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AN ENHANCED RGB PROJECTION ALGORITHM FOR CONTENT BASED IMAGE RETRIEVAL

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ABSTRACT

Content based image retrieval (CBIR) is one of the most popular and rising research areas of the digital image processing. Most of the available image search tools, such as Google Images and Yahoo Image search, are based on textual annotation of images. In these tools, images are manually annotated with keywords and then retrieved using text-based search methods. Therefore, the performances of these systems are not satisfactory. The goal of CBIR is to extract visual content of an image, like colour, texture, and shape automatically and to get accurate results with lower computational time. The CBIR technology can be used in several applications such as digital libraries, crime prevention, photo sharing sites, etc. Such a system has great value in apprehending suspects and identifying victims in forensics and law enforcement. This article presents an enhanced Red Green Blue (RGB) projection Algorithm to address the limitations of RGB Projection algorithm and reduce semantic gap in content-based image retrieval using bitmapping algorithm, image scale algorithm and Weighted Euclidean distance. The enhance technique was evaluated using WANG dataset, which contains 10800 colored images. The results show that the enhanced technique has higher precision than the existing system.

Keywords: RGB projection, Image retrieval, image processing, Content Based Image Retrieval

INTRODUCTION

Several institutions and agencies maintain a database of images for different purposes. A large collection of images is referred to as image database. An image database is a system where image data are integrated, coupled and stored. Image data include raw images and information extracted from images by automated or computer assisted image analysis (Kumar and Saranya, 2014). When searching for an image in a small collection of images, browsing can quickly identify the image. However, this is not the case for large and varied collection of images. In a large collection of digital images, an image retrieval system is used to browse, search and retrieve images. Image retrieval is classified mainly in two types: Text Based Image Retrieval (TBIR) and Content Based Image Retrieval (CBIR) (Dharani and Aroquiaraj, 2016).

Text-based Image Retrieval (TBIR) uses keywords, subject headings, or classification codes, to index images, which in turn are used as keys during search and retrieval. TBIR is non-standardized because different users employ different keywords for annotation. Text descriptions are sometimes subjective and incomplete because they cannot depict complicated image features very well. The drawbacks of TBIR are: (1) most descriptive annotations must usually be entered manually, which is impractical for a large image database; (2) most images are very rich in their contents and have more details, which makes an annotator to give different descriptions to images with similar visual contents; (3) textual annotations are language dependent (Mohammed et al., 2015). Thus, content-based image retrieval was introduced.

Content Based Image Retrieval (CBIR) is a technique that is used to search and retrieve digital images using image content. The CBIR technique retrieves semantically-relevant images from an image database based on automatically-derived image features (Sardey and Kharate, 2015). The main goal of CBIR technique is efficiency during image indexing and retrieval in order to reduce the need for human intervention in the indexing process. One of the main tasks for CBIR systems is similarity comparison, that is, extracting feature signatures of every image based on its pixel values and defining rules for comparing images. These features become the image representation for measuring similarity with other images in the database (Dharani and Aroquiaraj, 2016).

Color is one of the most important features in CBIR (Kumar and Esther, 2011). Despite the wide use of Red Green Blue (RGB) Projection Algorithm for color feature classification and extraction, only few CBIR systems utilize color as feature extraction (Gobiga et. al., 2014). Although RGB Projection systems have the potentials to increase accuracy of image retrieval, they require high complex computations to calculate similarity (Thawari and Janwe, 2011). This paper presents an enhanced content-based image retrieval system using RGB projection Algorithm.

The remaining parts of this paper are organized as follows; Section 2 describes the RGB and enhanced projection algorithms for image retrieval. Section 3 discusses the evaluation method used to determine the effectiveness of the developed technique. Section 4 discusses the results obtained while Section 5 concludes the paper.

MATERIALS AND METHOD

This section briefly discusses the working mechanism of the RGB Projection algorithm and the improvement provided to enhance the effectiveness and efficiency of the algorithm for image retrieval.

