Research Article

An Enhanced Triadic Color Scheme for Content-Based Image Retrieval

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1. Introduction

Recent developments in big data technology have produced a sizable number of image databases. A capable visual search tool is required for all of these image libraries. There are two methods for conducting a search. Keywords are used to annotate images in text-based image retrieval [1].

This approach has a number of drawbacks:

1. It is impossible to manually annotate large databases
2. The technique must be annotated by the end user, making it sensitive to human perception
3. Only one language is covered by these annotations

To address the above challenges with multimedia research, CBIR analyses large-scale images employing local and global features in digital image processing [2]. There are several ways in which this method differs from text-based image retrieval systems. The CBIR system’s most crucial element is feature extraction [3]. Because color extraction is usually straightforward and retrieval performance is quite high, it is frequently used in CBIR systems [4]. There are yet to be published complete and accurate definition of form features. The Fourier descriptor, aspect ratio, and circularity are all common ways for acquiring geometric form information. Furthermore, three texture-description approaches are used: statistical, structural, and spectral methods [5, 6].
Table 1: Conventional methods comparison.

| Reference | CBIR classifier | Method                  | Accuracy (%) |
|-----------|-----------------|-------------------------|--------------|
| [17]      | Random forest   | Multikey image hashing  | 72           |
| [18]      | Support vector machine | Two-step strategy     | 81           |
| [19]      | Naive bayes     | Statistical approach    | 65           |
| [20]      | K nearest neighbor | Discrete wavelet transform | 68.7         |
| [21]      | Fuzzy rule      | Discrete wavelet transform | 84           |

(2) We proposed a new framework that can be utilized with a variety of primary color approaches to capture and classify integrated heterogeneous image data.

2. System Model

The proposed method is hybrid features extracted from an individual RGB, YCbCr, and \( L^*a^*b^* \). To decrease the significant feature vector length of a recommended descriptor, the hybrid features were extracted from color and use gray level and color information from a color map to compute numerous color properties. A color histogram is made using RGB, YCbCr, and \( L^*a^*b^* \), among other digital color approaches. These tactics have a very high sensitivity of color recognition cells in human visual information. RGB to YCbCr and RGB to \( L^*a^*b^* \) conversions are used in digital picture processing. For RGB images of type unit 8 and unit 16, the range of values is \([0, 255]\) and \([0, 65535]\). We present a set of integrated color attributes in this paper that can be used to generate more relevant images. Feature extraction methods identify the most important features and simplify image retrieval computations. The combined color channel includes RGB, YCbCr, and \( L^*a^*b^* \) features, which are based on K-means classification and then reranking features. Certain images have greater color traits, while others have more sensitive image features. The RGB, YCbCr, \( L^*a^*b^* \), and optimal color attributes are integrated to make image retrieval easier.

In order to increase image retrieval rate and simplify computation of image retrieval methods, we conducted a number of analyses and comparisons on integrated color information. By deriving ideal combination features from original features, the retrieval rate is enhanced. RGB, YCbCr, and \( L^*a^*b^* \) are triadic color schemes that use gray level and color information from a color map to compute numerous color properties. Our goal is to make reranking picture results more relevant by maximizing image retrieval of mixed color features. The proposed color algorithms can be applied to medical imaging, face recognition, and form matching, to name a few. Figure 1 depicts the framework for combined color approaches.

2.1. Feature Extraction. Extraction of visual features to a considerable extent in order to improve categorization is known as feature extraction. The CBIR uses a number of different feature extraction approaches. Our analysis is based on a mix of color and frequency prominent properties extracted from the input images.
2.2. Procedure

2.2.1. RGB Color Space. The RGB color model is additive; therefore, the following can be used:

(1) Magenta = red + blue
(2) Red plus green = yellow
(3) Cyan is made up of two colors: blue and green

Color auto-correlogram features are the likelihood of color adjusted fluctuation with distance space information. In the auto-correlogram, color information and spatial information are integrated. In the same way, each pixel in the image might travel through all of its neighbors. The computation complexity is calculated as

\[ O(d^2 n^2), \]

where \( n \) is the number of neighbor pixels, and \( d \) is defined as pixel distance.

2.3. YCbCr Color Space. The basic color approach is YCbCr, which is included in images and videos and is expressed as one color luminance and two color-difference signals. The letters \( Y \), \( Cb \), and \( Cr \) stand for brightness (luma), minus luma (B-Y), and red minus luma (R-Y). Two color components, \( Cb \) and \( Cr \), are used to store color information. \( Cb \) indicates the difference between the blue and the reference value, while \( Cr \) indicates the difference between the red and the reference value.

\[
Y = 16 + 65.74R/256 + 129.06G/256 + 25.06B/256, \\
Cb = 128 + \frac{37.95R}{256} - \frac{71.54G}{256} + \frac{112.44B}{256}, \\
Cr = 128 + \frac{112.44R}{256} - \frac{94.15G}{256} - \frac{18.29B}{256},
\]

