Improved Image Retrieval based on Fuzzy Colour Feature Vector

Sami B. Abugharsa, and Ahlam M. Ben-Ahmeida

Abstract—One of Image indexing techniques is the Content-Based Image Retrieval which is an efficient way for retrieving images from the image database automatically based on their visual contents such as color, texture, and shape. In this paper will be discuss how using content-based image retrieval (CBIR) method by colour feature extraction and similarity checking. By dividing the query image and all images in the database into pieces and extract the features of each part separately and comparing the corresponding portions in order to increase the accuracy in the retrieval. The proposed approach is based on the use of fuzzy sets, to overcome the problem of curse of dimensionality. The contribution of colour of each pixel is associated to all the bins in the histogram using fuzzy-set membership functions.

As a result, the Fuzzy Colour Histogram (FCH), outperformed the Conventional Colour Histogram (CCH) in image retrieving, due to its speedy results, where were images represented as signatures that took less size of memory, depending on the number of divisions. The results also showed that FCH is less sensitive and more robust to brightness changes than the CCH with better retrieval recall values.


Keywords—Retrieval based on Fuzzy Colour Feature Vector

I. INTRODUCTION

IMAGE databases are becoming increasingly common and finding application in wide areas of disciplines such as medical images, digital libraries, criminology, satellite imagery, government documents and to trade marks justification. With the increase in the use of image databases, the need for fast search of similarities between query images and the database images increases. Content-based Image Retrieval (CBIR) system is a search engine for retrieving images from the image database automatically based on their visual contents. CBIR systems calculate visual similarities between a query image and images in a database. Accordingly, the retrieval result is not a single image but a list of images ranked by their similarities measures with the query image [4].

In local feature extraction, a set of features are computed for every pixel using its neighborhood (e.g., average colour values across a small block centered around the pixel). To reduce computation, an image may be divided into subimages and convert it to 1-D vector as a signature, but the amount of computation is only a fraction of that for obtaining features around every pixel. Let the feature vectors extracted at block or pixel location. Exploration of colour features was active in nascent CBIR, with emphasis on exploiting colour spaces, e.g.(Hue, Saturation and Value), The HSV coincides better with human vision than the basic (Red, Green and Blue), In recent years, research on colour features has focused more on the summarization of colours in an image, that is, the construction of signatures out of colours [5]. For instance, in a colour feature extraction approach, an image is divided into several regions (e.g., red, green, and blue intensities) are computed for every image, and after converting it from RGB colour space to HSV colour space. The overall image is thus represented by a vector of colour components where a particular dimension of the vector corresponds to a certain to several regions in an images. The advantage of colour feature extraction is its high speed for both extracting features and computing similarity.

This paper is organized as follows: Section 2 describes the Colour Space Representations. Section 3 is for fuzzy set and fuzzy variables and image signature using FCH. Section 4 for image experimental results and section 5 conclusions.

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II. Colour Space Representation

A colour space is a coordinate system that allow colours to be measured and quantitatively specified [5]. RGB and HSV systems, are good examples of colour space representations.

A. RGB Colour Space

Most of image processing applications treat an image as collections of pixels comprised of red, green, and blue (RGB) values. RGB at 3-axis range [0 1] and each gray scale along the diagonal of each component is quantized into 256 levels [0:255]. The total number of different colours of 24 bits RGB colour space that can be produced is \(2^{24} = 16,777,216\) colours.

B. HSV Colour Space

Human do not perceive colours by combining different amounts of red, green and blue. Colours are perceived in terms of Hue (H), Saturation(S) and Value (V) as shown in Figure (1). HSV seeks to depict relationships between colours, and improve upon the RGB colour model. Standing for hue, saturation, and value, HSV depicts three-dimensional colour, the center axis goes from white at the top to black at the bottom, with other neutral colours in between. The angle from the axis depicts the hue, the distance from the axis depicts saturation, and the distance along the axis depicts value.

