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Query Based Image Retrieval by Using GLCM Technique

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***Abstract*— As the number of internet users are increasing day by day. So amount of data also increases, so fast response is desired by different users. So most of the researchers are working in relevant information retrieval. So this work focus on the retrieval of images by utilizing the visual and textual features. In order to increase security whole retrieval is done in encrypted form. So by passing text and visual query in encrypted form image retrieval is done by finding similarity with the dataset. Text query provide initial filtration of the dataset, than GLCM texture feature is use for visual query distance evaluation. So proposed work provide retrieval of image in high protective environment with less execution time. Experiment was done on real and artificial set of images. Result shows that proposed work is better on different evaluation parameters as compare to previous existing methods.**

Keywords— Digital Image Processing, Information Extraction, feature extraction, Re-ranking.

I. INTRODUCTION

WITH the rapid growth of digital devices, internet infrastructures, and web technologies, video data nowadays can be easily captured, stored, uploaded, and shared over the Web. Although general search engines have been well developed, searching video content over the Web is still a challenging task. Typically, most Web search engines index only the metadata of videos and search through a text-based approach. However, without the understanding of media content, general search engines have limited capacity of retrieving relevant video information effectively. Thus, there is much scope to improve the retrieval performance of traditional meta-data based search engines through exploiting media content. With the emergence and spread of digital cameras in everyday use the number of images in Humanal and online collections grows daily. For example, the FlickrTM photo repository now consists of more than four billion images. Such huge image databases require efficient techniques for navigating, labeling, and searching.

Users want to see visually similar images corresponding to their query within the initial pages of the search results. Thus initiating from text based search results, a system that can list the visually relevant images in the first places and move the irrelevant images to the end, is likely to provide user satisfaction and be an alternative to visual based search engines. So this work focus on the goal of selecting relevant images given a query term, i.e. Finding images showing content that most people associate with the query term. More specifically we aim to solve this image search problem on a large-scale community database such as Flickr where images are often associated with different types of user generated metadata, e.g. tags, date & time, and location.

The image search task is assumed that the relevance or importance of an image is proportional to the number of images showing similar content. As it consider community databases, i.e databases with images from many different authors/photographers, this assumption is justified by the following: If an image has many close neighbors all showing the same content and being associated with similar metadata then the respective images' authors agree that this is an important shot of the respective content.

The main difficulty in such an approach is to reasonably define the similarity between two images, i.e. to determine if two images show the same content. The authors in [17] calculate the images' distance based on the number of matching local features between two images. This approach works well for landmarks or product images as in such cases typically many images exist showing the exact same object. However, when searching for object categories or scenes it cannot expect to reliably match the local image descriptors. Thus we use a more sophisticated image description based on automatic content analysis. Moreover we do not rely solely on the automatically extracted visual content description for similarity definition, but we also exploit an image description based on the available metadata. More specifically we also use a representation based on the author's tags.

II. Related Work

Bindita Chaudhuri et. al. [2] letter introduces a novel unsupervised graph theoretic approach in the framework of region-based retrieval of remote sensing (RS) images. The proposed approach is characterized by two main steps: 1) modeling each image by a graph, which provides region-based image representation combining both local information and related spatial organization, and 2) retrieving the images in the archive that are most similar to the query image by evaluating graph-based similarities. In the first step, each image is initially segmented into distinct regions and then modeled by an attributed relational graph, where nodes and edges represent region characteristics and their spatial relationships, respectively. In the second step, a novel inexact graph matching strategy, which jointly exploits a sub graph isomorphism algorithm and a spectral graph embedding technique, is applied to match corresponding graphs and to retrieve images in the order of graph similarity.

In [3], the color feature is extracted from the joint histogram based on the combination of the hue and saturation and the texture feature is extracted using the GCLM feature. The k-means clustering is used to cluster the feature of the image. The ROC curve is drawn in order to evaluate the performance of the feature extraction. The chi-square is used to find the similarity between the two images. The evaluation results demonstrate the accuracy of the retrieval based on the precision and recall false positive and negative ratio. The ROC curve is used to compare the efficiency of the color, texture and the combination of both the color and the texture.

