Content Based Image Retrieval Using Enhanced Vocabulary

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Abstract: ***Content Based Image Retrieval is a technique that makes use of the visual content of an picture, to search for similar pictures in large-scale image databases, as per a user's interest. The CBIR is driven by the requirement to go looking the exponentially increasing set of image and video databases expeditiously and effectively. The visual content of a picture is analyzed in terms of low-level options extracted from the image. In CBIR system, it's usual to cluster the image options in three main classes :color, texture and form. Ideally, these options ought to be integrated to supply higher discrimination within the comparison method. For example by constructing an object vocabulary containing query-associative objects by mining frequent object patches from the resulting image collection of the expanded query set. After representing each image as a bag of objects, the retrieval model can be derived from a risk-minimization framework for language modelling. In this paper we proposed a technique which uses enhanced vocabulary to map the features extracted from the images and give the relevant result The experimental results show that the proposed methods can significantly outperform the existing approaches.***

Keywords: CBIR, Feature Extraction, GLCM, SVM, DML

1. Introduction

Content-Based Image Retrieval, usually alluded to as CBIR, is the programmed recovery of computerized pictures from huge databases. This system makes utilization of the innate visual substance of a picture to perform an inquiry. Rather than prior picture recovery techniques which included the manual literary explanations of pictures, CBIR frameworks recognize the pictures via naturally removed linguistic components.[1] Content Based Image Retrieval (CBIR) system utilizes picture substance to seek and recover advanced pictures. Content based picture recovery is an arrangement of methods for recovering semantically-applicable pictures from a picture database in light of consequently determined picture highlights. The primary objective of CBIR is effectiveness amid picture indexing and recovery, along these lines decreasing the requirement for human intercession in the indexing process. The PC must have the capacity to recover pictures from a database with no human supposition on particular space, (for example, surface versus non- composition, or indoor versus open air). One of the principle errands for CBIR frameworks is similitude correlation; extricating highlight marks of each picture taking into account its pixel values and characterizing rules for contrasting pictures. These components turn into the picture representation for measuring closeness with different pictures in the database. A picture is contrasted with different pictures by ascertaining the distinction between their comparing highlights. [10] The picture recovery framework goes about as a classifier to partition the pictures in the picture database. into two classes, either relevant or irrelevant. In this sense, a commented on picture can be spoken to by an element vector x, e.g. an arrangement of picture elements or eigen elements, and its mark y that is either relevant or irrelevant. It appears that numerous administered learning methodologies could be utilized to way to deal with this classification issue. Sadly, they are faced by two primary difficulties. The first one is that the annotated or labelled training samples are too limited. Generally, the labels are provided by queries and relevance feedbacks, which won't be numerous. Constrained preparing information would just result in powerless characterization.

Another test is the dimensionality of learning, since high dimensional visual information would posture reasonable troubles for highlight weighting, selecting and dimensionality decrease. Restricted preparing information would likewise avert compelling dimensionality diminishment plans. Consequently, another learning plan required for such a testing situation. Considering there are an expansive number of unlabelled pictures in the given database, we might utilize them to help the frail classifier gained from the restricted named information, since unlabelled information contain data about the joint appropriation over components .

The fascinating pictures to the client are just a little partition of the vast picture database, in which most pictures stay unlabelled. Much work sees the issue as a strict two class arrangement issue, with equivalent medications on both positive and negative illustrations. It is sensible to accept positive cases to group in certain way, yet negative illustrations for the most part don't bunch since they can have a place with any class.

The rest of the paper is organized as follows. In Section II Related work, Section III Problem Identification Section IV Techniques used, Section V Experiments and results, Section VI Performance Evaluation Section VII concludes the paper.

2. Related Work

Image Relevance Prediction Using Query-Context Bag-of-Object Retrieval: In this paper, Yang Yang et al, designed a unique bag-of-object retrieval model to predict image relevancy, that is especially effective for object queries. First, AN object vocabulary is built containing query-relative objects by mining frequent object patches from the result image collection of the distended query set. For image search re-ranking, a supervised framework is adopted to mix multiple ranking options from completely different assumptions. For image search result report, a two level ranking method is projected that optimizes not only representativeness but also adds image attractiveness [1]

