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Scalable Image Search Re-ranking through Content Based Image Retrieval (CBIR) Method

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Abstract: There are number of ways for searching images through popular search engines like Google, Yahoo, Bing etc..,. The latest survey in the Data Mining proves that there is a vast increase in the percentage, in searching the images related to the text, while surfing the Internet for the personal, educational and professional as well. The perpetual and former ways for searching the images from the net and Re-ranking endure from the unreliable ranking assumptions than the initial text based image search results that are used within the remote Re-ranking methods. This paper is designed mainly to focus and to propose a prototype based Re-ranking technique to deal the drawback of text based image searching in a scalable fashion. Validation aspects like Energy, Entropy, Contrast, Homogeneity, shape, color, skew and Euclidean distance measures are considered. K-Means clustering, SVM classifier and Re-ranking algorithmic technique are used to get the efficient prototype based scalable result. The experimental results on a representative internet image search dataset comprising of 350 queries demonstrate that the projected technique outperforms the present supervised and unsupervised Re-ranking approaches. Moreover, it improves the performance and precision over the text based image searching by twenty-five percent.

***Keywords*:** Data Mining, Re-ranking, Meta Re-rankers, Clustering, Visual Reranking

1. INTRODUCTION

The obtainable Web Image Search engines [1] (Google, Bing and Yahoo) retrieve and rank images based on textual information. To improve the precision of the text-based image search ranking, Visual Reranking[2] is used. The main motivation for this paper is to make the Web Search easier and to display the Relevant Images. To make the retrieval process to be Smarter and Faster. To improve the precision over the text based image search Reranking. To produce quality dataset. Based on the images the initial result visual prototypes [3] are generated. Each of the prototypes is used to construct a Metareranker to produce a reranking score. Scores from all Metarerankers are aggregated to produce the final relevance score to define its position in the reranked result list. The existing methods for image search reranking suffer from the unreliability of the assumptions.

2. RELATED WORK

The explosion [4] of the Internet provides us with a tremendous resource of images shared online. It also confront vision scientists the problem of finding effective methods to navigate the vast amount of visual information. Semantic image understanding plays a vital role towards solving this problem. One important task in image understanding is object recognition, in particular, generic object categorization. Critical to this problem are the issues of learning and preparing datasets. Abundant data helps to train a robust recognition system, while a good object classifier can help to collect a large amount of images.

Visual search reranking [5] aims to improve the text-based image search with the help from visual content analysis has rapidly grown into a hot research topic. The interestingness of the topic stems mainly from the fact that the search reranking is an unsupervised process and therefore has the potential to scale better than its main alternative, namely

the search based on offline-learned semantic concepts. However, the unsupervised nature of the reranking paradigm also makes it suffer from problems, the main of which can be identified as the difficulty to optimally determine the role of visual modality over different application scenarios. Image search engines apparently provide an effortless route, but currently are limited by poor precision of the returned images. It is an offline approach and restriction on number of Images to download. A multimodal [6] approach employing text, metadata, and visual features is used to gather many high-quality images. The task is then to remove irrelevant images and re-rank the remainder. First, the images are re-ranked based on the text surrounding the image and metadata features. Second, the top-ranked images are used as training data and an SVM visual classifier is learned to improve the ranking further. Each of the prototypes is used to construct a Meta reranker to produce a Reranking score.

3. IMPLEMENTATION

3.1 Query Image: Image, which is a query string, is provided as a text to the search engine. Search engine displays all the corresponding images along with uncategorized images. Image clusters for each text given are formed. The clusters are partitioned into positive and negative for the class. Clusters are used as exemplars to train a classifier based on Visual (shape, color and texture) features.

3.2 Download Associate Images: When query word is submitted to the web search, then all the images [7] linked with are downloaded. Each returned image is treated as a "seed", further images are downloaded from the webpage where the seed image originated. The query word is restricted to a single word like "cat" or specific descriptions like "cat animal".

3.3 Filtering Process: The Drawing and Symbolic images are filtered by applying text [8] and vision features. Filtering is used to train the visual classifier to remove or filter the symbolic and drawing Images during the ranking process.

