISR) is a technique that aims at refining text-based search results by excavating images visualcontent. Feature extraction and the design of ranking function aretwo key steps in ISR. Current commercial search engines have taken image re-ranking for improving the web based search of images. At first the images are retrieved and displayed. This images are based on textual similarity, select one image fromthe initial result as query image and the residual images are re-ranked based on their visual resemblance with the queryimage. Here, a framework for Advanced Web Image Search Re-ranking is suggested. Relevance Labelling is an exciting procedureto advance the performance of Image Retrievalmethods even when using low-level features alone. It individually and automatically learns the different input keywords instead of manually describing a universal concept dictionary. In this way the semantic space associated to the image to be re-ranked becomes slender, because of the query keyword provided by users. Principal Component Analysis [PCA] helps to optimize the performance speed. The query-specific semantic spaces can more precisely model the images to be re-ranked, since they have omitted other potentially unbounded number of irrelevant concepts, which serves as noise and depreciate the re-ranking enactment on both accuracy and computational cost.

KEYWORDS: Feature Embedding, Image Reranking, Relevance Labelling, Image Retrieval, PCA.

I.INTRODUCTION

Web Image Searching is a technique that uses keywords as queries and surrounding textual similarities are used as source. But this method suffers from vagueness, because it is very difficult for user to describe all visual features in words. For instance, using “apple” as an input keyword, the recovered images belong to different categories. In order to solve the vagueness, content-based image retrieval [2] with relevance feedback [10] is widely used. It requires users to select multiple relevant and irrelevant image instances, from which graphic similarity metrics are cultured through online training. The images are arranged based on the visual similarities. Still, for web-scale commercial systems, user’s feedback has to be limited to the least without online training.

Feature extraction and design of ranking function are two key steps in ISR Initially searched images are distributed intrinsically in a hypersphere [1], [11], where relevant images are inside it while irrelevant images are outside it. This is in accordance with the idea of hypersphere in one-class classification in which the relevant images are target data and the irrelevant ones are outliers, A novel spectral embedding algorithm named Hypersphere-based Relevance Preserving Projection (HRPP) [11] is used. The algorithm learns a linear transformation matrix under the locality constraint on the data and relevance constraints on different relevance degree examples. Thus, HRPP algorithm transforms the original graphical feature space to an intrinsical feature space.

In this paper, a framework for Web ImageReranking is proposed. It individually and automaticallylearns the different queries instead ofmanually describing a universal model dictionary. Inthis way the semantic space related to the image to bere-ranked becomes slender, because of the inputkeyword provided by users. The query-specific semanticspaces can more precisely model the images to bere-ranked, since they have omitted other potentiallyunlimited number of irrelevant perceptions, which serveonly as noise and run down the re-rankingenactment on both accuracy and computationalcost.

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II. SYSTEM MODEL

The existing methods for Image Search Reranking [ISR] suffer from the unfaithfulness of the assumptions beneath which the text-based images search result. The resulting images contain more irrelevant images. Hence the re ranking thought arises to re rank the recovered images based on the text around the image and data of data of image and visual property of image. A number of approaches are distinguished for this re-ranking. The high ranked images are used as noisy data and an algorithm named k means algorithm is used for classification.Most of the feature extraction methods for ISR treat the initially searched images equally, which is not appropriate since these images usually have two or more than two relevance degrees, e.g., relevant, fair and irrelevant. Generally, image groups with different relevance degree have distinct properties. Ignorance of the difference between different relevance degree groups cannot ensure the appropriate visual representations, and degrades the final ISR performance.

An Advanced Web image Search Reranking Method is proposed, that uses a feature selection technique to reduce the dimensionality of the image feature space. The target of Advanced Web Image Search Reranking is to retrieve images relevant to a query of a user. Here Text Based (Tag Based) Image Retrieval [TBIR] is used along with feature extraction methods. The Framework of the Proposed System is shown in fig.1.