HSV is usually referred to as Perceptual Colour Space (PCS) [6]. A computer may describe a colour using the amounts of red, green and blue phosphor emission required to match a colour [8].

\[
H = 60 \times \left\{ \begin{array}{ll}
G - B & \text{if } \max = R \\
\frac{\Delta B - R}{\Delta B + \Delta G} & \text{if } \max = G \\
\frac{4 + \Delta R - G}{\Delta G} & \text{if } \max = B \\
\text{Undefined} & \text{if } R = G = B
\end{array} \right.
\]

\[
S = \left\{ \begin{array}{ll}
0 & \text{if } \max = 0 \\
\frac{\delta}{\delta \max} \times 255 & \text{Otherwise}
\end{array} \right.
\]

\[
V = \max
\]

III. Fuzzy Variables and Fuzzy Colour Histogram (FCH)

In our CBIR system, each pixel value is converted to 6 (Hue) X 3 (Saturation) X 1 (Value) which is equivalent to 18 bins values. In addition 3 (Gray scale) is added for special case where Hue is undefined compute the signature from RGB histogram [7]. A signature histogram is constructed by accumulating the value for each of the 21 histogram bins. The image signature will consist of 21 values.

To overcome the colour distribution problem in CCH system as shown in Figure (2), the image will be divided into 2 or 3 or 4 regions or parts as shown in Figure (3), and one fuzzy colour histogram is obtained for each region making the dimension of the signature equal to \(2X21=42\) bins, if the image division into 3 parts the length of signature equal to \(3X21=63\) bins, if the image division into 4 parts the length of signature equal to \(4X21=84\) bins, thus the multiply in 21 will be for all the regions in the image after division to know the difference between results and do comparing between them [10][12].

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**Figure 1**: HSV Colour space

**Figure 2**: Two perceptually different images with equal colour distribution
For all membership function we have used Triangle membership is defined by a lower Limit a and an upper Limit b, and a value θ, where \( a < \theta < b \) as follows:

\[
\mu_A(x) = \begin{cases} 
0, & \text{if } x \leq a \\
\frac{x-a}{\theta-a}, & \text{if } x \in [a, \theta] \\
\frac{b-x}{b-\theta}, & \text{if } x \in [\theta, b] \\
0, & \text{if } x \geq b
\end{cases}
\] (4)

FCH is constructed from fuzzy rules which are fuzzy rules represented by IF-THEN construction that have the general form of "IF A THEN B" where A is called a premise and B is called a consequence. IF-THEN rules exploits the tolerance for imprecision and uncertainty [9]. In this respect, constructing the FCH from fuzzy rules is as shown in Table (1), as an example:

**C. Value**

The membership of the value is representing as shown in Fig. (7). The fuzzy set of the value representing as full rank from 0 to the 255. Each value of the Hue is multiplied by the saturation and multiplied by value.

**D. Gray Scale**

Black, Gray and White colours are represented by three separate bins, since they are not included in the hue bins and the value of the Hue is undefined when these colours are equal shown in Fig. (8).

The consequence part represents the increase of the FCH bin which corresponds to the rule. Every subset has a center where its membership equal 1 [7]. The HSV spectrums are divided into several centers as follows:

**A. Hue Center**

The Hue value is represented by six subsets as shown in Fig. (5). The centers of the subsets are defined empirically by the following values: \( \{0, 60, 120, 180, 240, 300 \text{ and } 360\} \). Each value will activate only two subsets [11].

**B. Saturation**

The highest saturation is 255 will corresponds to 1 membership while 0 saturation corresponds to 0 membership. The saturation represents the strength of the colour. The higher the saturation, the higher the membership. Each Hue value is multiplied by the saturation. Values which are not activated will be zero and will not be affected by the saturation. Fig. (6) shows an example of the saturation of green colour [11].