SVM(Support Vector Machine) [9] Classifier is used to classify the images based on the features. Algorithm for SVM Classifier is:

candidateSV = { closest pair from opposite classes }
while there are violating points do
Find a violator
candidateSV = candidateSV U violator
if any $\alpha p < 0$ due to addition of c to S then
candidateSV = candidateSV \ p
repeat till all such points are pruned
end if end while

3.4 Re-Ranking Process: After downloading the Images, the goal is to re rank the retrieved images. Re-ranking [10][11] of returned images is based on text and metadata. HSV (Hue, Saturation and Value) plane is considered for content based image retrieval (CBIR). Contextual re-ranking algorithm is applied to get the relevant images. Color is the most used features in content based image retrieval. This color space is suitable since it reflects human perception and identification of image. A Re-Ranking algorithm that uses Image Processing techniques [12][13] to analyze contextual information.

$t \leftarrow 0, A_t \leftarrow A$
while $t > T$ do initialize Affinity Matrix(W, 1)
for all $img_i \in C$ do
for all $img_j \in$ KNN(img_i) do (K-Nearest Neighbor)
grayImg $\leftarrow$ createGrayScaleImage (img_i, img_j ,A_t, L)
grayImg' $\leftarrow$ processGrayScaleImage (grayImg, L)
W $\leftarrow$ incrementaAffinityMatrix(grayImg', W, j)
end for end for
$A_{t+1} \leftarrow$ computeDistanceMatrix(W)
t = t + 1, performReRanking(A_t)
end while

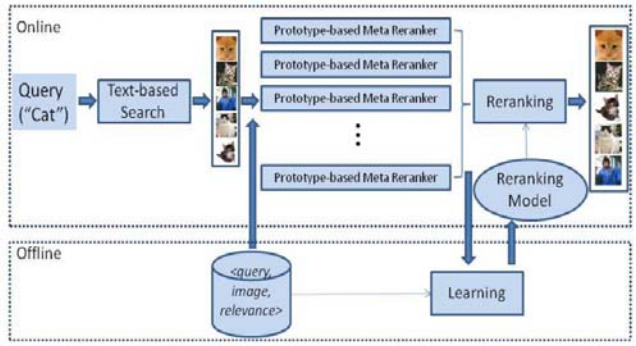

Fig 1: Re-Ranking Illustration

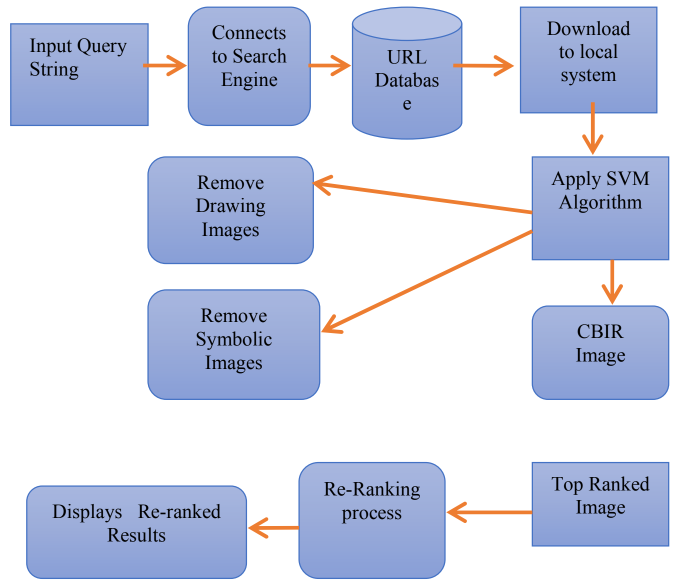

Fig 2: System Architecture

4. VALIDATION ASPECTS/PARAMETERS:

Validation parameters to be considered for Re-Ranking [14] [15] the images and to get the better visual prototypes of images are listed below:

4.1 Energy: Energy [16] measures the homogeneousness of the image and can be calculated from the normalized Co-Occurrence Matrix (COM). It is a suitable measure for detection of disorder in texture image.

$$J = \sum_{i=1} \sum_{j=1} (p(i,j))^2$$

4.2 Entropy: Entropy [16] gives a measure of complexity of the image. Complex textures tend to have higher entropy Where**,** p(i , j) is the Co-Occurrence Matrix.

$$S = -\sum_{i=1} \sum_{j=1} p(i,j) \log(p(i,j))$$

4.3 Contrast: Measures [16] the local variations and texture of shadow depth in the Gray Level Co-Occurrence Matrix (GLCM).

$$I = \sum\sum(x-y)^2 p(x,y)$$

4.4 Homogeneity: Measures [16] the closeness of the distribution of elements in the Gray Level Co-Occurrence Matrix (GLCM) to the Gray Level Co-Occurrence Matrix (GLCM) diagonal.

$$H = sum(sum(p(x , y)/(1 + [x-y])))$$

4.5 Skew: Skewness is a measure of the asymmetry of the Probability Density Function (PDF). The lines that are neither parallel nor intersecting are called Skew lines.

$$Skew= (\mu - \acute{\upsilon})/ \sigma$$

4.6 Color Retrieval: Color retrieval system [17] works in two stages. In the first stage, Histogram based comparison is done and matching images are short listed. In the second stage, the Color Coherence Vectors of the short-listed images are used to refine the results.