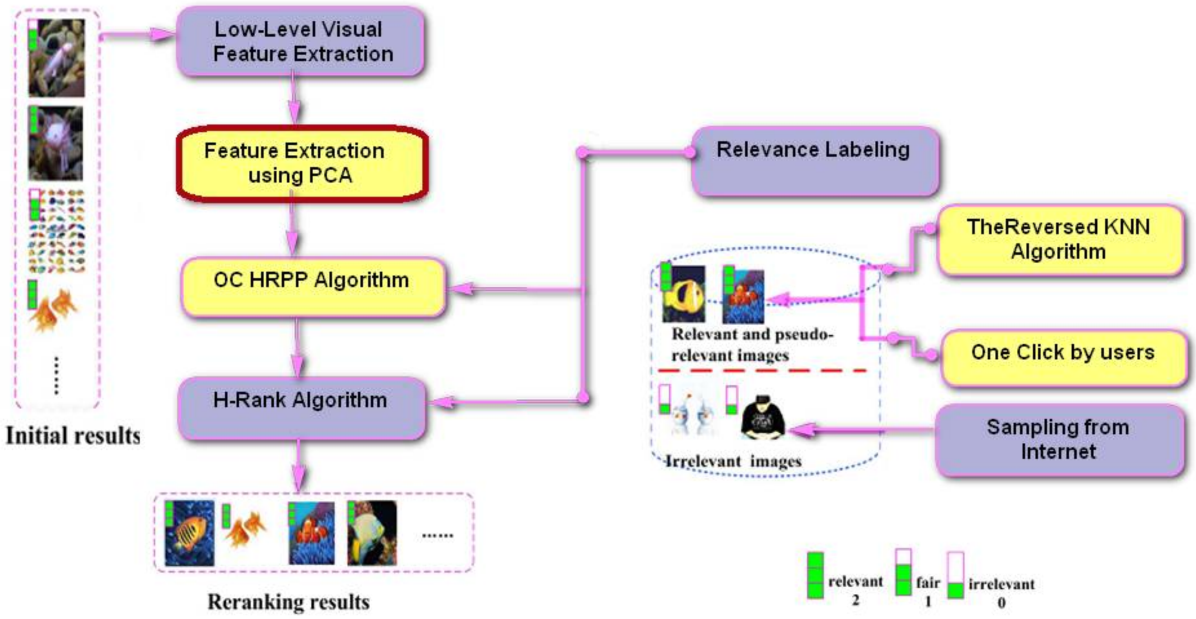

Fig.1 Framework of the Proposed System

At first, a textual keyword is given as the input query. A group of images are displayed if the text matches with any of the associated tags of the dataset. Take the query 'fish' for example, when it is submitted to a web image browser, an initial text-based quest result is returned to the user (only some top images are given for illustration). The result is insufficient because some blaring images are recovered as top results. Among those images, select any one of the image, that image is used for KNN algorithm to find the k-relevant images. That k- images are used to project all images to a hyperplane. To improve the retrieval performance, the proposed H-Reranking method is adopted. Original low-level features are first mined to characterize their visual contents. Then PCA is used for feature extraction. This helps to minimize the time required to get the results. And then, some relevant and irrelevant images are labeled manually or automatically for the implementation of OC-HRPP and H-Rank algorithm. H-ranking is used to rank all images in the hypersphere according to their distances from the center of the hypersphere.

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TEXT BASED IMAGE RETRIEVAL [TBIR]

An image retrieval system is a computer system for browsing, searching and retrieving images from a huge database. Most traditional and common means of image retrieval utilize some method of giving metadata like captioning, or descriptions towards the images so that retrieval can be achieved over the annotation words. TBIR is the image retrieval method used in this thesis. In Text Based (Tag Based) Image Retrieval, each image is annotated with a textual description [Tag] and their retrieval is based on matching the user's textual query to the annotation of the image. Text based means, when the user give an input textual query, it looking for the tag that the user entered as a search query in the database. It looks the similar tag that has been attached with the image and retrieves the image to the operator. It didn't scrutinize the content of the image; it only checks the tag in the image.

