ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 6, Issue 11, November 2017

# Genetic Approach based Image Retrieval by Using Histogram and Textual Features

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*Abstract*— As the number of internet users are increasing day by day. This work focus on the retrieval of images by utilizing the visual and textual features. In this work two type of features are used for the clustering of the image dataset. So Based on the similarity of text and histogram features of the image clusters are created. For clustering genetic approach is used while teachers learning based optimization algorithm was used for clustering. Here user pass two type of query first is text while other is visual, this help in selecting appropriate cluster for retrieval of image. Experiment was done on real and artificial set of images. Result shows that proposed work is better on different evaluation parameters as compare to UBLH 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 are assume 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.



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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 an representation based on the author's tags.

## II. Related Work

Liu [2] surveyed BOW show in picture recovery framework. The creators gave insights about BOW demonstrate and clarified distinctive building procedures in view of this model. To begin with, specialist displayed a few strategies that can be taken in BOW demonstrate. At that point, clarified some famous key point indicators and descriptors. At last, he took a gander at techniques and libraries to creating vocabulary and do the hunt.

Alfanindya et al. [3] displayed a strategy for CBIR by utilizing SURF with BOW. To start with, they utilized SURF to processed intrigue focuses and descriptors. At that point, they made a visual word reference for each gathering in the COREL database. They finished up from their tests that their technique beats some different strategies as far as precision. The significant test in their work was that the proposed strategy is exceedingly directed. It implies that they n need to decide the quantity of gatherings before they perform arrangement.

Satish Tunga et al. [4] exhibited a similar investigation of CBIR methods This paper introduces a short study on business related to the energizing fields of substance based picture recovery and gives a point by point survey of the works done in this field. This paper additionally talked about the different procedures utilized for separating the notable low level elements and different separation measures to discover the comparability between pictures in lessening the semantic crevice between the low level components and the abnormal state semantic ideas. A talk of different methodologies of CBIR and correlation of different systems regarding information are additionally made.

In [5] In this paper, analyst propose a novel unsupervised hashing technique called unsupervised bilinear neighborhood hashing (UBLH) for anticipating nearby component descriptors from a high dimensional element space to a lower-dimensional Hamming space by means of minimized bilinear projections instead of a solitary extensive projection network. UBLH takes the framework articulation of nearby components as information and jelly the element to-highlight and picture to-picture structures of neighborhood includes at the same time.

Vadivel, An et. al., [6], did a definite investigation of the properties of the HSV (Hue, Saturation and Intensity Value) shading space, laid accentuation on the visual impression of the shade of a picture pixel with the variety in tone, immersion and force estimations of the pixel. Utilizing the aftereffects of this examination, they decided the relative significance of tint and force in view of the immersion of a pixel and connected this idea in histogram era for content-based picture recovery (CBIR) from vast databases. In customary histograms, every pixel contributes just to one part of the histogram. In any case, they proposed a technique utilizing delicate choice that adds to two parts of a histogram for every pixel.

## III. Proposed Work

### Overview of Different Modules

Whole work is divide into different modules base on the steps of calculation from the user query to final output on the screen. In fig. it is seen that there are two different modules. First include query pre-processing. Then in second phase by



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utilizing the initial rank of the image reteive images and generate there features, of each image is generate, after this find distance from one image feature to other query.

**Visual Pre-Processing**

Read a image means making a matrix of the same dimension of the image then fill the matrix correspond to the pixel value of the image at the cell in the matrix.

In this step image is resize in fix dimension. As different image have different dimension. So conversion of each is done in this step. This can be understand as if one image have an dimension of the 30X30 and other image has the dimension of 29X28 then it need to resize it either in 30X30, so that it matrix operation can be easily perform on both matrix. One more work is to convert all images in gray format. Aa different image has RGB, HSV, etc. format so working on single format is required.

**Feature Extraction**

In this work histogram feature was used. As most of the object present in the image can be classify by the color. Here sixteen bins are used for the histogram feature extraction. As each image having similar colors have almost same type of bins. This feature vector help in TLBO algorithm.

**Generate Population**

Here assume some cluster centers from the different images of dataset. This is generate by the random function which select fix number of image cluster for the centroid. This can be understand as let the number of centroid be Cn, then one of the possible solution is {C1, C2, …..Cn}. In the similar fashion other possible solutions are prepared which can be utilize for creating initial population matrix (PM).

