Content Based Image Retrieval using Neural Network

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Abstract— Traditional methods of image retrieval using text are proven to be insufficient for the large image database. There are some drawbacks of Text based image retrieval, like assigning the labels to each image in large database using text is extremely time consuming and it is language dependent, valid for only one language at a time. Another drawback is for same image different users can assign different labels. These drawbacks can be avoided by using contents present in that image for retrieval of image. This type of retrieval of image is called as Content Based Image Retrieval.

CBIR or Content Based Image Retrieval is the retrieval of images based on visual features such as color, texture and shape. There are two types of features present in an image, low level features and High level features. In CBIR, features of images stored in database are extracted and compared to the features of the query image. There are two important steps in CBIR, first is Feature extraction and second is Similarity measurement. An extensive set of experiments has been conducted to show that the new algorithm can improve the retrieval accuracy. In our project DML and ANN algorithms are used to measure the similarity between images. The experiment also indicates that the new algorithm(ANN) is more effective and more efficient than alternative algorithm.

Index Terms —content-based image retrieval, relevance feedback, semantic gap, log-based relevance feedback, Distance metric Learning, Neural Network, log database

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1. INTRODUCTION

In Content Based Image Retrieval (CBIR) Content-based means that the search will analyze the actual contents (features) of the image[1][2][3]. In the image two types of features are present Low Level Features and High Level Features. High level features like emotions in an image , or different activities present in that image. Extracting High level features from image is very difficult and time consuming, But they gives relatively more important meanings of objects and scenes in the images that are perceived by human beings. So low level features like color, texture and shape are used for retrieval of the image. These low level features can be easily extracted from the image. These features are extracted from the query image and same features are extracted from the images present in the database. These features are compared by using similarity measurement algorithms like DML(Distance Metric Learning) and ANN(Artificial Neural Network) and closest images to our query image are retrieved. A query image is nothing but an image you already have, or you can draw rough sketch and use it as query. Images retrieval using content based technique is useful in many areas like medical diagnosis, satellite communication, security, crime prevention, web searching, home entertainment etc. In this paper section 2 involves the block diagram. Section 3 gives Implementation & design details. In section 4 different methods for similarity measurement (Algorithms) are given. Methodology is given in section 5. Section 6 is conclusion and followed by acknowledgement and references.
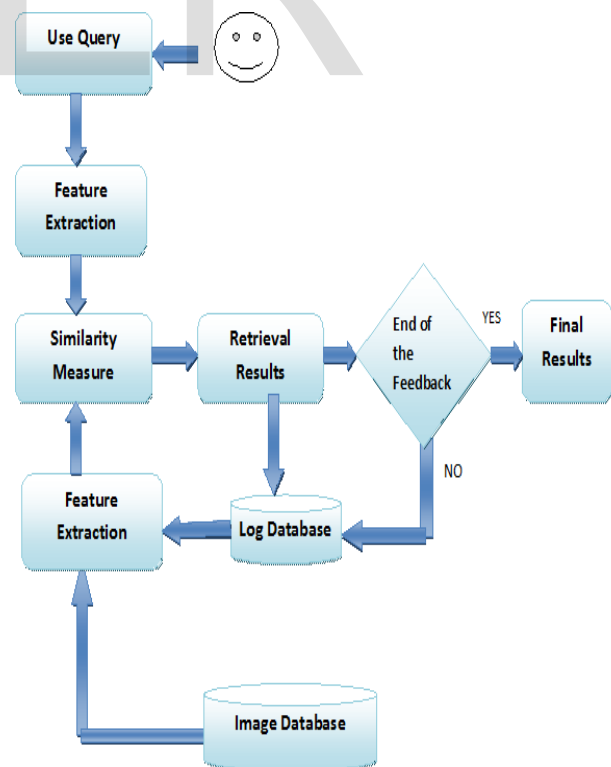
1. BLOCK DIAGRAM OF CBIR

Figure 2.1. Block diagram of CBIR System with relevance feedback

Objective of the System:-

Above figure 2.1.Shows the block diagram of the CBIR system with relevance feedback.