2.4. \( L^*a^*b^* \) Color Space. Gray-scale information is represented using the \( L^*a^*b^* \) approach. More gray-scale information is indicated by the letter \( L^* \). Both \( a^* \) and \( b^* \) are used to indicate color information. The \( L^*a^*b^* \) formula is dubbed perceptually uniform since it is designed by the Euclidean distance difference between colors:

\[
L^* = 116 \left( \frac{R}{R_n} \right)^{1/3} - 16, \text{ for } \frac{R}{R_n} > 0.009, \\
L^* = 903.3 \left( \frac{R}{R_n} \right)^{1/3}, \text{ for } \frac{R}{R_n} < 0.009, \\
a^* = 500 \left( f \left( \frac{S}{S_n} \right) - f \left( \frac{T}{T_n} \right) \right), \\
b^* = 200 \left( f \left( \frac{S}{S_n} \right) - f \left( \frac{T}{T_n} \right) \right).
\]

Color feature extraction and concatenation were conducted on each of the original color image channels, such as the \( R \), \( G \), and \( B \) channels. RGB, YCbCr, and \( L^*a^*b^* \) are applied to the color image channels. Each channel’s distance is calculated separately, and the best values are used. To match a completely RGB, YCbCr, and \( L^*a^*b^* \) image, the Euclidean distance is employed. This method is applied to all color-characteristics channels. Single feature extraction does not provide optimal performance, which is one of the main reasons for missing the proper feature values. The combined RGB, YCbCr, and \( L^*a^*b^* \) three channel characteristics are a great compromise for long-range tasks because they are exceptionally fast to retrieve.

3. Ranking Procedure and Metrics

3.1. Distance Metrics. There are two points, \( q \) and \( t \), in the Euclidean distance. The database images are identified by the letters \( t \) and \( q \), respectively. At points \( t = (t_1, t_2, t_3, t_4, t_n) \), \( q = (q_1, q_2, q_3, q_4, \ldots, q_n) \), measure the Euclidean distance. The reranking algorithm is used after the Euclidean distance.

4. Experimental Evaluation and Analysis

CBIR image datasets include the Corel Collection, Wang Collection, ZuBuD, Coil-100, UW, INRIA Holiday, DP challenge, and Google Flickr, to name a few. Corel databases
were used in most of the input. The experimental databases used are listed in Table 2 and are taken from Kaggle website. The performance of the proposed technique is measured in terms of precision, recall, and accuracy. When compared to other similar color approaches that are already in use, our combined color feature approach outperforms them.

Color images are used to populate entire databases. Humans, animals, flowers, food, and other objects are included in the database. WANG Datasets, Holidays Datasets, and other CBIR approaches rely heavily on them. When compared to several database images, the retrieval result was high. Over 50 image query tests are put to the test using the approaches we have proposed. These tests assist us in determining the outcome and level of achievement. Finally, we used 80% datasets for training and 20% datasets for testing in our Corel database experiment.

4.1. Performance Analysis. Three important metrics are analyzed for performance evaluation. The measure values where its efficiency and accuracy are evaluated over the Corel Database using precision (Pr), recall (Re), and F-score (Fs) using equations (5) to (7):

\[
\text{Precision} = \frac{\text{Relevant images count}}{\text{Total images count}} \quad (5)
\]

\[
\text{Recall} = \frac{\text{Relevant images fetched}}{\text{Total relevant images}} \quad (6)
\]

\[
F = \frac{2PR}{P + R} = \frac{2}{\left(\frac{1}{R}\right) - \left(\frac{1}{P}\right)} \quad (7)
\]

The proposed method's overall performance evaluation has shown to be satisfactory. Figure 2 displays the outcomes of finding the top images. The triadic color method, also
known as the hybrid method, explains how to get an upgraded top comparable image in the right order. Figure 3 depicts an image performance metric comparison, whereas Figure 4 depicts a dataset performance metric comparison. When compared to a current method, the suggested method significantly increases the average value of the performance metrics, as shown in Figure 5.

From Figure 3, it can be observed that the tire image is recognized with 85% accuracy which is higher than other images. Guitar is the least identified image with 78% accuracy. Chair and tire recognizing accuracy is almost the maximum difference by 1%. F-score for airplane and chair equals 70%. The comparison analysis for various datasets is depicted in Figure 4. The accuracy of the Corel Dataset is 88% in comparison with other datasets. Coil-100 dataset gives the lowest F-score 86% which is 7–8% lower than the Corel dataset. From Figure 5, it is shown that image partitioning has the lowest accuracy of 83% and highest accuracy of 93% in comparison with other methods.

5. Conclusion

In this study, a novel model of combined color features is presented that computes distinct color features from color information with a limited number of chosen pixels, making it computationally appealing. The suggested method performed better than earlier detectors and was also compared to other color-characteristics techniques, such as RGB, YCbCr, and $L^*a^*b^*$, which are less noise-sensitive and result in more comparable images. The Corel Dataset was used to test this method, and the results showed that most of the images had issues. The results of the evaluation revealed that the suggested triadic color features method outperforms the existing method in terms of accuracy.

Data Availability

The article contains the data that were utilized to support the study’s findings.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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