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RERANKING IMAGE RETRIVAL USING ATTRIBUTE FEATURES

Soumya Hooli
PG Scholar Department of Computer Science and Engg
B.L.D.E.A CET, Vijayapura, Karnataka, India

M. S. Shirdhonkar
Department of Computer Science and Engg
B.L.D.E.A CET, Vijayapura, Karnataka, India

Abstract— **Reranking of image retrieval is an effective approach to overcome from text-based image search from huge image database. In this paper, we used attribute-assisted hypergraph learning, image features and attribute features. We can retrieve the image textual information using hypergraph; images will be searched from of low-level visual features for each image. An attribute feature consisting of the predefined classifiers for an image there will be Hue Saturation Values (HSV). We have conducted experiments on different query images, from different datasets. The results demonstrate the effectiveness of our approach.**

Keywords— **Text-based image searching, Reranking Image Retrieving, Hypergraph, Hue Saturation Value.**

I. INTRODUCTION

From the last decade, in our day-to-day life internet is accessible to more and more people. In image search reranking, to progress the result in an efficient way for web based image search there are many commercial search machine such as Google, Yahoo and Bing have worked on matching textual information of the images against text queries given by users. A user provide a query keyword, e.g., “Flower”, then the searching tool returns corresponding images by processing the associated textual information, e.g., file name, surrounding text, URL, etc. But in the old search engines, i.e., text based image retrieval has difficulties that are caused mainly by the “incapability” of the associated text to appropriately describe the image content.

As we know how to search the image in the hard disk, files and in folders, by typing the name of file or folder we may get the image. But it is hard to find the image in folders by image search. Because the image will be having set of features, by which we distinguish the differences between the images. The attributes of the image like size, shape, color, pixels, texture etc. The existing visual reranking methods can be typically categorized into three categories as the clustering, classification and graph based methods. In clustering method we used mean-shift, K-means, and K-medoids, for initial search results from text-based retrieval can be grouped by visual characteristics. In classification based methods, to select training image classifier or a ranking model Pseudo Relevance Feedback (PRF) is applied [1]. In graph based methods have been proposed recently and received increasing attention to be effective. The multimedia entities in top ranks and their visual relationship can be represented as a collection of nodes and edges. To improve the effectiveness of rank lists, using graph analysis are very powerful for discovering the local patterns or salient features. Semantic attributes have received attention recently effectiveness in broad applications, including face verification, object recognition fine-grained visual categorization, classification with humans-in-the-loop and image search. Semantic attribute could also be viewed a description of image data.

In content-based image retrieval (CBIR) visual information instead of keywords is used to search images in large image databases. Typically in a CBIR system a query image is provided by the user and the closest images are returned according to a decision rule. In a hypergraph a set of vertices is defined as a weighted hyperedge; the magnitude of the hyperedge weight indicates to what extent the vertices in a hyperedge belong to the same cluster. Based on the returned images, both visual features and attribute features are extracted. In particular, the attribute feature of each image consists of the responses from the binary classifiers for all the attributes. These classifiers are learned offline. Visual representation and semantic description are simultaneously exploited in a unified model called hypergraph.

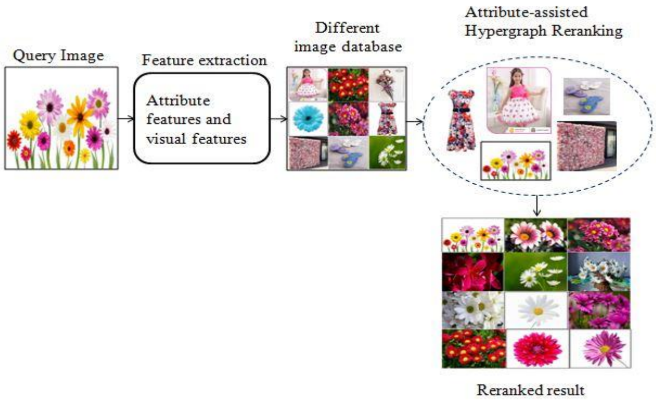

Fig 1: System Architecture an Attribute Assisted Re-ranking model.