<table>
<thead>
<tr>
<th>Hue</th>
<th>V13</th>
<th>V14</th>
<th>V15</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAGENTA</td>
<td>V16</td>
<td>V17</td>
<td>V18</td>
</tr>
<tr>
<td>Undefined</td>
<td>V19</td>
<td>V20</td>
<td>V21</td>
</tr>
</tbody>
</table>

The out of the premise part is defined as: \( \mu_{\text{premise}} = (\mu_{\text{Hue}}, \mu_{\text{Saturation}}) \)

**TABLE I**

**STRUCTURE OF LINGUISTIC FUZZY RULE BASE**

<table>
<thead>
<tr>
<th>Hue</th>
<th>Saturation</th>
<th>Low</th>
<th>Media</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td>V1</td>
<td>V2</td>
<td>V3</td>
<td></td>
</tr>
<tr>
<td>Yellow</td>
<td>V4</td>
<td>V5</td>
<td>V6</td>
<td></td>
</tr>
<tr>
<td>Green</td>
<td>V7</td>
<td>V8</td>
<td>V9</td>
<td></td>
</tr>
<tr>
<td>CYAN</td>
<td>V10</td>
<td>V11</td>
<td>V12</td>
<td></td>
</tr>
</tbody>
</table>

Where the parameters a and b represent the left and right boundary of the set \( \theta \) represents the center of the set as shown in Fig. (9), the \( \theta \) denotes the model value.
IV. EXPERIMENTAL RESULTS

The size of web-crawled database which contains 9,908 images is about 338 Mb, size of FCH files is sure less than 338 Mb depending on the number of division this means depending on length of the signature, Obviously, for taking all signatures for all images in CCH requires four times more, the representation of the features of 42 Bins and the values or length of signature increase by division.

A. Distance Measure

A similarity measure is metric which expresses how close or far two n-dimensional feature vectors. When a query is executed the similarity between the query image (or query images) and every image in the database is calculated. The images which are closest (those with the smallest distances from the query) are expected to be better results. There are several distance measures. Each distance measure compares two vectors, u and v. Both vectors have a dimensionality of n [8].

L1 distance: (also known as Manhattan distance and city block distance) is the sum of the absolute difference of all the corresponding points in the vectors u and v. It is typically used to compare image features such as colour histograms. The L1 distance between vectors u and v is:

\[ L1 (u, v) = \sum_{i=0}^{n} |u_i - v_i| \]  

B. Sample of Images Selected to Measure Recall Measurement

The experiments were performed on a large heterogeneous database of up to 9,908 Bmp images with a lot of images, used as queries, demonstrate that set stages in the FCH technique performs better than the CCH technique depending on the divisions selected. In next samples, are seen that the ratio of Recall for FCH is highs compared with Recall for CCH.

In order to measure the Recall of the system performance, the CBIR system was tested with a database contains 100 images, and any 9 images were similar to each other. The value of Recall for such a representation is given by the function [17]:

\[ \text{Recall Value} = \frac{\text{Number of relevant documents that retrieved}}{\text{Total number of relevant documents}} = \frac{|Ra|}{|R|} \]  

Where Ra denotes a subset of relevant documents, which appear in the retrieved document list [17]. For example, if the database comprises of 100 relevant documents for a query, and the search procedure was able to retrieve only 10 of these relevant documents, then the Recall of the system for this particular query would be 10%.

C. Results Analysis and Comparison

The proposed technique is tested on three database as follows:

WEB-CRAWLED database: It contains about 9,908 of natural scenes of images of sizes ranging from 128 x 85 to 128 x 96 pixels or 85 x 128 to 96 x 128 pixels. This database is internationally used as a benchmark for CBIR testing. Results using this database.

COUNTRY FLAGS database: This is a simple database taken from the original database, used for primary testing. It contains the flags of about 100 countries. Results using this database are shown in Fig. 11, 12, 13, 14 and 15.

OWN database: This database is created by us to test the system. It contains about 100 colour images taken under different conditions from WEB-CRAWLED database.
As a result notes FCH better than CCH of saluting the accuracy of the results even after change the brightness in the images and experience the results, because considers the contribution of each pixel into all bins, hence reducing the sensitivity of the signature, time reducing, this gives some spatial sensitivity, but increases the computing power and storage needed.