Ordinal Distance Metric Learning for Image Ranking: In this paper, Changsheng Li proposed et al a linear ordinal Mahalanobis DML model that tries to conserve each the local geometry data and also the ordinal relationship of the information. Then a nonlinear DML technique is developed by kernelizing the on top of model, considering of real-world image information with nonlinear structures. To further improve the ranking performance finally a multiple kernel DML approach is developed impressed by the concept of multiple-kernel learning that performs completely different kernel operators on different styles of image options. [2]

A new matching strategy for content based image retrieval system" Elsevier, Applied soft computing: In this paper, M.E. El Alami et al has given a new matching strategy for content based image retrieval system. He represented model into three phases comprising of extracting features and matching. In feature extraction part, it extracts a color and texture features. Combination of multiple features were included to induce higher results. the artificial neural network (ANN) during this model is a classifier so the chosen options of question image area unit the input and its output is one in all the multi categories that have the highest similarity to the query image. This model presents an efficient feature matching strategy that depends on the concept of the minimum space between 2 vectors to compute the similarity score between a query image and also the images within the determined class. [3].

Content based Image Retrieval classification using neural networks: In this paper, Shereena et al, has combined color and texture features as extraction features of image and then they have used neural network for classification purpose to retrieve images from database [4].

Computer-aided diagnostics of screening mammography using content-based image retrieval: In this paper Thomas M. Deserno et al, proposed a computer-aided medical specialty tool for screening the diagnostic technique exploitation content primarily based image retrieval technique. during this work, Support Vector Machine (SVM) classification technique was used for uncertain tissue pattern extraction in an image. supported that, the retrieval of the system enforced mistreatment cbir for detection the diagnostic technique of the image [5].

Content-based binary image retrieval using the adaptive hierarchical density histogram: In this paper Panagiotis Sidiropoulos et al, proposed a scheme for binary image retrieval. it used black and white binary depicted values as image feature and it named because the accommodative hierarchical density histogram that develops the allocation of the image points on a two-dimensional space. this method uses the assessment of purpose density histograms of image regions that ar computed by a pyramidic grid that's repeatedly simplified through the calculation of image geometric centroids. This extracted descriptor includes each global and native possessions which will be utilized in differing kinds of binary image databases for the retrieval of images [6].

Improving the ranking quality of medical image retrieval using a genetic feature selection method: In this paper, Sergio Francisco da Silva et al, proposed methodology for rising the ranking quality for medical image retrieval victimization genetic feature choice method. Here the authors have used single-valued genetic functions for evaluating the rankings to increase a group of feature selection strategies supported the genetic algorithmic rule approach to enhance the preciseness of content primarily based image retrieval systems [7]

Evaluation of Euclidean and Manhattan Metrics in Content Based Image Retrieval System: In this paper, Gunjan Khosla et al, has calculated the color histogram of images as feature vectors. They have used distance metrics Manhattan distance and Euclidean distance to determine similarities between a pair of images [8].

Content based image retrieval using feed forward back-propagation neural network: In this paper, Arvind Nagathan et al, has used color histogram as color descriptor, GLCM (gray level co-occurrence matrix) as texture descriptor and edge histogram as edge descriptor. Then they classify the images using neural network to retrieve images from database [9].

Negative-Voting and Class Ranking Based on Local Discriminant Embedding for Image Retrieval: In this paper, Mei-Huei Lin et al, proposed a model that utilizes the native discriminant embedding methodology. The advantage of native discriminant embedding is to map information points from the initial feature house into a lower-dimensional mathematical space whereas keeping similar information points nearer and pushing dissimilar information points away. Linear discriminant analysis (LDA) considers the geodesic distances between information points, and is shown to be a useful gizmo for feature extraction and classification. The LDA framework seeks to dissociate every category from each other, and not solely retains the similarity, however additionally takes the difference into thought. whereas maintaining the initial neighboring relations for information points of a similar category is very important, it's additionally crucial to differentiate and separate information points of various categories once the embedding.[10]

Contextual Feature Discovery and Image Ranking for Image Object Retrieval and Tag Refinement: In this paper, Minnu Joseph et al , propose a general framework, which integrates both visual and textual contextual feature discovery. It avoids the limitations in both text based and content based image retrieval. This reduces the semantic gap problem. Here a Contrast limited adaptive histogram equalization (CLAHE) algorithm is used to enhance the low contrast image. The semantic and contextual feature discovery framework is applied to augment each image with Auxiliary visual words (AVW) and Gray Level co-occurrence matrix (GLCM). The second task is tag refinement that augments every image with semantically connected texts. Similarly, the framework on the matter domain is applied by exchanging the role of visual and matter graphs in order that propagation is achieved and choose relative and representative tags for every image. Here similarity measurement is done by finding Euclidean distance and Independent component analysis (ICA). [11]