From the Fig 1 illustrates the system architecture of our proposed method. After a query image "flower" is submitted, an initial result is obtained via a text-based search engine. It is observed that text-based search often returns "inconsistent" results. Some visually similar images are scattered in the result while other irrelevant results are filled between them, such as "dress" and "umbrella". Based on the returned images, both visual features and attribute features are extracted. The attribute feature of each image consists of the responses from the binary classifiers for all the attributes. These classifiers are learned offline. Visual representation and semantic description are simultaneously exploited in a unified model called hypergraph [1]. The preliminary version of this work, which integrates attribute feature and visual feature to improve the reranking performance [2]. Through the process of hypergraph learning the selection of attribute features could be conducted simultaneously such that the effects of semantic attributes could be further tapped and incorporated in the reranking framework. Comparing with the previous method, a hypergraph is reconstructed to model the relationship of all the images, in which each vertex denotes an image and a hyperedge represents an attribute and a hyperedge connects to multiple vertices. We define the weight of each edge based on the visual and attribute similarities of images which belongs to the edge. The relevance scores of images are learned based on the hypergraph. Recently Haralick Texture Feature is used to calculate the pixel with the intensity, Gray Level Co-occurrence Matrix (GLCM) a statistical method for examining texture features that consider the spatial relationship of pixels, also known as Gray Level Spatial Dependence.

The main contribution of this paper is:

1) To find out the new difficulties in image retrieving by using different feature methods.
2) To improve the time efficiency of image retrieval and the performance of the image searching practically on hypergraph.
3) To improve the image retrieval performance of an attribute-assisted reranking model for image search.

The rest of the paper is organized as follows. Literature survey in section II. Proposed method for an attribute-assisted reranking model in section III. Experimental results are presented in section IV. Concluding remarks are given in section V.

II. LITERATURE SURVEY:

A. Web Image Search Reranking: Y. Huang et. al [3]. To achieve the optimal rank list by exploiting visual content, here the basic functionality is to reorder the retrieved multimedia entities. The most common relevant results are moved to the top of the result list while the less relevant ones are reordered to the lower ranks. According to the statistical analysis model used, the existing reranking approaches are categorized into three categories including the clustering based, classification based and graph based methods.

a) Clustering-based methods: It is very useful method to estimate the inter-entity similarity. One good example of clustering based reranking algorithms is the Information Bottle based scheme developed by Hsu et al [4]. Here in this method, the initial result of the images are primarily grouped into some set of clusters. Then the re-ranked result list is created initially by ordering the clusters according to the cluster conditional probability and next by ordering the samples within a cluster based on their cluster membership value.

b) Classification-based methods: In this method, visual reranking is formulated as binary classification problem aiming to identify whether each image search result list is relevant or irrelevant images. For instance, a classifier or a ranking model is learned with the pseudo relevance feedback (PRF) [5].

c) Graph-based methods: These methods have been proposed recently and received increased attention and it is effective. Jing and Baluja proposed a Visual Rank framework to efficient model similarity of Google image search results with graph [6]. The framework casts the reranking problem as random walk on an affinity graph and reorders images according to the visual similarities. The final result list is generated via sorting the images based on graph nodes' weights. In [7], Tian et al. presented a Bayesian reranking framework formulating the reranking process as an energy minimization problem.

B. Semantic Attributes: Y. Su et al. [8] Semantic attributes can be regarded as a set of mid-level semantic preserving concepts. Different from low-level visual features, each attribute has an explicit semantic meaning, Due to the advantages of being semantic aware and easier to model, attributes have been studied recently and are revealing their power in various applications such as object recognition and image/video search. Thus, attributes are expected to narrow down the semantic gap between low-level visual features and high-level semantic meanings. By using attribute classifiers, he proposes to alleviate the semantic gap between visual words and high level concept, focusing on polysemy phenomenon of particular visual words.

C. Hypergraph learning: D. Zhou, et al. [9]. In a simple graph, samples are represented by vertices and an edge links the two related vertices. Learning tasks can be performed on a simple graph. Assuming that samples are represented by feature vectors in a feature space, an undirected graph can be constructed by using their pairwise distances, and graph-based semi-supervised learning approaches can be performed on this graph to categorize objects. It is noted that this simple graph cannot reflect higher-order information. Compared with the edge of a simple graph, a hyperedge in a hypergraph is able to link more than two vertices.

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D. Web image re-ranking by bag-based: I. W. T. L. Duan, et al [10]. Bag- based re-ranking framework is used for large scale Text Based Image Retrieval (TBIR). First cluster important images using both textual and visual features. Each cluster as a "bag" and the images in the bag are considered as "instances," gives this issue as a multi-instance (MI) learning problem. To identify the ambiguities on the instance labels in the positive and negative bags under GMI setting. GMI is to improve retrieval performance by propagating the labels from the bag level to the instance level. To acquire bag annotations for GMI learning, a bag ranking method to rank all the bags according to the defined bag ranking score.

