PERFORMANCE ANALYSIS IS BASIS ON COLOR BASED IMAGE RETRIEVAL TECHNIQUE

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ABSTRACT

Many existing color based image search techniques searches image based on color of entire image irrespective of foreground and background which have disadvantage of retrieving images based on dominant color in the image (mostly background) but many a time user might be interested in foreground information. We are focusing on image search based on foreground color. Obviously since locating object accurately is one of the most challenging and open problem in computer vision, in this work we limit our self to human dress as foreground. We are able to extract images with excellent precision and recall on our own dataset collected from web.

1. INTRODUCTION

In the past few decades, Content Based Image Retrieval has become a hot subject of research, which is the key technology on the important research item as the multimedia database and digital library and So Content-Based Image Retrieval is to find a similar picture or pictures in the database based on the feature such as color, shape, texture, space location or the combination of the subject or region in the image and this technology not only incarnates the information image to all needed main technical characteristics but also fully combines the traditional database technology. The study of Content Based Image Retrieval also has the important meaning for impelling and enriching the theory of signal and information processing. The various methods of color based image retrieval and its limitations are explained in section 2. Section 3 describes the proposed method of retrieval using K-Nearest Neighbor based on foreground objects. Section 4 reports the significant experimental results. Conclusions and future directions are given in section 5.
2. FRAMEWORK

To search image database color approach is used in this paper as related paper work here. Color is an important cue for image retrieval. Color not only adds beauty to images but also gives more information, which is used as a powerful tool in content based image retrieval. There are number of approaches in color based image retrieval. The simplest approach is color histogram matching. Color Histograms are way to represent the distribution of colors in images. A distance between query image histogram and a data image histogram can be used to define similarity match between the two distributions.

3. CHALLENGES

Regarding color feature to image processing bellow challenges are targeted.

1. Automatic annotation of previous unseen image.
2. Retrieval of database images based on semantic queries
3. Handling larger spectral image database
5. High level image processing as accessing complex feature of image.
6. Low level image processing to larger image with various similarities.
7. Stability and scalability in image regarding changes in image with larger scope of size.
8. Identification of color distribution by feature compression of image.

4. SIGNIFICANT

In this paper Content based Image retrieval is a promising approach to search image database by means of image features such as color, texture, shape, pattern or any combinations of them.

5. OBJECT

In Color Indexing, for any given Query image the goal is to retrieve all the images whose color is similar to those of query image.

6. USED METHOD

6.1 Approaches in Color based Image Retrieval on Conventional Histogram-Based Matching Method

The histogram-based method is very suitable for color image retrieval because they are invariant to geometrical information in images, such as translation and rotation. Histogram intersection method (HIM) [1,4] is to measure the intersection area between two images' histograms. They are usually named as reference image (R) for the query input and model images (M) from the image database. A histogram of image \( h(R) \) is an n-dimensional vector, in which each element \( (Rj) \) represents the number of pixels of color \( e \) in the n-color image. With regardless of the image size, each element is normalized before comparison and
the resulting normalized histogram is $H(R)$ Similarity measure between $R$ and $M$ is then performed by calculating the histogram intersection $I(R,M)$ [5] determined. The larger the value $I(R,M)$ the more similar the images $R$ and $M$ is. Images $M$ could then be ranked from the image database. The same color distribution histograms between different brightness conditions of the two digital images result in smaller intersection value and make the highly visually similar images becomes lower ranked.

6.1.1 Dominant Color Region Based Indexing

Dominant color region in an image can be represented as a connected fragment of homogeneous color pixels which is perceived by human vision. [6,7]. Image Indexing is based on this concept of dominant color regions present in the image.

The segmented out dominant regions along with their features are used as an aid in the retrieval of similar images from the image database. Image path, number of regions found, region information like color, normalized area and location of each region are stored in file for further processing. The main drawback of this technique [8] is it never retrieves the same objects of varying sizes as the similar image. For the smaller object the background will be the dominant region as shown in figure 1, whereas in bigger object that objects itself is dominant. Even though the semantics of the objects are same, they are not retrieved as similar images.