RGB Projection Algorithm

In RGB Projection algorithm (Wang and Qin, 2009), image features are extracted and used as comparer between the images. The system defines a similarity between contents of two images using color features. The RGB projection algorithm evaluates an image vertically and horizontally to determine the size of the image by sensing every pixel in both horizontal and vertical direction; basically, it calculates the horizontal and vertical projection. The projection uses the frequency and deviation of the image pixels from the source image. It makes use of image comparer which determines whether an object is less than, equal to or greater than the other. It also uses a mapping technique where the key is used to sort and uniquely identify the elements and stores the content associated with the key. The technique also maintains a dictionary frequency which automatically classifies the test images from non-target images. The classification is based on the similarities between the target and the non-target images. The RGB Projection algorithm uses projection histogram for feature extraction. Color histogram describes the global color distribution in an image and it is frequently used for content-based image retrieval. The projection histogram is defined using Equation 1 and Equation 2.

$$P_H\,(x) \;=\; \frac{1}{h}\sum\nolimits_{y=1}^{h} H(x,y)\,, x = 1,2,\ldots w \qquad (1)$$

$$P_H\,(y) \;=\; \frac{1}{w}\sum\nolimits_{y=1}^{h} H(x,y)\,, y = 1,2,\ldots h \qquad (2)$$

Where w and h denote the width and height of the image and H is the histogram. H (x, y) are the H component images in (x, y) pixel values.

The RGP Projection algorithm uses weighted mean to determine similarity between source and destination images. Instead of each data point contributing equally to the final mean, some data points contribute more "weight" than others. Weighted mean is calculated using Equation 3.

$$\bar{x} = \frac{\sum_{i=1}^{n} w_i H_i}{\sum_{i=1}^{n} w_i} \qquad (3)$$

where w denotes the weight and H denotes the histogram value of the image.

Color histogram is robust to translation of object and rotation about the viewing axis. However, color histogram does not include any spatial information. In addition, due to its statistical nature, these types of histograms can only index the content of images in a limited way. This makes histogram inefficient while distinguishing images with the same color but different color distributions. To address these limitations, the Enhanced RGB Projections algorithm uses color moments.

Enhanced RGB Projection Algorithm

Listing 1 shows the Enhanced RGB (ERGB) Projection algorithm. The algorithm extracts unique features using color moments 1, 2 and 3 (Jau-Ling & Ling-Hwei, 2002) as described in equations 4, 5 and 6.

Listing 1: Enhanced RGB Projection Algorithm

Begin

Step 1: The input images are color images in RGB color space.

Step 2: Calculate the color features using equations 3, 4 and 5 to extract the vertical and horizontal projection.

Step 3: Compute similarity for both vertical and horizontal projection

Step 4: Initialize source image projection and destination image projection.

Step 5: Calculate the weighted mean using equation 3.

Step 6: Using bit map algorithm (Listing 2) to resize the images

Step 7: Apply image scaling algorithm (Listing 2)

Step 8: Calculate the distance between the Input image and the images in the database that has the smallest distance with the input image using equation 7.

Step 9: Compare Source image with Destination Images

Step 10: Return source image with the similar image and corresponding images.

End

Moment 1: Mean

$$E_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \quad (4)$$

Moment 2: Standard Deviation

$$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N}\left(P_{ij} - E_i\right)^2\right)} \quad (5)$$

Moment 3: Skewness

$$S_i = \sqrt[3]{\left(\frac{1}{N}\sum_{j=1}^{N}\left(P_{ij} - E_i\right)^3\right)} \quad (6)$$

Similarities between two images are calculated and maximum value is returned. The projected image is resized using bit map algorithm David (2018) as shown in Listing 2.

Begin

Step 1: Read source pixel (i, j)

Step 2: Extract the red, green and blue values

Step 3: Multiply these values by dx*dy and add them up per color

Step 4: Repeat step 1 to 3 for all overlapping pixels

Step 5: Pack the summed red, green and blue colors

Step 6: store destination bitmap (x, y)

End

Listing 2: Bit Map Algorithm

After resizing the projected image, a scaling algorithm (Horé et al., 2012) is applied to generate feature vectors. The scaling algorithm is shown in Listing 3.