**Teacher Phase**

For finding difference between images Eludician Distance formula is use for evaluating the similarity between the image visual features while annotations of the image is also consider for finding the image distance as well. The Euclidean distance d between two image X and Y is calculated by

d = [SUM((X-Y).^2)]^0.5

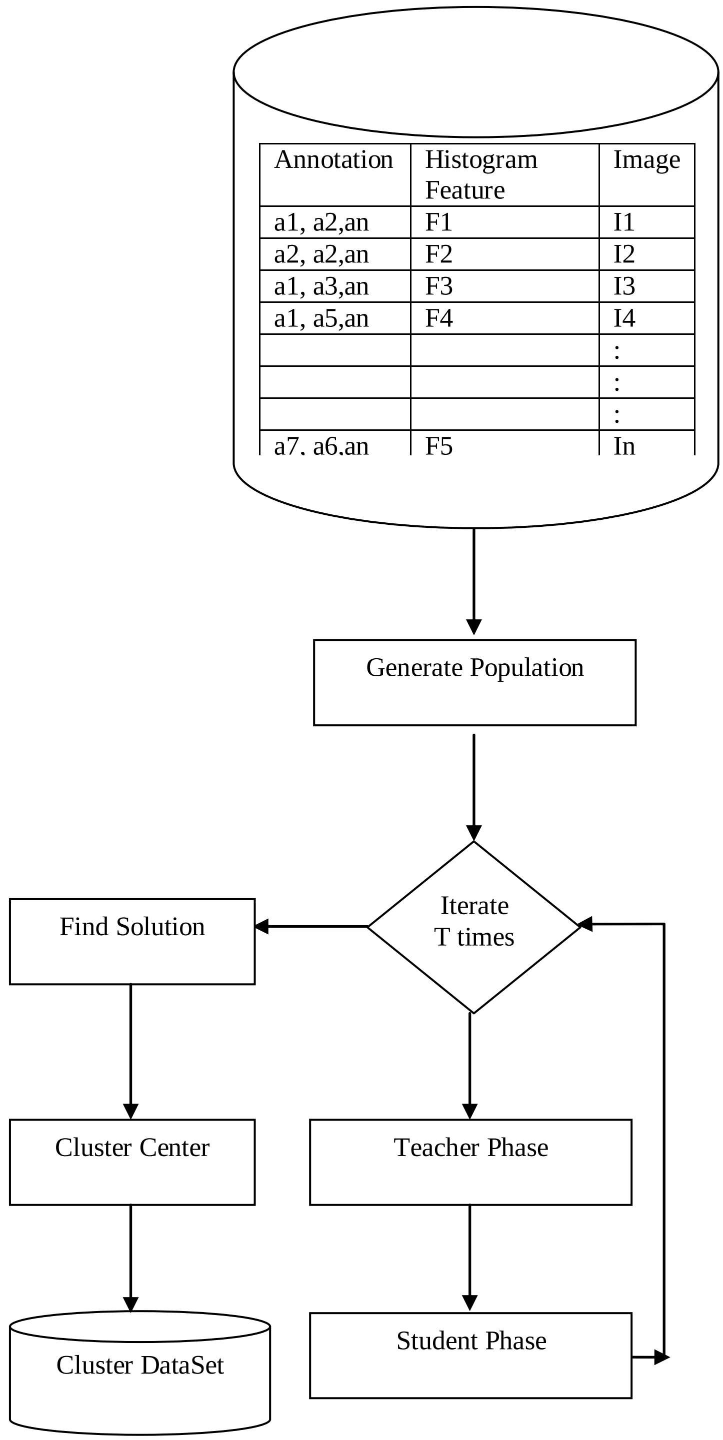


Fig. 1 Block Diagram of proposed work.



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ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 6, Issue 11, November 2017

In similar fashion annotations are used for calculating the centroid distance from the other images in the dataset. So number of same keywords are consider as the similarity measure for filtering the image to the relevant cluster. As higher the number of similarity closeness is high. Now sort the similarity matrix in descending order to assign the image to the centroid as per the annotations. So this feature give its separate index to the population of the genetic algorithm name as Annotation_Index. Hence final index can be calculate by the below operation:

Final_Index = Annotation_Index*X1 +Visual_Index*X2

Where X1 and X2 are weight for the features range between 0 to 1.

Top possible solution after sorting will act as the teacher for other possible solutions. Now selected teacher will teach other possible solution by replacing fix number of centroid as present in teacher solution. By this all possible solution which act as student will learn from best solution which act as teacher.

Main motive of this step is to find best solution from the generated population. Here each possible solution is evaluated for finding the distance from each centroid image so that image closer to the centroid are cluster together. Then calculate the fitness value which give overall rank of the possible solution.

This difference modifies the existing solution according to the following expression

$$X_{new,i} = \text{Difference}\ (X_{teacher,i}, X_{student,i})$$

Where Xnew,i is the updated value of $X_{student,i}$. Accept $X_{teacher,\ i}$ value.

**Student Phase**

In this phase all possible solution after teacher phase are group for self learning from each other. This can be understand as let group contain two student then each student who is best as compare to other will teach other solution. Teaching is similar as done in teacher phase, here replacing fix number of centroid is done which is similar as in best student of the group.