![Figure 1 Dominant Background Images](image)

The proposed method can answer this problem because of considering only the foreground information and neglecting background details.

6.2 K-Nearest Neighbor Method Based on Foreground Objects

K-Nearest Neighbor based on foreground objects retrieves more number of similar images based on foreground color irrespective of size.

The foreground information of the images are enough to identify the images properly. This is implemented by the proposed algorithm.

6.2.1 Image Segmentation

Image segmentation is the motivation of this research work, and is used to distinguish this technique from previous works of image retrieval based on dominant color Identification. The color image is converted into the grayscale image and then using threshold method that will be converted into the binary image.

In binary image the foreground is represented by maximum intensity value (1) and background is represented by minimum Intensity value (0). The binary image is converted into the color image by retaining the color values only in the foreground of the image.
6.2.2 Color Space Categorization

The entire RGB color space is described using small set of color categories. This is summarized into a color look-up table. A smaller set is more useful since it gives a coarser description of the color of the region thus allowing it to remain same for some variations in imaging conditions. The color lookup table in Table 1, consists of 25 colors chosen from 256 color palette table. The efficiency of retrieval system can be improved whenever the dominant color can be identified within the smaller set of colors. Whenever the entire RGB color space is used for identifying the dominant color of an image then the efficiency of the retrieval method will be decreased.

Table 1. Color Look-Up Table

<table>
<thead>
<tr>
<th>COLOR</th>
<th>B</th>
<th>R</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sea green</td>
<td>0</td>
<td>162</td>
<td>0</td>
</tr>
<tr>
<td>Light green</td>
<td>0</td>
<td>255</td>
<td>0</td>
</tr>
<tr>
<td>Olive Green</td>
<td>90</td>
<td>72</td>
<td>0</td>
</tr>
<tr>
<td>Aqua</td>
<td>36</td>
<td>146</td>
<td>170</td>
</tr>
<tr>
<td>Bright Green</td>
<td>36</td>
<td>266</td>
<td>0</td>
</tr>
<tr>
<td>Blue</td>
<td>73</td>
<td>36</td>
<td>170</td>
</tr>
<tr>
<td>Green</td>
<td>73</td>
<td>146</td>
<td>0</td>
</tr>
<tr>
<td>Turquoise</td>
<td>73</td>
<td>219</td>
<td>170</td>
</tr>
<tr>
<td>Dark Red</td>
<td>109</td>
<td>36</td>
<td>0</td>
</tr>
<tr>
<td>Blue Gray</td>
<td>109</td>
<td>109</td>
<td>170</td>
</tr>
<tr>
<td>Lime</td>
<td>109</td>
<td>219</td>
<td>0</td>
</tr>
<tr>
<td>Lavender</td>
<td>140</td>
<td>0</td>
<td>170</td>
</tr>
<tr>
<td>Plum</td>
<td>140</td>
<td>109</td>
<td>0</td>
</tr>
<tr>
<td>Teal</td>
<td>146</td>
<td>192</td>
<td>170</td>
</tr>
<tr>
<td>Brown</td>
<td>192</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Magenta</td>
<td>182</td>
<td>73</td>
<td>170</td>
</tr>
<tr>
<td>Yellow Green</td>
<td>182</td>
<td>182</td>
<td>0</td>
</tr>
<tr>
<td>Floret Green</td>
<td>182</td>
<td>255</td>
<td>170</td>
</tr>
<tr>
<td>Red</td>
<td>219</td>
<td>73</td>
<td>0</td>
</tr>
<tr>
<td>Rose</td>
<td>219</td>
<td>140</td>
<td>170</td>
</tr>
<tr>
<td>Yellow</td>
<td>219</td>
<td>255</td>
<td>0</td>
</tr>
<tr>
<td>Fink</td>
<td>255</td>
<td>36</td>
<td>170</td>
</tr>
<tr>
<td>Orange</td>
<td>255</td>
<td>146</td>
<td>0</td>
</tr>
<tr>
<td>White</td>
<td>255</td>
<td>255</td>
<td>255</td>
</tr>
</tbody>
</table>