There are large number of images present in the image database. We have used WANG Database of 90 images for our project which contains images in 'jpeg' format. Initially query image is given, then low level features like color, texture and shape are extracted from the query image. For color feature extraction three color moments are used in three color channels(H,S,V), So there are 9 color features. For texture feature extraction we have used 3 Level DWT, So there are total 9 texture feature and. For shape feature extraction Canny edge detection method is used. There are 18 shape features. Total 36 features of Query image are extracted. Then feature vector is calculated. Same features are extracted from the images present in the image database. The database is made to store the feature vectors calculated for the images present in the database. After Feature extraction next step is similarity measurement. For similarity measurement different algorithms are used like Distance Metric Learning(DML), Artificial Neural Networks(ANN) etc. The top closest images to our query image are retrieved. The search is usually based on similarity rather than exact match. Then user gives the feedback in the form of 'relevance judgments'.Relevant images are the images obtained in first iteration which are from the same class as that of Query. In first iteration These values are relevant and non-relevant .Relevant means the image relevant to the user and non-relevant means the image is definitely not relevant. If the user is satisfied with the obtained results, then feedback loop stops otherwise it continues until user get satisfied with results. In Fig. 2.1, the block diagram consists of following blocks image database, log database, feature extraction, similarity measurement, and feedback algorithm. Finally, obtained results are compared using certain parameters like Accuracy, Precision, Recall rate etc.

2. IMPLEMENTATION AND DESIGN DETAILS

a. **Feature Extraction:-**

Low-level Image Feature Representation

Low-level image feature representation is one of the key components for CBIR systems. Three types of visual features were used in this work, including color, shape and texture. The same set of image features have been used in the previous research on image retrieval.

1. Color:-

Color is one of the most widely used visual feature in content-based image retrieval. While we can perceive only a limited number of gray levels, our eyes are able to distinguish thousands of colors and a computer can represent even millions of distinguishable colors. Color has

been successfully applied to retrieve images, because it has very strong correlations with the underlying objects in an image. Moreover, color feature is robust to background complications, scaling, orientation, perspective, and size of an image. Although we can use any color space for computation of a color histogram HSV (hue, saturation, value), HLS (hue, lightness, saturation), and CIE color spaces (such as CIELAB, CIELUV) have been found to produce better results as compared to the RGB space. Since these color spaces are visually (or perceptually) uniform compared to the RGB, they are found to be more effective to measure color similarities between images.

RGB Color space is perceptually not similar to human color vision. So it is necessary to convert RGB color space into other (Perceptually close to human color vision).HSV , CIE,LUV color spaces are there. Above olor spaces can be obtained by Non-Linear transformation of RGB color space.

CIE color space is Inconvenient ,because of calculation complexities of the transformation to and from RGB color space. So we have used HSV color space , which is perceptually uniform.

$$H = \frac{COS^{-1}(1/2[(R-G)+(R-B)])}{\sqrt{(R-G)^2+(R-B)(G-B)}}$$

$$S = 1 - \frac{3[MIN\,(R,G,B)]}{R+G+B}$$

$$V = \frac{R+G+B}{3}$$

There are different color feature extraction methods like:-

1. Color Histogram

2. Color Coherence Vector

3. Color Moments

Color Histogram method is relatively insensitive to position and orientation changes and they are sufficiently accurate. But they do not capture spatial relationship of color region. So they are limited to discriminating power. Color Coherence Vector method is better than color histogram method. This method combines the special correlation of color regions as well as the global distribution of local special correlation of colors. But ther is one disadvantage of this method it requires very expensive computations. So in our project we have used color moment method for color feature extraction. This method is more robust and runs faster than histogram based methods.
So,
Color feature index size=No. Of color channels * 3 moments

= 9 color features

We are extracting 9 color features for CBIR. We have used color mean, color variance and color skewness in 3 different color channes(H,S,V).