Listing 3: Image Scaling Algorithm

```
MaximizeScale(projection, max){
            minValue = MaxValue;
            maxValue = MinValue;
            for (i = 0; i < projection.Length; i++)
                   if (projection[i] > 0)
                       projection[i] = projection[i] / max;
                   End If
                   if (projection[i] < minValue)
                        minValue = projection[i];
                   else if (projection[i] > maxValue)
                        maxValue = projection[i];
                   End If
             End For
             if (maxValue == 0)
                 return;
             End If
            for (int i = 0; i < projection.Length; i++)
                if (maxValue == 255)
                    projection[i] = 1;
                else
                    projection[i] = (projection[i] - minValue) / (maxValue - minValue);
                End If
            End For
}
```

Unlike the RGB Projection algorithm that uses weighted mean to determine similarity between images, the enhanced RGB Projection algorithm uses Weighted Euclidean distance to calculate the distance between the source and the destination images. A function of similarity between a query image q and a datasets images d is defined as the sum of the weighted differences between the moments of the two distributions. The distance between the query image and the database images is calculated using Equation 7.

$$\left\|\mathrm{q}-\mathrm{d}\right\| = \sqrt{W_E \sum_{i=1}^{r}((E_i{}^1 - E_i{}^2)^2 + W_\sigma \sum_{i=1}^{r}(\sigma_i{}^1 - \sigma_i{}^2)^2 + W_S \sum_{i=1}^{r}(S_i{}^1 - S_i{}^2)^2} \quad (7)$$

Where q and d are the two images to be compared.
W is the value of the weight between the images.
i is the current image component index that is 1= R, 2 = G, and 3 = B.
r is the number of image layers.
$E_i{}^1 and\ E_i{}^2$ are the means of the two images in the ith component.
$\sigma_i{}^1 and\ \sigma_i{}^2$ are the standard deviations of the two images in the ith component.
$S_i{}^1 and\ S_i{}^2$ are the skewness of the two images in the ith component.

A test image is projected onto each target and non-target images in the dictionary. The target image is then compared with the sum of the images belonging to non-target images to determine a similar image. Image comparer identifies the duplicate and similar images by scanning the entire collection of images, analyzing the content and locating similar images. The comparer then returns the image pairs along with their similarity percentage.

Evaluation

The ERGB Projection system was evaluated using a number of queries to randomly select images from WANG image database. The WANG image database is a subset of the Corel database of 1000 images and was updated to 10800 by Li &

Wang (2003). The images in the database are grouped into 10 classes; each class contains more than 100 images. The image categories in the WANG database are people, beaches, buildings, buses, dinosaurs, elephants, roses, horses, mountains and food. All the categories were used in the evaluation. A retrieved image is considered a match if and only if it is in the same class as the query image.

The performances metrics used to determine the efficiency and effectiveness of the ERGB Projection algorithms are Precision, Recall and F-score (Malik & Baharum, 2012). The Precision, Recall and F-score are determined using equations 8, 9 and 10. The evaluation uses RGB Projection algorithm for comparative analysis.

$$Precision = \frac{\text{Number of Relevant Images Retreived}}{\text{Total Number of Images Retreived}} \quad (8)$$

$$Recall = \frac{\text{Number of Relevant Images Retreived}}{\text{Total Number of Relevant Images in the DB}} \quad (9)$$

$$F - score = 2 \times \frac{precision \times recall}{precison + recall} \quad (10)$$

RESULTS AND DISCUSSION

The results of the evaluation of RGB Projection and ERGB Projection systems are presented in this section. Table 1 shows the results of the comparative evaluation of the RGB and ERGB Projection algorithms.

The ERGB Projection algorithm performed better when retrieving images from the Dinosaurs, Roses, Elephants and Buildings classes compared to the other categories. The precision of the ERGB projection algorithm is also higher than that of the RGB Projection algorithm in all the categories except the Beaches class. The recall values of the ERGB Projection algorithm is better than that of the RGB Projection algorithm in all the classes except the Mountains class. For the F-score value, the ERGB Projection algorithm outperforms the RGB Projection algorithm in all the categories. On average, the precision, recall and F-score values of the ERGB Projection algorithm are 0.16, 0.26 and 0.23 higher than that of the RGB Projection algorithm respectively.