6.2.3 Color Matching and K-Nearest Neighbor

The Segmented image is modified into 25 color combination image. It involves mapping all pixels to their categories in color space. For each pixel in the image, a color is selected from 25 predefined colors which are very near to image pixel color and it will be stored as new color pixel in the image. Using p, the image pixel value and C, the corresponding color table entry, color distance Cd is calculated using Euclidean distance formula as specified in the equation below.

\[ Cd = \min \left( pr - Cir \right)^2 + \left( pg - Cir \right)^2 + \left( pb - Cib \right)^2 \] (1)

where \( i = 1 \) to 25

The dominant color of the foreground image is determined as the color response of each pixel in the modified image and stored in frequency table. The frequency table is sorted in descending order and then the first occurrence color will be the dominant color of the foreground of the respective image.
6.3 K-Nearest Neighbor Classification

1. In pattern recognition, the K-NN is a method for classifying objects based on closest training examples in feature space.

2. An object is classified by a majority vote of its neighbor, with the object being assigned to the class most common amongst its k nearest neighbor.

![Figure 2 K-Nearest Neighbor Classification](image)

6.3.1 Example of K-NN Classification

1. The test sample (green circle) should be classified either to the first class of blue squares or to the second class of red triangles. If \( k = 3 \) it is classified to the second class because there are 2 triangles and only 1 square inside the inner circle. If \( k = 5 \) it is classified to first class (3 squares vs. 2 triangles inside the outer circle) [9].

2. Usually Euclidean distance is used as the distance metric; however this is only applicable to continuous variables.

3. The classification accuracy of "k"-NN can be improved significantly if the distance metric is learned with specialized algorithms such as e.g. Large Margin Nearest Neighbor or Neighborhood Components Analysis.

![Figure: 3 System Workflow](image)
6.4 Image Segmentation

Image segmentation is the motivation of this research work, and is used to distinguish this technique from previous works of image retrieval based on dominant color identification. The color image is converted into the grayscale image and then using threshold method that will be converted into the binary image[3]. In binary image the foreground is represented by maximum intensity value (1) and background is represented by minimum Intensity value (0). The binary image is converted into the color image by retaining the color values only in the foreground of the image.

6.4.1 Parameter Selection

The best choice of $k$ depends upon the data; generally, larger values of $k$ reduce the effect of noise on the classification, but make boundaries between classes less distinct[10]. A good $k$ can be selected by various heuristic techniques, for example, cross-validation. The special case where the class is predicted to be the class of the closest training sample (i.e. when $k = 1$) is called the nearest neighbor algorithm. The accuracy of the $k$-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance. Much research effort has been put into selecting or scaling features to improve classification. A particularly popular approach is the use of evolutionary algorithms to optimize feature scaling. Another popular approach is to scale features by the mutual information of the training data with the training classes. In binary (two class) classification problems, it is helpful to choose $k$ to be an odd number as this avoids tied votes. One popular way of choosing the empirically optimal $k$ in this setting is via bootstrap method.

6.4.2 Properties

The naive version of the algorithm is easy to implement by computing the distances from the test sample to all stored vectors, but it is computationally intensive, especially when the size of the training set grows. Many nearest neighbor search algorithms have been proposed over the years; these generally seek to reduce the number of distance evaluations actually performed. Using an appropriate nearest neighbor search algorithm makes $k$-NN computationally tractable even for large data sets. The nearest neighbor algorithm makes $k$-NN computationally tractable even for large data sets. The nearest neighbor algorithm has some strong consistency results. As the amount of data approaches infinity, the algorithm is guaranteed to yield an error rate no worse than twice the Bayes error rate (the minimum achievable error rate given the distribution of the data) $k$-nearest neighbor is guaranteed to approach the Bayes error rate, for some value of $k$ (where $k$ increases as a function of the number of data points). Various improvements to $k$-nearest neighbor methods are possible by using proximity graphs.