Iyad Aldasouqi and Mahmoud Hassan [4], proposed a fast algorithm for detecting human faces in color images using HSV color model without compromising the speed of detection. The algorithm is fast and can be used in some real-time applications.

Vadivel, A et. al., [5], did a detailed analysis of the properties of the HSV (Hue, Saturation and Intensity Value) color space, laid emphasis on the visual perception of the color of an image pixel with the variation in hue, saturation and intensity values of the pixel. Using the results of this analysis, they determined the relative importance of hue and intensity based on the saturation of a pixel and applied this concept in histogram generation for content-based image retrieval (CBIR) from large databases. In traditional histograms, each pixel contributes only to one component of the histogram. However, they proposed a method using soft decision that contributes to two components of a histogram for each pixel.

Shamik Li Liu et. al. [6], Traditional global representations gather local features directly to output a single vector without the analysis of the intrinsic geometric property of local features. In this paper, we propose a novel unsupervised hashing method called unsupervised bilinear local hashing (UBLH) for projecting local feature descriptors from a high dimensional feature space to a lower-dimensional Hamming space via compact bilinear projections rather than a single large projection matrix. UBLH takes the matrix expression of local features as input and preserves the feature-to-feature and image-to-image structures of local features simultaneously.

Chun et. al., [8], proposed a content-based image retrieval method as its texture features, BDIP and BVLC moments of the value component image are adopted. The color and texture features are extracted in multi resolution wavelet domain and combined.

Young Deok et. al., [9] proposed block difference of inverse probabilities (BDIP) and block variation of local correlation coefficients (BVLC), for content-based image retrieval and then presented an image retrieval method based on the combination of BDIP and BVLC moments.

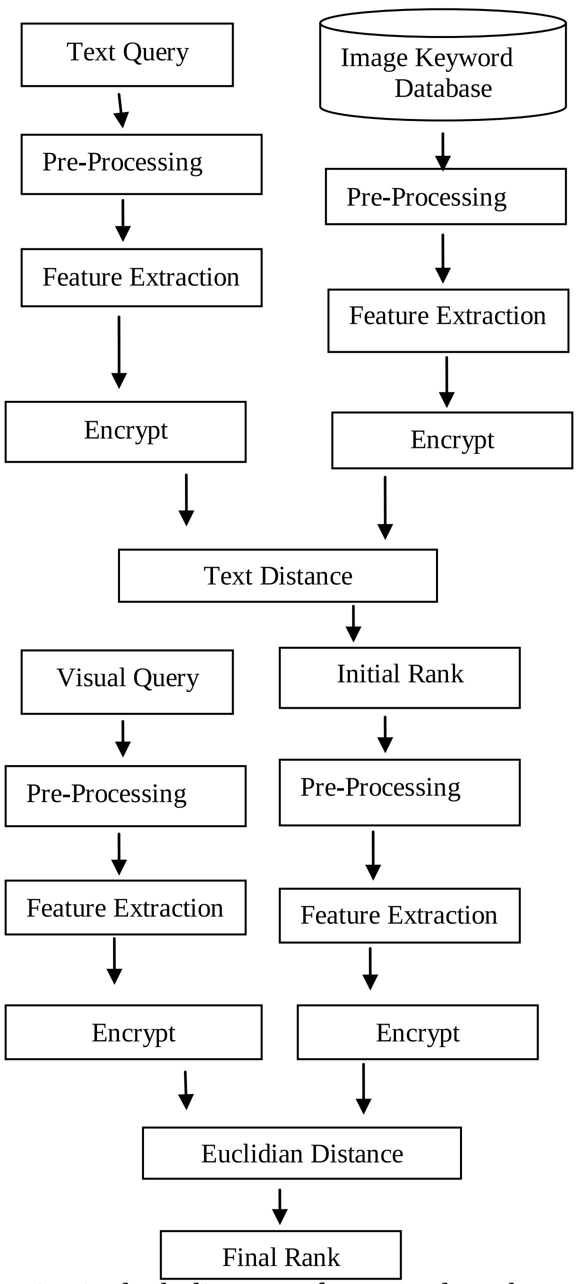

Fig. 1 Block diagram of proposed work.