2.   Texture:-

Texture is another popular features used in CBIR. We used texture features based on wavelet transformation. The Discrete Wavelet Transformation (DWT) was first applied to images with a Daubechies-4 wavelet filter. 3-levels of wavelet decomposition is used to obtain ten subimages in different scales and orientations. One of the subimages is a subsampled average image of the original one and was discarded because it contains less useful information. Then entropies of the other nine subimages are used texture feature of an image. Major characteristic of texture is the repetition of a pattern or patterns over a region in an image. The elements of pattern are called as textons. The difference between two textures can be due to degree of variation of the textons. It can also be due to spatial distribution of the textons in the image. So 9 texture features are used here.

Enropy, H= k*log(1/P)

P=1/n

$H(x) = -\sum_{i=1}^{n} P(xi) * \log P(xi)$

3.   Shape:-

Edge features have been shown to be effective in CBIR since it provides information about shapes of different objects. Canny edge detection is used to obtain the histogram for edge direction. Then, the edge direction histogram was quantized into 18 bins of each of 20 degrees. So there are 18 different shape features are used to extract shape feature from an image .Shape can roughly be defined as the description of an object minus its position, orientation and size. Therefore, shape features should be invariant to translation, rotation, and scale, for an effective CBIR, when the arrangement of the objects in the image are not known in advance. To use shape as an image feature, it is essential to segment the image to detect object or region boundaries; and this is a challenge. Techniques for shape characterization can be divided into two categories.

The first category is boundary-based, using the outer contour of the shape of an object and the second category is region-based, using the whole shape region of the object. The most prominent representatives of these two categories are Fourier descriptors and moment invariants. The main idea behind the Fourier descriptors is to use the Fourier-transformed boundaries of the objects as the shape features, whereas the idea behind moment invariants is to use region-based geometric moments that are invariant to translation and rotation.

3. ALGORITHM

Similarity Measures

After feature extraction next step is similarity measurement. Similarity between images is measured by using following algorithms.

1.   Distance Metric Learning Algorithm(DML):-

Suppose we have some set of points {xi}mi=1 ε Rnv and are given information that certain pairs of them are "similar"

S: (xi,xj) ε S

Consider learning a distance metric of the form

d(x,y)=dA(x,y)=||x-y || A=√(X-Y)TA(x-y)

A simple way of defining a criterion for the desired metric is to demand that pairs of points (xi,xj) in S _ have, say, small squared distance between them:

$$\text{Minimize A} \sum_{(xi,xj) \in S} ||xi - xj||^2 \text{ A}$$

We have used k-means method for clustering and then clusters are formed. These clusters are used in DML to measure the similarity.

2.   Artificial Neural Network(ANN):-

Steps of CBIR:-

1.   Input Query image I.
2.   Perform color feature extraction and get 9 color features.
3.   Calculate feature vector for mean, variance and skewness.
4.   Perform texture feature extraction and get 9 texture features. And calculate feature vector for texture.
5.   Perform shape feature extraction using canny edge detection and get 18 shape features.
6.   Combine all three feature vectors into one.
7.   Perform steps 2,3,4,5 on images in database.
8.   Combine all three feature vectors into one.
9.   Calculate the distance d(H,I) between two images using
      i.   DML   ii.   ANN
10. Increment j and repeat all steps for all images in database.
11. Then find minimum distance and give similar images as result.
12. If user is not satisfied with these results relevance feedback continues.
13. Submit query to results obtained in first iteration so as to get better results.
14. Precision and accuracy is calculated using following formulae.

$$\text{Precision} = \frac{\text{(No.of retrieved images that are relevant)}}{\text{Total no.of retrieved images}}$$

$$\text{Accuracy} = \frac{\text{(No.of true positives+No.of true Negatives)}}{\text{No.of TP+TN+FP+FN}}$$

Where,

TP=True positive rate=Correctly classified positive cases

TN=True Negative Rate=Correctly classified negative cases

FP=False positive rate= Incorrectly classified negative cases

FN=False Neegative rate= Incorrectly classified positive cases

4. METHODOLOGIES

The solution proposed is to extract the primitive features of a query image and compare them to those of database images. The image features under consideration are color, texture and shape. The color, texture and shape features of one image are compared and matched to the corresponding features of another image using matching and comparison algorithms. This comparison is performed using distance metrics of color, texture and shape. Then, these metrics are applied one after another, to retrieve database images that are similar to the query image. The similarity between features is to be calculated using algorithms.