Kernel-based distance metric learning for content-based image retrieval: In this paper, Hong Chang, et al, proposed an efficient kernel based distance metric learning method based on semi-supervised metric learning to improve the retrieval performance of Euclidean distance without distance learning, it also outperforms other distance learning methods significantly due to its higher flexibility in metric learning. [12]

3. Problem Definition

Image search re-ranking boosts the relevant images to the top of the search. Image search result summarization discovers a small group of images that are both relevant and representative to the query, providing the user with an overview of the search result list. For both of the approaches, predicting image relevance serves as a key technology and is considered as one of the most challenging problem. The two main problems we have identified are as follows:

a) For images retrieved by object queries, usually some parts of the image are relevant to the object query, while the others are not. . Effective text to object mapping is required for image retrieval based on text queries. The object vocabulary needs to be updated for better search result.
b) Text-based search engines may sometimes be confused by concepts with overlapping key words but different meanings. This is referred to as "the ambiguity problem". This problem may have negative effect to the quality of object vocabulary. First, because these ambiguous objects visually close to each other, they cannot be simply detected as outliers. Second, we can observe that some ambiguous objects are also similar with the relevant images. Therefore, the main challenge here it to successfully identify such images so as to prevent them from being boosted.

4. Techniques Used

a) Gray Level Co-occurrence Matrix:

Gray Level Co-occurrence Matrices (GLCM) may be a standard illustration for the texture in images. They contain a count of the amount of times a given feature (e.g., a given gravy level)occurs in a very explicit relation to a different given feature. GLCM, one among the foremost best-known texture analysis strategies, estimate image properties associated with second-order statistics. we tend to used GLCM techniques for texture description in experiments with fourteen statistical features extracted from them.The process involved is follows:

1) Compute co-occurrence matrices for the images in the database and also the query image.
2) Four matrices will be generated for each image [6].
3) Build up a 4×4 features form the previous co-occurrence matrices as shown in Table 1

Table 1: Four main features used in feature extraction

Feature	Formula
Energy	$\sum_i \sum_j P^2(i,j)$
Entropy	$\sum_i \sum_j P(i,j) \log P(i,j)$
Contrast	$\sum_i \sum_j (i-j)^2 P(i,j)$
Homogeneity	$\sum_i \sum_j \frac{P(i,j)}{1+\lvert i-j \rvert}$

b) Support Vector Machines

Support Vector Machines have demonstrated their abilities in pattern recognition. The goal of SVM classification strategy is to find the best hyper-plane isolating significant and unimportant vectors augmenting the measure of the edge (between both classes). Introductory technique accept that significant and unessential vectors are directly divisible. The SVM separate the entire image database into two classes. The two classes are additionally incorporating the unlabelled images with two sorts they are important and superfluous unlabelled images. The significant unlabeled image is expounded to the relevant labeled pictures within the image information. In similar method the unsuitable unlabeled image is said to the unsuitable labeled pictures within the information. This SVM is additionally classifying the unlabeled pictures in preciseness [10]

c) Relevance Feedback

As image databases more often than not contain unlabelled images, these can be abused to help supervised learning so as to learn the client to name them. The objective is actually to minimize asking assistance from the client. The connections of all the information focuses in the element space utilizing a complex positioning calculation and develops a weighted diagram that contains all images; the positioning scores of named illustrations are iteratively spread to close-by named and unlabelled images. The Relevance Feedback is utilizing the probability capacities used to relate the specific information focuses in the image class. These capacity is characterize the significance of every information point to the client given question. This is most valuable to offer rank to unlabelled images in the image database . The learners are prepared with named and unlabelled images. At that point the procedure is converged in type of positive image. That image having the high confidence degree for introducing the required client in the outcome structure.[20]

d) Gray Conversion

The use of color in image process is motivated by two principal factors; 1st color could be a powerful descriptor that always simplifies object identification and extraction from a scene. Second, human will distinguish thousands of color shades and intensities, compared to regarding solely large integer reminder grey. In RGB model, every color seems in its primary spectral parts of red, green and blue. This model relies on co-ordinate system. pictures diagrammatic in RGB color model accommodates three element pictures. One for every primary, once fed into an RGB monitor, these 3 pictures combines on the phosphor screen to provide a composite color image. the quantity of bits wont to represent every picture element in RGB area is termed the picture element depth. contemplate an RGB image during which every of the red, inexperienced and blue pictures is an 8-bit image.