Algorithm for Color Retrieval:

- Read the image f(x,y)
- Convert from RGB (Red, Green, Blue) to HSV (Hue, Saturation, Value)
- Find HSV histogram and create vectors v1.
- Read the vectors from database and compare one by one by one with vector v1.
- Shortlist all the images which fall within the threshold.
- Find coherency of the query image for each color and create coherency vector c1.
- Compare coherency vectors of all the short-listed images.
- Store all matching images in results folder.

4.7 Shape Retrieval: The proposed shape [17] retrieval system based on the automatic segmentations process to get approximate information about the shape of an object. It begins by segmenting the image into classes depending on their brightness. Mass, Centroid and Dispersion for each class are calculated and stored as the shape vector. For retrieval, the vectors of the query image and database images are compared and the most matching images are short listed as results.

Algorithm for shape Retrieval

- Read the image
- Convert it from RGB to grayscale
- Determine the range and number of classes.
- Calculate the number of pixels
- Calculate the centroid and dispersion for each class.
- Compare that class's mass and dispersion with respective class.
- Increase the count if it satisfies certain threshold.
- Consider second class and repeat steps 6-8 till all classes.
- Take another image from the database and repeat the comparison.
- Display the images with maximum count.

4.8 Euclidean Distance/ Similarity Measure: Euclidean distance measures the similarity between two different feature vectors using the formula

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

4.9 Similarity Measure:

Algorithm for Similarity Measure:

If I is the database [17] image and I is the query image, then the similarity measure is computed as follows,

- Calculate histogram vector v = [v1, v2, ….vn] and Co-Concurrency Vector (CCV) vector c = [c1, c2, ….cn] of the database images.
- Calculate the vectors ‘v’ and ‘c’ for the query image
- The Euclidean distance between two feature vectors can then be used as the similarity measurement.
- If $d \leq \tau$ (threshold) then the images match.
- From all the matching images, we display top 20 images as a result.

5. EVALUATION RESULTS:

Experimental result shows the comparison of Text-based and Prototype-based with Content Based Image retrieval system. Performance increases with Prototype based image retrieval system rather than Text based image system. Prototype and Text based together also yields good results.

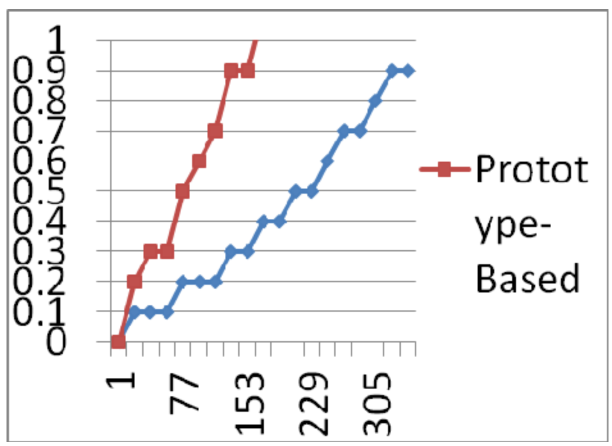

Chart 1: Performance comparison of Text-Based and Prototype-Based Image Retrieval

Methods	MAP
Text- Baseline	0.569 (4.39%)
Prototype-set	0.703 (23.60%)
Prototype-set+ text	0.714 (25.48%)

Table 1: Percentage improvement

6. CONCLUSION & FUTURE ENHANCEMENTS:

A prototype-based Re-ranking framework, which constructs Meta-Re-ranker corresponding to visual prototypes representing the textual query and learns the weights of a linear Re-ranking model to combine the results of individual Meta Re-rankers and produce the Re-ranking score of a given image taken from the initial text-based search result. It improves the performance by 25.48% over the text-based search result by combining Content Based Image Retrieval (CBIR), visual prototypes and textual ranking features.

We could further speed up the *Prototype-Set* method variant while decreasing the precision degradation by utilizing the online learning algorithms. Next is to automatically estimate the query-relative reliability and accuracy of each Meta-ranker and then incorporate it into the Re-ranking model.

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