Table 1: The performances of RGB and ERGB Projection Algorithms

Categories	**Precision**		**Recall**		**F-score**	
	ERGBP	**RGBP**	**EGRBP**	**RGBP**	**EGRBP**	**RGBP**
Dinosaurs	0.99	0.80	0.97	0.78	0.98	0.79
Roses	1.00	0.85	1.00	0.84	1.00	0.84
Horses	0.98	0.71	0.97	0.70	0.97	0.70
People	0.96	0.87	0.98	0.76	0.97	0.81
Buses	0.96	0.84	0.96	0.52	0.96	0.64
Beaches	0.92	0.94	0.91	0.50	0.91	0.65
Elephants	1.00	0.80	1.00	0.62	1.00	0.70
Buildings	1.00	0.84	0.83	0.47	0.91	0.60
Mountains	0.96	0.89	0.88	0.90	0.92	0.89
Food	0.98	0.63	0.98	0.76	0.98	0.69
Average	**0.98**	**0.82**	**0.95**	**0.69**	**0.96**	**0.73**

The precision, recall and F-score of a CBIR system show the accuracy, robustness and efficiency of image retrieval with relevance to a query and database images. The ERGB Projection algorithm has a precision of 1.00 when retrieving images relevant to image queries for Roses, Elephants and Buildings classes. This shows that the images all the images retrieved by the queries are relevant to the class. Similarly, the recall value of ERGB Projection algorithm when retrieving images from the Roses and Elephants classes is 1.00, which shows that all the relevant images in the Roses and Elephants classes were retrieved. Although, the ERGB Projection algorithm is effective in retrieving relevant images from the Buildings class, only a substantial number of the relevant images were retrieved because the recall value is 0.83. Also, the ERGB Projection algorithm is accurate in retrieving relevant images from the Dinosaurs, Horses, People, Buses, Mountains and Food classes, although the algorithm retrieved irrelevant images and did not retrieve all the relevant images in each class, which is particularly higher for the Buildings and Mountains classes. However, the accuracy and robustness of the ERGB Projection is low when retrieving images from the Beaches class. This is likely due to variations in the number of color and color features in the images from the Beaches class.

Furthermore, the effectiveness of image retrieval for the ERGB Projection algorithm is substantial (F-score = 1.00) when retrieving images relevant to Roses and Elephants classes, which is a reflection of the effectiveness (precision = 1.00) and robustness (recall =1.00) of the algorithm. The ERGB Projection algorithm is also effective when retrieving images from the Dinosaurs, Horses, People, Buses and Foods classes. In addition, the effectiveness of the ERGB

Projection algorithm is generally low when retrieving images from the Beaches, Buildings and Mountains classes. Comparatively, the ERGB Projection algorithm substantially performed better than the RGB Projection algorithm irrespective of the image class. Although the RGB Projection algorithm is slightly more accurate (Precision = 0.94) than the ERGB Projection algorithm (Precision = 0.92) when retrieving images from the Beach class, the RGB projection algorithm retrieved only 50% of the relevant images from the Beaches class, which is significantly lower than that of the ERGB Projection algorithm. On the contrary, the ERGB Projection algorithm has a better accuracy than the RGB Projection algorithm when working with the Mountains class, however, the robustness (recall = 0.90) of the RGB projection algorithm is comparatively better. Nonetheless, the accuracy (Recall = 0.92) of the ERGB Projection algorithm in the Beaches class is comparatively better because the algorithm retrieved more relevant images than the RGB Projection algorithm. Generally, the results showed that the ERGB Projection algorithm is more effective in retrieving relevant images than the RGB Projection algorithm. This shows that using Weighted Euclidean distance for similarity measure between two images is better than using weighted mean.

CONCLUSIONS

A CBIR technique termed Enhanced RGB Projection Algorithm was presented in this paper as an improvement over the RGB Projection algorithm. The developed algorithm was evaluated using the WANG image database. The performance of the developed algorithm and an existing technique were comparatively determined using precision, recall and F-score. The ERGB Projection algorithm performed better than its counterpart. As for the future, the developed algorithm can be further evaluated using different benchmark image dataset with different semantics and categories. The algorithm can also be improved to increase searching ability and effectiveness, and reduce latency incurred between issuance of a request and arrival of the corresponding grant.

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