Image formation using sensor and other image acquisition equipment denote the brightness or intensity I of the light of an image as two dimensional continuous function F(x, y) where (x, y) denotes the spatial coordinates when only the brightness of light is considered. Sometimes three-dimensional spatial coordinate are used. Image involving only intensity are called gray scale images

Gray Conversion converts the true colour image RGB (24 bits) to the gray scale intensity image (8 bits).

$$\text{grayscale image} = ((0.3 * R) + (0.59 * G) + (0.11 * B))$$

where R, G and B represent the red, blue and green values of a pixel.

In RGB color model, every color seems in its primary spectral components of red, green, and blue. the color of a element is created of 3 components; red, green, and blue(RGB), represented by their corresponding intensities. color elements are called color channels or color planes (components). within the RGB color model, a color image may be pictured by the intensity operate. I RGB =(FR ,FG ,FB) wherever FR(x,y) is that the intensity of the element (x,y) within the red channel, f G(x,y) is that the intensity of element (x ,y) within the inexperienced channel, and fB(x,y) is that the intensity of element (x,y) within the blue channel. The intensity of every color channel is typically hold on victimization eight bits, that indicates that the quantisation level is 256. That is, a element in an exceedingly color image needs a complete storage of twenty four bits. A twenty four bit memory will specific as 224 =256×256×256=16777216

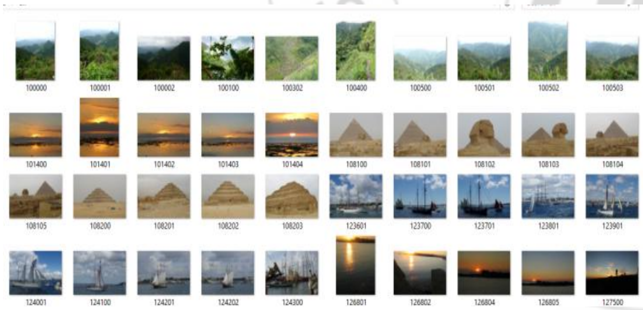

Figure 1: Dataset containing images obtained from "Holiday's dataset"

e) Similarity Measurement

After removing the feature vector, a function is utilized that measure the likeness among the query image and database images highlight vector in CBIR frameworks. Generally, the similarity measure function used is distance metric. The value of distance metric indicates the level of similarity among the query image and database image. A database image is said to be similar to query image if the calculated distance is „small‟. Some of the methods for similarity measurement are Manhattan Distance Euclidean Distance, Mean Square Error, Sum of Absolute Differences, NN Classifiers, K-Nearest Neighbor Algorithm, and Mahalanobis Distance[22]

Table 2: Finding from the methods

S.N	*Title*	*Method Used*	*Findings*
1	Image Relevance Prediction Using Query-Context Bag-of-Object Retrieval Model	Bag-of-object model, pseudo relevance feedback	Optimizes image representativeness and image attractiveness
2	Ordinal Distance Metric Learning for Image Ranking	DML, Kernel based DML	Preserves local geometry and ordinal relation of data.
3	Negative-Voting and Class Ranking Based on Local Discriminant Embedding for Image Retrieval	Linear Discriminant Embedding	mAP is reached to 89.28%
4	Contextual Feature Discovery and Image Ranking for Image Retrieval and Tag Refinement	CLAHE, GLCM,AVW	Almost 21 contextual features and semantic features are extracted from both query and data base image.

5. Performance Evaluation

The thought behind performance evaluation is to make an expectation on the CBIR framework performance regarding recovery rate. The regular techniques used to gauge the execution are User examination, rank of best match, Average rank of recovery images, Recall and Precision, Error rate and so forth. The greater part of the scientists utilized Recall rate and Precision rate as an execution metric in CBIR frameworks. Precision rate gives the proportion of relevant images retrieved and the recall rate gives proportion of relevant images that are retrieved. We have evaluated the performance on the basis of Accuracy, Sensitivity, Specificity, Precision, Recall, F-Measure and G-mean. It can be calculated as follows:

p = no. of relevant images.
n = no. of irrelevant images.
N = p + n
tp = Total relevant images retrieved
tn = Total irrelevant images retrieved
fp = n - tn
fn = p - tp
tp_rate = tp/p
tn_rate = tn/n
accuracy = (tp + tn) / N
sensitivity = tp_rate
specificity = tn_rate
precision = tp / (tp + fp)
recall = sensitivity
f_measure = 2*((precision*recall)/(precision + recall))

$$\text{gmean} = \sqrt{tp\_rate * tn\_rate}$$

Table 3.1 and Table 3.2 shows the values of performance evaluation

Class	p	n	Accuracy	G_Mean
Mountains	8	2	0.8	0.71429
Corals	6	2	0.75	0.66667
Underwater	12	4	0.66667	0.6
Boats	8	2	0.57143	0.53846