1. For i = 1: Pn
2. Randomly select two learners Xi and Xj, where i is not equal to j
3. If f (Xi) < f (Xj) // f is the fitnees value of the selected population.
4. $X_{j,x}$ = Difference ($X_{i,x}$, $X_{j,x}$) // x: position of the cluster center in population vector
5. Else
6. $X_{i,x}$ = Difference ($X_{j,x}$, $X_{i,x}$)
7. End If
8. End For

Once student phase is over then check for the maximum iteration for the teaching if iteration not reach to the maximum value then GOTO step of teacher phase else stop learning and the best solution from the available population is consider as the final centroid of the work. Now image are cluster as per centroid.

**Final Solution**

In this work after sufficient number of iteration cluster centers are obtained and assign images to those clusters. Here each cluster is represent by its cluster center. So as per the different number of image type available in the dataset number of clusters are generate.


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**Testing Phase**

In this phase user has submit text query and image as the input in the system. Here visual query is preprocessed first than calculate the histogram feature from the image, next fetch keywords from the user query and find the most relevant cluster from the store image dataset.

**Cluster Score**

Here user query distance is calculate from each cluster center where Euclidian distance of the visual features of query image are compared with cluster center is compared. In similar fashion query keywords are compared with the cluster center images. So cluster having maximum number of matched keywords and minimum distance from the cluster is consider as the highest score of the cluster.

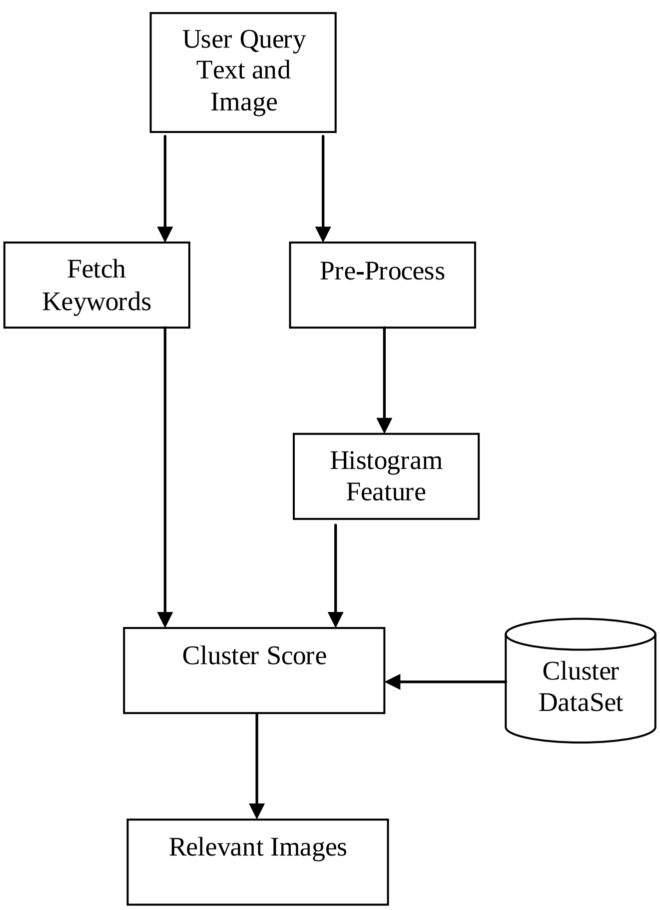


Fig. 2 Testing module of the work.

**Rank relevant Image**

Finally distance from the images in the cluster is calculate from the the query imager where Euclidian distance of the visual features of query image are compared with cluster center is compared. Relevant Rank is obtained by arranging cluster image in the

## 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.

**Results**

| Images | | NDCG Values @ 10 | |
|---|---|---|---|
| | | Genetic Retrieval | **UBLH** [6] |
| 1 | Objects | 0.648932 | 0.235659 |
| 2 | Insect | 0.422575 | 0.201291 |
| 3 | Human | 1 | 0.403617 |

Table 2. NDCG comparison of Genetic Retrieval and UBLH methods.



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

| Images | | Accuracy | |
|---|---|---|---|
| | | Genetic Retrieval | **UBLH** [6] |
| 1 | Objects | 0.5 | 0.16 |
| 2 | Insect | 0.3 | 0.12 |
| 3 | Human | 1 | 0.36 |

Table 3. Accuracy comparison of Genetic Retrieval UBLH methods.

From the above table it is find that the including of the new feature has increase the accuracy of image retrieval. Here genetic approach for clustering increase the accuracy value as well. In different categories of the images one can find that results are improved.

| Images | | Execution time in second | |
|---|---|---|---|
| | | Genetic Retrieval | **UBLH** [6] |
| 1 | Objects | 7.22043 | 11.235 |
| 2 | Insect | 5.3261 | 8.2379 |
| 3 | Human | 7.4487 | 9.30301 |

Table 4. Execution time comparison of Genetic Retrieval and UBLH methods.

From the above table it is find that the including of the new text feature has reduce the execution time of image retrieval. 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.

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