6.4.3 for Estimating Continuous Variables in Parameter Selection

The $k$-NN algorithm can also be adapted for use in estimating continuous variables. One such implementation uses an inverse distance weighted average of the $k$-nearest multivariate neighbors[1]. This algorithm functions as follows.
1. Compute Euclidean or Mahalanobis distance from target plot to those that were sampled.
2. Order samples taking for account calculated distances.
3. Choose heuristically optimal $k$ nearest neighbor based on RMSE done by cross validation technique.
4. Calculate an inverse distance weighted average with the $k$-nearest multivariate neighbors.

The optimal $k$ for most datasets is 10 or more that produces much better results than 1-NN. Using a weighted $k$-NN, where the weights by which each of the $k$ nearest points' class (or value in regression problems) is multiplied are proportional to the inverse of the distance between that point and the point for which the class is to be predicted also significantly improves the results.

**6.4.4 Retrieval Method**

For all the color images in the database, the above said technique is applied to determine the foreground dominant color and then the extracted feature of dominant color is stored. Whenever the query image is supplied by the user, the dominant color for foreground information is determined. The retrieval technique detects the database images whose foreground dominant color is similar to the Foreground dominant color of query image. Those images are retrieved as the similar images for the query image.

**7. ANALYSIS**

Database images (100 numbers) of different sizes consisting of different colors of dress of celebrity are collected from various websites. The experimental results show that the proposed technique has better performance and retrieve more number of meaningful images compared to existing technique. The Performance of retrieval result is measured by Precision and Recall as given formula in equation 1 and 2.

\[
\text{Precision} = \frac{\text{Total no of images retrieved}}{\text{No of Relevant images retrieved}}
\]

\[
\text{Recall} = \frac{\text{Total no of relevant images in database}}{\text{No of Relevant images Retrieved}}
\]

Here the precision measures the hit-rate that the class of the retrieved images is the same as that of input reference image from the whole database.

The recall measures the capability of finding the images with the same class from the whole class of images in the database.
Table 2 Performance Analysis

<table>
<thead>
<tr>
<th>Sample query image</th>
<th>existing recall</th>
<th>existing precision</th>
<th>proposed recall</th>
<th>proposed precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>No.1</td>
<td>0.63</td>
<td>0.96</td>
<td>0.99</td>
<td>0.98</td>
</tr>
<tr>
<td>No.2</td>
<td>0.6</td>
<td>1</td>
<td>0.895</td>
<td>1</td>
</tr>
<tr>
<td>No.4</td>
<td>0.42</td>
<td>0.41</td>
<td>0.82</td>
<td>0.65</td>
</tr>
<tr>
<td>No.5</td>
<td>0.41</td>
<td>1</td>
<td>0.89</td>
<td>1</td>
</tr>
<tr>
<td>No.6</td>
<td>0.46</td>
<td>0.77</td>
<td>0.84</td>
<td>1</td>
</tr>
</tbody>
</table>

In Table 2, the performance of existing dominant color region based indexing and proposed content based image retrieval using dominant color identification based on foreground objects are compared by precision and recall metrics. The Recall and precision value for some sample query images are computed and compared for existing and proposed techniques.

8. EXPERIMENTAL RESULTS

From the experiment result, it is proved that the performance of proposed K-Nearest Neighbor classification based retrieval having highest recall and precision rates compared to the existing dominant color region based indexing as shown in figure 4, figure 5.

Figure:4-Performance between existing dominant color region indexing and proposed technique to recall values.
9. CONCLUSION

The proposed technique of K-Nearest Neighbor Classification based on foreground objects is a meaningful technique to retrieve the images based on color. The first step of segmenting foreground from background is a good improvement over a work of existing dominant region color indexing in which there is a chance of considering the background as the dominant color region even though that doesn’t provide any semantics to the image. Identifying background as dominant color region is restricted in the proposed technique. Modifying the image into 25 color combination image will narrow the process of identifying the dominant color and improve the efficiency of retrieval system. The Experimental result shows that the proposed technique is efficient compared to the existing dominant color region based Indexing.

10. FUTURE WORK

In future, it is recommended to improve the efficiency of segmentation process to separate foreground from background. Color lookup table having some minimal set of colors can be used instead of having 25 colors. Shape feature can be incorporated to retrieve more meaningful images.

REFERENCES