E. Web image re-ranking using query-specific semantic signatures: K. L. X. T. Xiaogang Wang, et al. [11] Framework has two parts: offline and online part. At the offline stage, get different semantic spaces for different query keywords. These semantic signatures are based on projecting the visual feature of images to the semantic spaces specified by the query keyword. At the online part, comparing the semantic signatures is acquired from the semantic space and images are re-ranked. The query-specific semantic signatures significantly increase both the accuracy and effectiveness of image re-ranking.

III. PROPOSED ALGORITHM

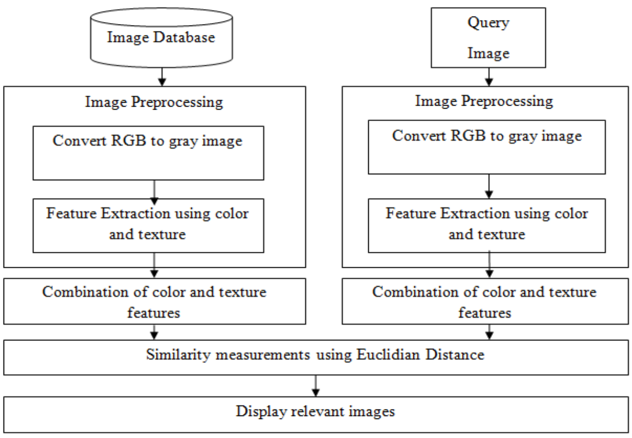

Fig 2: Proposed method of an Attribute assisted reranking model (AARM)

Before analyzing images based on their feature extraction from databases of images, pre-processing methods in images are performed in all types of images. Like, firstly, the images resize according to the region of interest for the faster retrieval of images. Deleting and removing complicated background will speed up further image processing.

From the above Fig 2 when the query image is given to retrieve the similar attribute features images. In the image processing firstly convert RGB color image to gray image, then feature extraction is done with similar attribute with color and texture features. At the same time from the standard image database sets of images will be retrieved same procedure is followed to get relevant images. Then combination of color and texture from image database and query image features are extracted. After this to measure the distance between the two images is calculated using Euclidian Distance . Lastly Relevant images will be displayed.

A. Reranking Image Retrieval from Attribute Features–

a) Image Features

Here 2 types of features have been included color, texture and both, which are good for material attributes; edge is useful for shape attributes; and scale-invariant feature transform (SIFT) descriptor is useful for part attributes. Color descriptors were densely extracted for each pixel. For differentiating image feature, use K-means clustering with 128 clusters by which the same image pixel feature can be extracted.

The color descriptors and Texture descriptors both together are used for each image is quantized into a 128-bin histogram and then computed for each pixel as the 48-dimensional respectively. The texture descriptors of each image were then quantized into a 256-bin histogram. Using a standard canny edge detector edges were found and their orientations were quantized into 8 unsigned bins. Since semantic attributes usually appear in one or more certain regions in an image, we further split each image into 2×3 grids and extracted the above features from each grid respectively.

b) Attribute Learning

We learn a Support Vector Machine (SVM) classifier for each attribute. However, simply learning classifiers by fitting them to all visual features often fails to generalize the semantics of the attributes correctly. For each attribute, we need to select the features that are most effective in modeling this attribute. It is necessary to conduct this selection based on the following two observations:

Low level features are extracted by region or interest point detector, which means this extraction, may not aim to depict the specific attribute and include redundant information. Hence we need select representative and discriminative features which are in favor to descry be current semantic attributes. The process of selecting a subset of relevant features has been playing an important role in speeding up the learning process and alleviating the effect of the curse of dimensionality.

c) Attribute-assisted Hypergraph Construction

An attribute-assisted hypergraph learning method to reorder the ranked images which returned from search engine based on textual query. The weight is incorporated into graph construction as tradeoff parameters among various features. Our modified hypergraph is thus able to improve reranking performance by mining visual feature as well as attribute

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information. The SIFT method is used for extract image features.

IV. EXPERIMENT AND RESULT

A. *IMAGE DATABASE*

In our experiment the images are selected from the internet. Some set of similar images downloaded are used to evaluate the results for reranking image retrieval. The Fig 4.1 shows sample database is having subsets of 1500 images, which have been manually selected to be a database of 12 classes of 100 images for each folder.