Their presented retrieval method yields about 12% better performance in precision vs. recall.

III. Proposed Work

Text Pre-Processing: Text preprocessing is consisting of words which are responsible for lowering the performance of learning models. Data preprocessing reduces the size of the input text query significantly. Stop-words are functional words which occur frequently in the language of the text (for example a, the, an, of etc. in English language), so that they are not useful for classification.

Feature Extraction

Here words which are not stop word are considered as feature of the query. Now assign number to each text of the query. So that a dictionary of words with their number is created where each text is identified by separate number. Such as

D[] = [1, 2, 3, 4, 6, 7, 8, 9]

So for n document has its own vector sequence D[n].

Pailler Encryption

This cryptosystem is base on the public and private key concept. Here input vector D[n], will be encrypt by this algorithm.

1. Choose two large prime numbers p and q randomly and independently of each other such that $\gcd(pq,(p-1)(q-1))=1$.
2. Compute RSA modulus $n = pq$ and Carmichael's function $\lambda=(pp-1,qq-1)$
3. Select generator g, Select α and β randomly from a set $\mathbb{Z}n*n$ then calculate $g=(\alpha n+1)\beta*\beta \bmod(n*n)$
4. Calculate the following modular multiplicative inverse
   $\mu=\bmod(n)\ /\ (L(g\lambda\ \bmod(n*n)-1$

Where the function L is defined as $(u)=(u-1)/n$.

So The public key is (n, g), private key is (λ, μ).

Query Distance

Here input query after encryption is transform in other numeric value. So conversion of same text has same value for comparison. This can be understand as let “College” word have numeric value 28 after encryption its transform value is 2456. So if “college” present at server for image keyword then its transform value is also 2456 only for same set of encryption key.

In this step count of similar query words found in image keywords is use for ranking. This can be understand as let query be {2456, 1324, 2783} and I1 content is {2456, 1324, 2711}, while I2 content is {1256, 1114, 2783} then distance of query from I1 and I2 is [2, 1]. Base on distance vector I1 image has high rank as compare to I2.

Visual Pre-Processing

In this step image is resize in fix dimension. As different image have different dimension. So conversion of each is done in this step. One more work is to convert all image in gray format. AS different image has RGB, HSV, etc. format so working on single format is required.

Grey Level Co-occurrence Matrix (GLCM)

In order to get the texture of the image one of the important method is GLCM. Here GLCM present this texture property by the correlation of the neighbouring pixels [5]. It quantificational describes the texture feature. In this paper four features is selected including energy, contrast, entropy, inverse difference.

Energy

$$Energy = \sum_{i=1} \sum_{j=1} (m(i,j))^2 \quad (4)$$

It is a gray scale image texture measure of homogeneity changing, reflecting the distribution of images gray-scale uniformity of weight and texture.

$$Contrast = \sum_{i=1} \sum_{j=1} (i-j)^2 * m(i,j) \quad (5)$$

Contrast is the main diagonal near the moment of inertia. Which measure the value of matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth.

$$Entropy = -\sum_{i=1} \sum_{j=1} m(i,j) \log[m(i,j)]$$

$$InverseDifference = \sum_{i=1} \sum_{j=1} \frac{1}{(1+(i-j)^2} m(i,j)$$

Contrast is large means texture is deeper. Entropy measures image texture randomness, when the space co-occurrence matrix for all values are equals it achieved the minimum value on the other hand if the value of co-occurrence matrix is very uneven its value is greater. Therefore the maximum entropy implied by the image gray distribution as random.

Algorithm for GLCM: Here Image is in RGB format then use it for the calculation of the Energy, Entropy, Contrast and Inverse Difference.Then Sum all value in a group for representing the Energy, Entropy, Contrast and Inverse Difference and term as CCM feature.