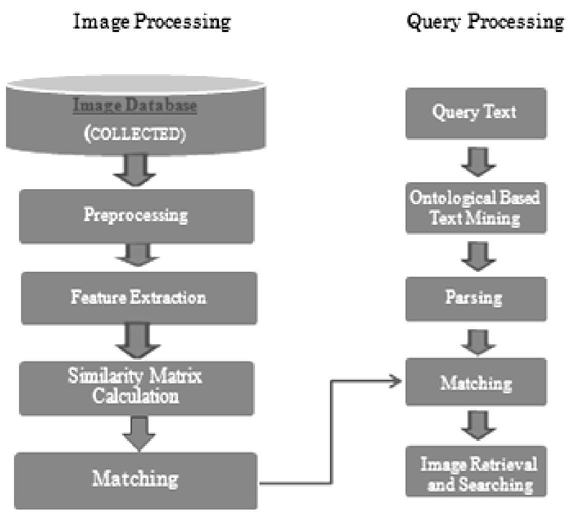

Figure 2: Block diagram of proposed system.

6. Experiment and Result

To evaluate the effectiveness of the proposed retrieval model, we perform test on a publicly available dataset Holidays dataset, comprising 200 images. Figure 2 shows the block diagram of the proposed system. Following are the main processes carried out during image retrieval:.

a) *Query processing:* In this part the user enters the query which is processed for image retrieval. For pre-processing the query, two algorithms are applied which removes the useless and noisy words or alphabets from the query. "Stopwords" is used to remove all the noisy words and helping verbs present in the query. After this "Stemmer" is applied to the result obtained. The alphabets have to be converted into lowercase before applying stemmer. The query is parsed as follows:
   1) Enter the query.
   2) Parse the query to get head_word.
   3) Match headword with the class labels to get the head_class.
   4) Features of the head_class image are extracted and stored in Test_data.mat.

Table 3.1: Performance Evaluation

Class	Precision	Recall	F_Measure
Mountains	0.71429	1	1
Corals	0.66667	1	1
Underwater	0.6	1	1
Boats	0.53846	1	1

Table 3.2: Performance Evaluation

b) *Image processing:* In image processing, the feature extraction is done. The dataset is selected and features of all the images are retrieved. In the feature extraction process color features are extracted using GLCM(gray level coccurrence matrix). Mainly four features are extracted. They are shown in table 1. LAB conversion of the images is done following with determining the color histogram of images. After feature extraction the result is stored in a matrix called Train_data.mat. The algorithm is discussed below:
   1) Load the dataset.
   2) Feature extraction is done and result is stored in Train_data.mat.

c) *Matching:* In this part the Manhattan distance between the feature vectors are calculated. It is done by subtracting the Test_data with Train_data. The image with the least distance is retrieved as it has the maximum features matching. Formula is given below:

$$\text{Distance} = \sqrt{test_{data}} - train_{data}$$

7. Conclusion

CBIR technology has been utilized in many applications like fingerprint identification, diverseness info systems, digital libraries, crime bar, medicine, historical analysis. in this paper, image retrieval strategies are mentioned. the most downside areas are mentioned. merits and demerits of existing algorithmic rule area unit mentioned that motivates the investigator for future work. Re-ranking and retrieval strategies are studied to provide the higher precision and recall values. we tend to made four categories of objects and distributed experiments with completely different queries. the improved vocabulary for query process improves the retrieval rate of images.. A information consists of various forms of images has enforced on the system. completely different options like histogram, GLCM, lab conversion is taken into thought for extracting similar images from the information. From the experimental result's taken into thought for extracting similar photos from the data. From the experimental result it's seen that combined choices can provide higher performance than the sole feature. therefore selection of feature is one in all the important issues inside the image retrieval. The system is claimed to be economical if linguistics gap is minimum .The result area unit usually improved in future by introducing feedback and user‟s choice.

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