THE HRPP AND REVERSED KNN ALGORITHMS

A spectral analysis algorithm, HRPP (Hypersphere-based Relevance Preserving Projection), which finds a low dimensional embedding of the data examples with the idea of one-classification and spectral analysis. And then, a simple but effective ranking algorithm named H-Rank (Hypersphere- Ranking) to order the data examples according to their relevance to the query. Finally, a web Image Search Reranking framework is used with algorithms of HRPP and H-Rank.

The HRPP Algorithm

Given a textual query q, let X = $[x_1; :::; x_n]$ ε $R^{D \times n}$ be the set of initial search result, where D is the original feature dimensionality, n is the total example number. Let L =$[x_1; :::; x_r; x_{r+1}; :::; ::;x_{r+h}]$ be the labeled set from X, where r is the labeled number of the relevant examples, h is the labeled number of irrelevant examples. Using the labeled data, the aim of our proposed HRPP algorithm is to find an embedding matrix W = $[w_1; :::;w_d]$ ε $R^{D \times d}$ that maps X = $[x_1; :::; x_n]$ ε $R^{D \times n}$ to low-dimensional compact vectors Y = $[y_1; :::; y_n]$ ε $R^{d \times n}$ (d « D) as well as keeping the intrinsical hypersphere distribution. The transformation process can be implemented by Y = W^TX, whose one-dimensional case is $y_i = w^Tx_i$.

Relevant examples are clustered together from two aspects. One is that the relevant examples should be close to the hypersphere center, which represents the users search intention. We use the mean vector m of the labeled relevant examples as the hypersphere center for simplicity, i.e.:

$$\mathbf{m} = \frac{1}{r}\sum_{i=1}^{r}\mathbf{y}_i = \frac{1}{r}\mathbf{w}^T\sum_{i=1}^{r}\mathbf{x}_i.$$

The objective function can be written as:

$$J_R = \min_{\mathbf{w}} \sum_{i=1}^{r} \|\mathbf{y}_i - \mathbf{m}\|^2.$$

The other one is that the relevant examples should be as close as possible and preserve the local information. The widely used Graph Laplacian regularizer can be employed, which is defined as:

$$J_W = \min_{\mathbf{w}} \sum_{i,j=1}^{r} S_{ij} \|\mathbf{y}_i - \mathbf{y}_j\|^2$$

where

$$\mathbf{S}_{ij} = e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}}$$

S_{ij} measures the similarities between x_i and x_j, and σ is a scaling parameter. To keep the irrelevant examples away, the objective function is defined as:

$$J_I = \max_{\mathbf{w}} \sum_{i=r+1}^{r+h} \|\mathbf{y}_i - \mathbf{m}\|^2$$

The final objective function of HRPP algorithm by maximizing the following expression:

$$J = J_I - J_R - J_W.$$

with constraint $\mathbf{w}^T\mathbf{w} = 1$

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The objective function J can be reduced to:

$$\begin{aligned} J &= YPY^T - YQY^T \\ &= YLY^T \end{aligned}$$

where

$$Q_{ii} = \begin{cases} 1+2D_{ii} & 1<i<r \\ 1 & r+1 \le i \le r+h \end{cases}$$

$$D_{ii} = \sum_{j=1}^{r} S_{ij}$$

and L = P-Q is a Laplacian matrix.