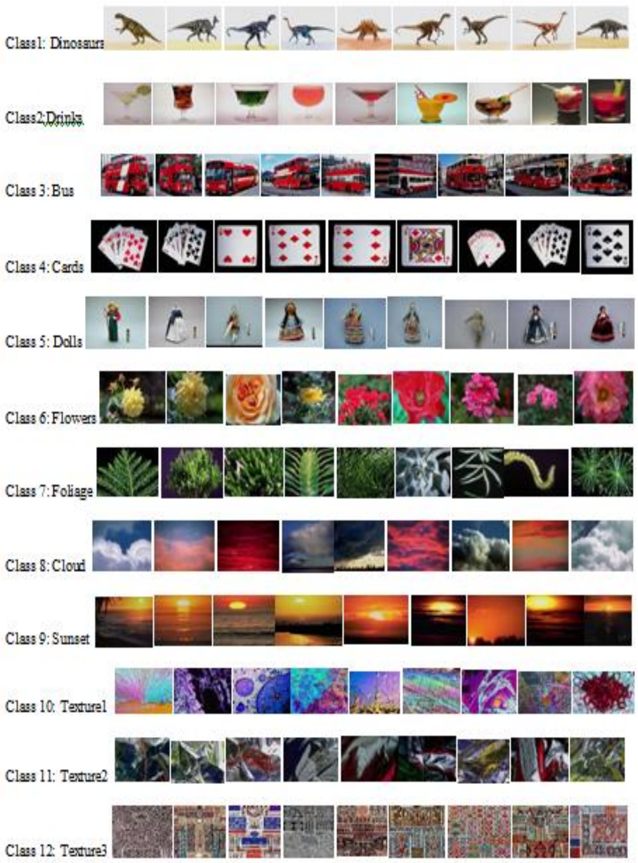

Fig 4.1 Examples Images from each of the 12 class of subset database.

B. *GRAPH RESULTS*

Using Matlab 8.5 software platform to perform the experimental results. The windows 8 personal computer for experimenting the project code, with an Intel P4 5.0GHz Personal laptop and 2GB memory. The proposed method is tested using downloaded sample images for image processing. The performance used to calculate the value of precision and recall as follows:

$$Precision = \frac{Number\ of\ Relevant\ retrieved\ Images}{Number\ of\ Retrieved\ Images}$$

$$Recall = \frac{Number\ of\ Relevant\ retrieved\ Images}{Number\ of\ Existing\ Retrieved\ Images}$$

Table 1 show the percentage of texture. For every data set of image class we calculated the precision and recall. The performance of retrieving the images from the database takes less time therefore time complexity will reduce.

Table 1: Experiment Result for Texture method.

Class	Texture (%)	
	Precision	Recall
Art_Dino	39.3	65
Pl_Flower	41.17	70
Sc_Sunset	48.71	95
Texture_1	4.76	5
Texture_5	9.09	10
Texture _6	16.61	21
Sc_Cloud	16.66	20

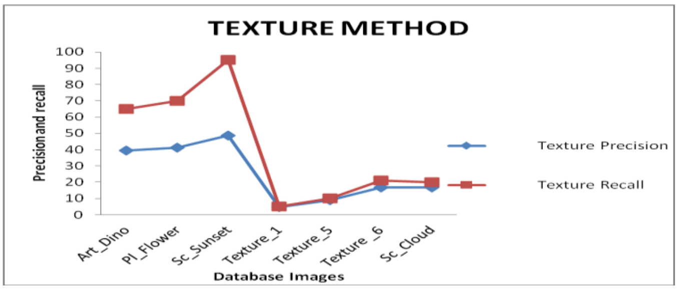

Fig 4.2 shows that percentage of texture feature is more in sunset database compare to other set of databases.

Tables 2, show the percentage of color. For every data set of image class we calculated the precision and recall. The performance of retrieving the images from the database takes similar color feature images from the database.

Table 2: Experiment Result for Color method.