Experimental results showed from Figures Previous and in tables below that the obtained FCH is less sensitive to brightness from CCH, the results are not consistent with how the images look to the human eye, because in CCH the problems with colour histogram this is however not the only problem associated with colour histograms. One other common problem is that of bin similarity. Figure (15) shows CCH results were obtained by changing in brightness using images database, and Figures (16, 17 and 18) show FCH results are obtained by changing in brightness images database for any division.
As can be seen, the following tables give the summary results for OWN images database.

**TABLE II**

<table>
<thead>
<tr>
<th>Number of divisions</th>
<th>FCH</th>
<th>CCH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2 Parts</td>
<td>3 Parts</td>
</tr>
<tr>
<td>Signature time</td>
<td>0.3312 min</td>
<td>0.4060 min</td>
</tr>
<tr>
<td>Image Loading time</td>
<td>0.1307 min</td>
<td>0.1399 min</td>
</tr>
<tr>
<td>Signature Size</td>
<td>0.002 MB</td>
<td>0.003 MB</td>
</tr>
</tbody>
</table>

**TABLE III**

<table>
<thead>
<tr>
<th>Number of divisions</th>
<th>FCH</th>
<th>CCH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2 Parts</td>
<td>3 Parts</td>
</tr>
<tr>
<td>size of expected answer</td>
<td>9 images</td>
<td>9 images</td>
</tr>
<tr>
<td>Average best matches</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>Recall value</td>
<td>78%</td>
<td>89%</td>
</tr>
<tr>
<td>Average Recall value with the change of 45% decrease brightness</td>
<td>55%</td>
<td>56%</td>
</tr>
</tbody>
</table>

**TABLE IV**

<table>
<thead>
<tr>
<th>Number of divisions</th>
<th>FCH</th>
<th>CCH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2 Parts</td>
<td>3 Parts</td>
</tr>
<tr>
<td>Number of divisions</td>
<td>9908 images</td>
<td>9908 images</td>
</tr>
<tr>
<td>Time of retrieval</td>
<td>0.2242 min</td>
<td>0.3033 min</td>
</tr>
</tbody>
</table>

**TABLE V**

<table>
<thead>
<tr>
<th>Number of divisions</th>
<th>FCH</th>
<th>CCH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2 Parts</td>
<td>3 Parts</td>
</tr>
<tr>
<td>Size of signature file for 9908 images</td>
<td>0.2812 MB</td>
<td>0.2988 MB</td>
</tr>
</tbody>
</table>

**TABLE VI**

<table>
<thead>
<tr>
<th>Number of divisions</th>
<th>FCH</th>
<th>CCH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2 Parts</td>
<td>3 Parts</td>
</tr>
<tr>
<td>Time of retrieval</td>
<td>0.2242 min</td>
<td>0.3033 min</td>
</tr>
</tbody>
</table>

**V. CONCLUSION**

In this paper, we have reported a novel approach to color image signature. The approach is based on the application of fuzzy set theory and fuzzy rules on the color image retrieval was compared with CCH, and the results clearly showed that our proposed image signature outperforms the CCH signature.
In this CBIR system, the HSV was used instead of RGB because the advantages of HSV over RGB space is that HSV represents colour the way they are perceived by the human vision. To overcome the histogram problem of CCH, dividing the image into two, three or four parts, and representing any part by the signature if division the image into two parts, this would be less than the number of comparisons because the length of signature is short, and to be more accuracy division the image to three and four parts. This will be number of comparisons more and results recovered better because of its proximity is queried, in addition to that, the length of the signature increases the size. To increase the speed of the CBIR system, we used the K-means algorithm to perform clustering the entire images in the database into several groups, where the search is limited to the centers of the clusters.

Using Graphical User Interface (GUI) in this CBIR system makes it easier for the users with nice and a friendly interface and bottoms for selection and for greater work efficiency. Thus, reducing the time of work and obtaining better effect to users.

REFERENCES