Therefore, the solution for the HRPP algorithm can be represented as follows:

$$\begin{cases} \max_{w} \; w^T XLX^T w \\ \text{s.t.} \; w^T w = 1. \end{cases}$$

By introducing the Lagrangian multiplier, HRPP algorithm can be solved by the following generalized eigen-decomposition:

$$XLX^T w_i = \lambda_i \; w_i$$

wherew_i is the generalized eigenvector of XLX^T and $\lambda_i$is the corresponding eigenvalue. Let the column vectors $w_{1......}w_d$ be the solutions of the algorithm can be well-arranged according to the first d largest eigenvalues. The embedding matrix can be expressed as:

$$x_i \to y_i = W^T \; x_i \; , W = [w_1, \ldots, w_d]$$

wherey_i is a d - dimensional vector and W is a D x d embedding matrix.

The main procedure of the HRPP Algorithm:
Step 1: Compute the mean vector m as the hypersphere center.
Step 2: Compute the similarities S_{ij}between two examples with the labeled relevant data.
Step 3: Compute the matrices D, P, Q and the resultant Laplacian matrix, L = P-Q.
Step 4: Perform the eigenvalue decomposition and construct D x d embedding matrix W.

THE REVERSED KNN ALGORITHM AND ONE-CLICK BASED HRPP (OC-HRPP)

A reversed KNN algorithm is used to obtain adequate pseudo-relevant images by necessitating that the user gives only one click on the initially searched images. The HRPP method combined with reversed KNN algorithm is called One-Click based HRPP (OC-HRPP).The steps of the reversed KNN algorithm are as follows:

1. The user clicks one relevant image that satisfies his/her intent from the initially searched results. This image is then put into a relevant-image pool.
2. The nearest neighbor of the clicked images from the top N initially searched images is chosen as a pseudo-relevant image by the k-Nearest Neighbor (KNN) algorithm, and this image is also plow into the relevant images pool. At present, there are two images in the pool.
3. Find the next pseudo-relevant image by calculating the least average distance between the images in that pool and the remained top N initially searched images.
4. Repeat the stage of (3) until the total image number in the pool extents the predefined threshold Tc.

Stage 3 is the most important stage in the reversed KNN algorithm, in which the image holding the minimum average distance with those in the pool is selected. This one do not select the k nearest neighbors with the clicked one. The idea behind it is that each selected image in the pool is regarded as an “expert”, and only those candidates acknowledged by all the experts can be well-thought-out to be relevant. Thus, it is a reversed process for KNN. Moreover, pseudo-

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relevant images are only chosen from the top N initially searched images. In this way, the quality of pseudo-relevant images in the pool can be guaranteed to a large extent. Therefore, enough relevant images can be harvested by only one-click, which makes the OC-HRPP algorithm quite important.

H-RANK ALGORITHM

After feature embedding, the transformed features are assumed to be distributed in a hypersphere space, where the relevant examples lie inside the hypersphere while the irrelevant examples lie outside the hypersphere. Thus, it is reasonable to consider that the examples near to the hypersphere center are more relevant to those far from it. Therefore, data can be ranked by their distances to the center, as shown in fig. 2.

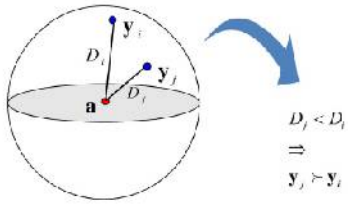

Fig. 2 Data ranking by their Distances.

In the H-Rank algorithm, Euclidean distance is adopted. Thus the distance is defined as:

$$D_i = \|\mathbf{y}_i - \mathbf{a}\| = \left\|\mathbf{W}^T\mathbf{x}_i - \mathbf{a}\right\|, \quad i = 1, \ldots, n.$$

where a is the hypersphere center in the transformed feature space. The smaller D_i is, the higher position x_i should be ranked in. In this way, the examples are ranked without the complex training stage or heavy computational burden. Specifically, the hypersphere center a is obtained with the method of Support Vector Data Description (SVDD).

$$\mathbf{a} = \sum_{i=1}^{r} \alpha_i \mathbf{y}_i$$

with the constraints $0 \leq \alpha_i \leq C$ $\quad \sum_i \alpha_i = 1.$

FEATURE EXTRACTION USING PRINCIPAL COMPONENT ANALYSIS [PCA]