Class	Color (%)	
	Precision	Recall
Art_Dino	31.9	45
Pl_Flower	50	100
Sc_Sunset	28.54	40
Texture_1	28.57	40
Texture_5	25.92	35
Texture _6	0	0
Sc_Cloud	9.09	10

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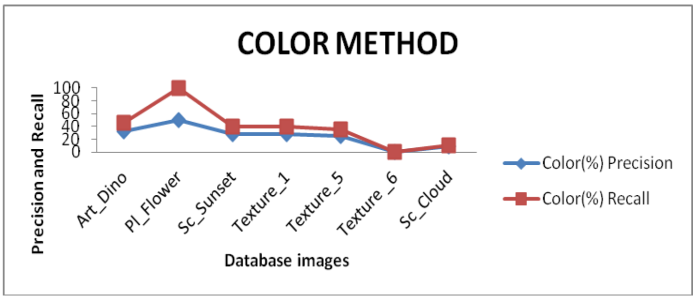

Fig 4.3 shows that percentage of color feature is more in flower database compare to other set of databases.

Tables 3, show the percentage of color-Texture. For every data set of image class we calculated the precision and recall. The performance comparison of retrieving the images from the database takes semantic attribute features color and texture feature images from the database.

Table 3: Experiment Result for Color-Texture method.

Class	Color-Texture (%)	
	Precision	Recall
Art_Dino	35.4	55
Pl_Flower	50	100
Sc_Sunset	50	100
Texture_1	16.66	20
Texture_5	20	25
Texture _6	37.5	60
Sc_Cloud	32.54	50

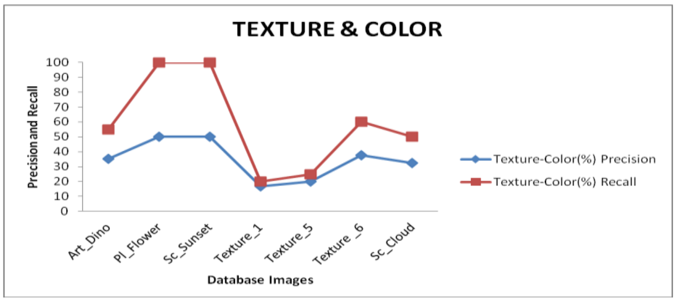

Fig 4.4 shows that percentage of feature extraction is more in flower and sunset databases compare to other set of databases.

V. CONCLUSION

The intended paper, describes about finding the similarity of a particular image in large databases. We present a novel approach for finding similarity of images using different features like color, texture and both (color & texture). We used K-means clustering for extracting the features of image. We used hypergraph learning to search the similar features of images. The results demonstrate the effectiveness of our approach.

VI. REFERENCES

[1] Junjie Cai, Zheng-Jun Zha,, Meng Wang, Shiliang Zhang, and Qi Tian, "An Attribute-assisted Reranking Model for Web Image Search". *IEEE transactions on image processing*, 2015.

[2] J. Cai, Z.-J. Zha, W.-G. Zhou, Q. Tian. "Attribute-assisted reranking for web image retrieval". *In Proceedings of the ACM International Conference on Multimedia*, 2012.

[3] Y. Liu and T. Mei. Optimizing visual search reranking via Pairwise learning. *IEEE Transactions on Muldimedia, vol. 13, no. 2, pp. 280-291*, 2011.

[4] W. H. Hsu, L. S. Kennedy and S.-F. Chang. "Video search rerankingvia information bottle principle". *In Proceedings of ACM Conference on Multimedia*, 2006.

[5] R. Yan, A. G. Hauptmann and R. Jin. "Multimedia search with pseudorelevance feedback". *In Proceedings of ACM International Conference on Image and Video Retrieval*, 2003.

[6] F. Jing and S. Baluja. "Visualrank: Applying pagerank to large-scale image search". *IEEE Transaction on Pattern Analysis and Machine Intelligence, vol.30, no.7, pp.1877-1890*, 2008.

[7] X. Tian, L. Yang, J. Wang, Y. Yang, X. Wu and X.-S. Hua. "Bayesian video search reranking". *Transaction on Multimedia, vol. 14, no. 7, pp. 131-140*, 2012.

[8] Y. Su and F. Jurie. "Improving image classification using semantic attributes". *In International Journal on Computer Vision, vol. 100, pp. 59-77*, 2012.

[9] D. Zhou, J. Huang, and B. Sch¨okopf. "Learning with hypergraphs: Clustering, classification, and embedding". *In NIPS'* 2006.

[10] I. W. T. L. Duan, W. Li and D. Xu, "Improving web image search by bag based re-ranking," *IEEE Trans. Image Process., vol. 20, no. 11, pp. 3280–3290, Nov*. 2011.

[11] K. L. X. T. Xiaogang Wang, Shi Qiu, "Web image re-ranking using query specific semantic signatures," *IEEE Trans on Pattern Analysis and machine intelligence, Vol. 36,No. 4, April* 2014.