Following methodologies are used in the proposed work

- Collection of Image Database
- Feature Extraction
- Similarity Measures
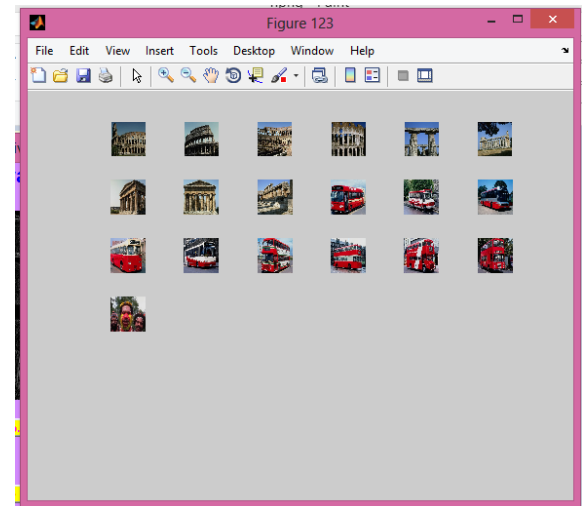- Comparison of results(DML and ANN)

5. RESULTS
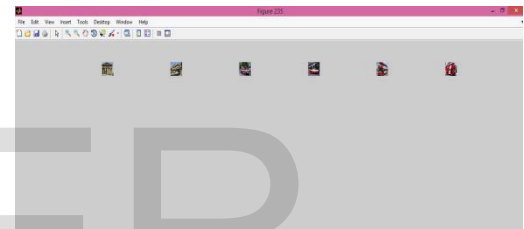
Results Using DML:-

Precision=60%
Accuracy= 42.10%

Results using DML after first iteration:-

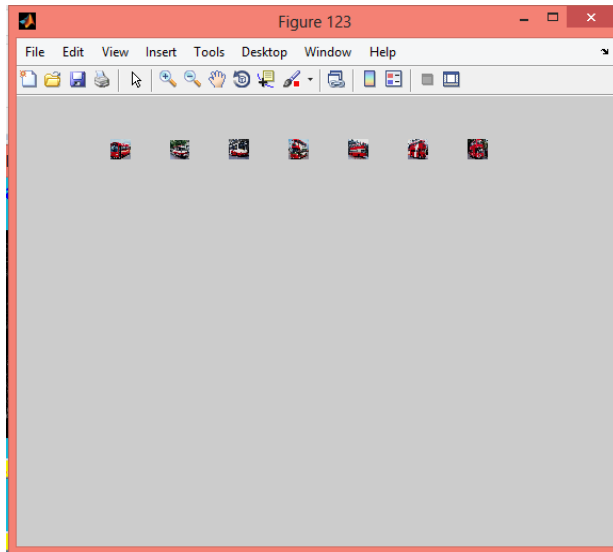Results using DML after second iteration:-

Results using ANN:-

Precision=100%
Accuracy=97.77%

Results After first iteration:-

6. CONCLUSIONS

Results obtained using ANN are more accurate as compared to DML algorithm. Accuracy obtained using DML is 42.10% and using ANN is 97.77%. So results obtained using ANN are more similar to query image. Precision using DML is 60% and using ANN is 100%.

Also relevance feedback mechanism is used in our project which improves the retrieval accuracy. In Results obtained using DML in first iteration 9 images are similar to query image. But after second iteration 2 images are similar to query. So rate of wrong result is reduced in second iteration results. So relevance feedback improves retrieval accuracy.

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