Feature extraction is a distinguishing method of dimensionality reduction and enfolds more information about the original image. The input query which is to be treated is transformed into a concentrated description set of features. This efficiently represents interesting portions of an image as a solid feature vector. This tactic is useful when image sizes are bulky and a reduced feature illustration is necessary to quickly complete tasks such as image matching and retrieval. Principal Component Analysis is used as a dimensionality reduction technique in which a covariance enquiry between factors takes place. The original data is replotted into a new coordinate system centered on the variance contained by the data. PCA put on a mathematical system for changing a number of correlated variables into a lesser amount of uncorrelated variables called principal Components. As much of the variability in the data is promising with the first PCA, and each succeeding component accounts for as much of the lasting variability as possible. PCA is useful when there is data on a large amount of variables, and if there is some redundancy among those variables. Redundancy means that some of the variables are interconnected with one another. Due to this redundancy, PCA can be used to reduce the observed variables into a concentrated number of principal components for most of the variance in the observed variables.

Steps involved in PCA

The PCA algorithm consists of the following main steps:

1) Transform an N x d matrix X into an N x m matrix Y
2) Mean value of the dataset is calculated

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3) Centralize the data [Subtract the mean from the dataset in all the n- dimensions]. From these values a new matrix is obtained
4) Calculate the d x d Covariance matrix of this mean-subtracted dataset

$$C = \frac{1}{N-1} X^T X$$

$$C_{i,j} = \frac{1}{N-1} \sum_{q=1}^{N} X_{q,i} \cdot X_{q,j}$$

$C_{i,i}$ (diagonal) - variance of variable i
$C_{i,j}$(off - diagonal) - covariance between variables i and j.

5) Eigen values of the dataset is calculated.
6) Using the Eigen values compute the Eigen vectors of the Covariance matrix of the dataset
7) Forming a feature vector by choosing the Eigen vectors having the largest Eigen values. These are the Principal Components of the Dataset

III.RESULT AND DISCUSSION

At first a Database is prepared. NUS-WIDE Dataset is used to prepare the database. The database contains ‘All Images’ and ‘Tag All’. ‘All Images’ consist of the image names and their respective tags are given under ‘Tag All’. When we give a name in that Tag, it will display all those pictures that matches the tag name. Each image is associated with a numerical value, for each value, some textual descriptions are given in the database. The textual descriptions are stored under ‘TagAll’.To search an image from, the web, first give an input text word as the query. Giving an input keyword is shown in fig.5.

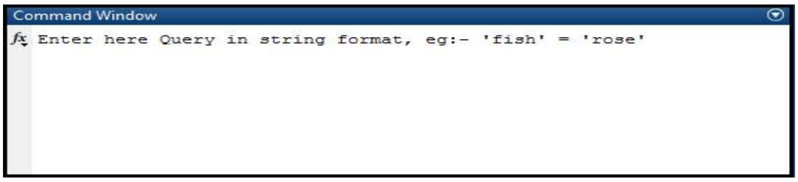

Fig.5 Input Query

When an input keyword is given as the query, an initial set of images are displayed as the search result. Initial search result consists of all those images whose tags matches with the input query. The Initial result when we give 'rose' as the input word is shown in the Fig.6.4.When we give an input text word, we get an initial set of images as the search result. Among the initial result, search any one of the image for Reranking purpose. Selection of image is shown in fig.6.

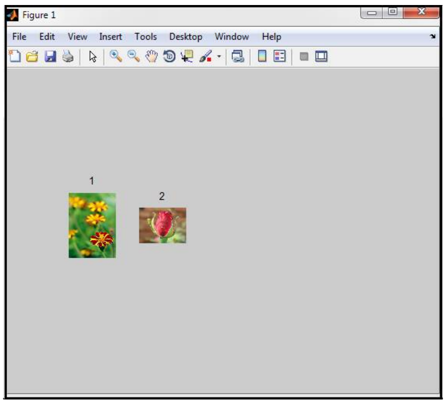

Fig.6 Initial Result

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When we give an input text word, we get an initial set of images as the search result. Among the initial result, search any one of the image for reranking purpose. Selection of image is shown in Fig.7.