Input: I // Image

Output: Glcm_feature

1. E = Enery(I) // Equation (5)
2. I = Contrast(I) // Equation (6)
3. S = Entropy(I) // Equation (7)
4. H = Inverse_diff(I) // Equation (8)
5. Glcm_feature = [E, I, S, H]

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Euclidian Distance

This can be understood as Let X is a query image matrix and Y be the dataset image matrix. Then distance between them is calculated by:

$$D = \sqrt{sum((X - Y)^2)}$$

Base on the minimum distance value between query and dataset image rank is assigned to the image. This is considering as final rank of the work.

IV. Experiment And Result

In this section, first introduce experimental settings, and then present the experimental results that validate the effectiveness of the approach. The experiments actually contain two parts. This work is compare with other several existing methods that adopt all features.

Evaluation Parameter: NDCG [6, 12] as the performance evaluation measure.

The NDCG measure is computed as

$$NDCG@P = Z_P \sum_{i=1}^{P} \frac{2^{l(i)} - 1}{\log(i+1)} \quad (9)$$

where *P* is the considered depth, *l(i)* is the relevance level of the *i* -th image and *ZP* is a normalization constant that is chosen to let the optimal ranking's NDCG score to be 1.

Data Sets and Preprocessing

In order to conduct the experiment an artificial dataset which is a collection of images from different category are utilize. As images are of different format so first it is necessary to make it in readable format for experiment tool MATLAB. Now these collections of images of different category are shown in table 1 for which one can make some important keyword collection for different images. In this way each image have one more feature to identify that is the keys of the images.

Category	Examples
Objects	Ipod, map
Insect	Butterfly, Gorrila
Scene	Taj Mahal, Hotel Taj
Human	Barack Obama, Lena

Table 1 Dataset of Different category.

By entering the query and search the desired image it was obtained that they can be categorize into few levels such as relevant or not. It can be further categorized into most relevant, relevant, less relevant, and irrelevant.

Fig 2. Above image are generate from two category relevant and irrelevant for two query 'Taj Mahal', 'Barack Obama'.

Fig 3. Results obtained by Proposed GLCM.

Results

Images		NDCG Values @ 10	
		Previous Work	Proposed Work
1	Objects	0.181444	0.410762
2	Insect	0.43609	0.573433
3	Scene	0.28952	0.489486
4	Human	0.28503	1

Table 2. Average Values of NDCG@10 by Different features and there combination.

From the above table it is finding that the including of the new feature has increase the NDCG of image re-ranking. In different categories of the images one can find that results are improved.

Images		NDCG Values @ 7	
		Previous Work	Proposed Work
1	Objects	0.183251	0.371686
2	Insect	0.504912	1
3	Scene	0.36159	0.484885
4	Human	0.274876	0.440405

Table 3. Average Values of NDCG@7 by Different features and there combination.

From the above table it is finding that the including of the new feature has increase the NDCG of image re-ranking. In different categories of the images one can find that results are improved.

Images		Execution time in second	
		Previous Work	Proposed Work
1	Objects	3.834435	3.710875
2	Insect	7.888375	3.36432
3	Scene	5.353875	3.277245
4	Human	5.060765	2.419205

Table 4. Average Values of execution for @10 by Different features and there combination.

From the above table it is finding that the including of the new feature has reduced the execution time of image re-ranking. In different categories of the images one can find that results are improved.

Images		Execution time in second	
		Previous Work	Proposed Work
1	Objects	8.676735	3.00039
2	Insect	5.223185	2.66404
3	Scene	4.1545	4.17155
4	Human	3.16859	2.58266

Table 5. Average Values of execution for @7 by Different features and there combination.

From the above table it is finding that the including of the new feature has reduced the execution time of image re-ranking. In different categories of the images one can find that results are improved.

V. Conclusions

In the research of Image retrieval, there are a lot of achievements in image semantic feature; they can be applied to content-based image retrieval to analyze the transition between visual features and semantic features of the images. This paper utilizes the new combination of text as well as visual features for ranking the image as both make the re-ranking process more powerful, which is shown in results. Here it is shown that use of single feature decrease the accuracy of the work. Looking for fast intelligent search algorithm and how to design user feedback mode while feedback fully is also an important research direction for the future.

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