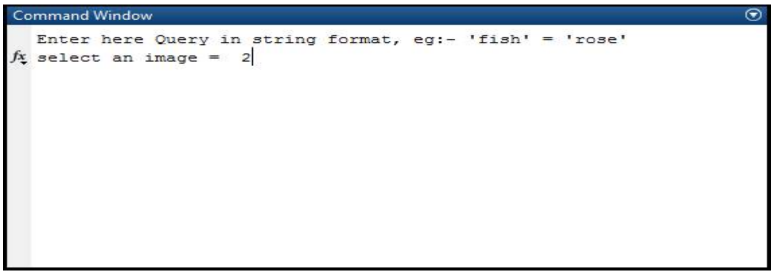

Fig.7. Image Selection

Selected image is used for reranking .The image that is more relevant with the input keyword is displayed first. The final result is shown in fig.8

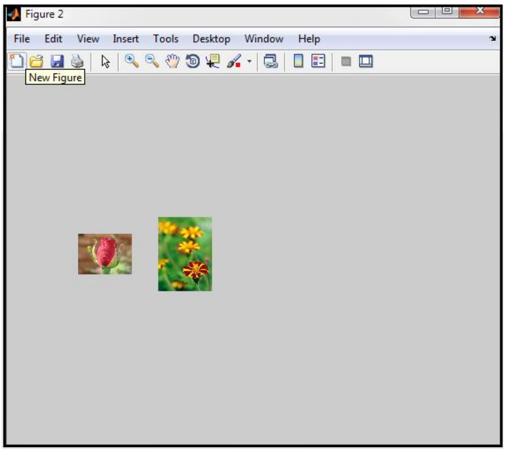

Fig. 8. Final Result

Speed optimization is possible with the present work. It gives better searching and takes only a little time for Reranking of images. Also it helps to reduce the semantic gap in between the input query and the obtained results. A Comparison between the Existing Method and Present Work while taking 'rose' as input query is shown in the graph in Fig.9.

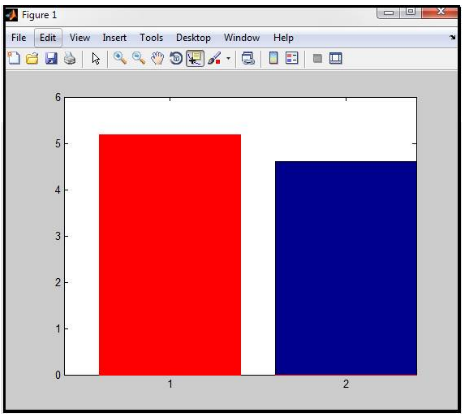

Figure 6.9: A Comparison between Existing Method and Present Work

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The graph plotted shows that the Present Work have high efficiency and it requires minimum Computational time. This shows the efficiency of the proposed Work. The proposed work needs minimum computational time and the results are more accurate.

IV.CONCLUSION

Based on the hypersphere idea in one-class classification, the feature extraction and ranking function problems in image searchreranking have been addressed in this work. Specifically, the HRPP algorithm transforms the original visual features space into an innately low-dimensional space by conserving the manifold structure and relevance relationship among the images. The H-Rank algorithm sorts the images with their distances to the hypersphere center .Moreover, a novel interactive method is used to capture the user's intent by demanding that the user provides only one click on the initially searched images, which makes the proposed Web Image Reranking method, a method having strong practical significance. PCA is used to lessen the number of features used to signify data. The benefits of this dimensionality reduction provides a simpler demonstration of the data, reduction in memory, and faster classification .Speed optimization and better efficiency is possible with present work.

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BIOGRAPHY

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