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Paper:

Fuzzy Relevance Feedback in Image Retrieval for Color Feature Using Query Vector Modification Method

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Fuzzy relevance feedback using Query Vector Modification (QVM) method in image retrieval is proposed. For feedback, the proposed six relevance levels are: "very relevant", "relevant", "few relevant", "vague", "not relevant", and "very non relevant". For computation of user feedback result, QVM method is proposed. The QVM method repeatedly reformulates the query vector through user feedback. The system derives the image similarity by computing the Euclidean distance, and computation of color parameter value by Red, Green, and Blue (RGB) color model. Five steps for fuzzy relevance feedback are: image similarity, output image, computation of membership value, feedback computation, and feedback result. Experiments used QVM method for six relevance levels. Fuzzy relevance feedback using QVM method gives higher precision value than conventional relevance feedback method. Experimental results show that the precision value improved by 28.56% and recall value improved 3.2% of conventional relevance feedback. That indicated performance Image Retrieval System can be improved by fuzzy relevance feedback using QVM method.

Keywords: fuzzy, relevance, feedback, QVM, CBIR

1. Introduction

Content-Based Image Retrieval (CBIR), a technique which uses visual contents to search images from large scale image databases according to user interests, has been an active and fast advancing research area since the 1990 [1–5]. Most existing CBIR system represent images as feature vectors using visual features, such as color, texture, and shape. The relevance feedback based approach to CBIR has been an active research area in the past few years. Relevance feedback is an interactive process which can fulfil the requirements of query formulation [6–8]. The system presents a set of images considered to be similar to a given query, the user can activate a relevance feedback process by identifying which of the retrieved images. System will reprocess image similarity and return some images that are more relevant to the query.

Query Vector Modification (QVM) method is one of relevance feedback in the CBIR. The QVM method approach repeatedly reformulates the query vector through user feedback so as it moves the query toward relevant images and away from non relevant ones. Then the new query formulation is calculated to similarity image.

From research which has been done in [6–8], the retrieved image is identified into two relevance levels, those are: "relevant" and "non relevant". The relevance levels are not able to represent the retrieved image. Fuzzy logic is able to represent two relevance levels into more relevance levels. This proposed paper is a fuzzy approach of QVM method for relevance feedback in content based image retrieval with more specific relevance levels. The fuzzy approach consists six relevance levels proposed this research. Six relevance levels are: "very relevant", "relevant", "few relevant", "vague", "non relevant", and "very non relevant".

Section 2 presents RGB (Red, Green, and Blue) color feature. The relevance feedback in the CBIR is introduced in Section 3. Section 4 presents QVM method. Section 5 presents fuzzy relevance feedback using QVM method. Experimental results of the effectiveness of the fuzzy relevance feedback using QVM method are given in Section 6. Finally, concluding remarks are given in Section 7.

2. RGB Color Feature

The existing CBIR techniques can typically be classified as those that perform image retrieval based on color, texture, shape or a combination of these. Color is an extensively utilized visual attribute in image retrieval that often simplifies object identification and extraction [9]. Color is especially convenient, because it provides multiple measurements at a single pixel of the image, often enabling the classification to be done without the need of complex spatial decision making [9]. The retrieval based on color similarity requires distances in color space to correspond to human perception [9].

There exists various color models, dictated by the means through which an image is intended to be used [9]. Most color space models define colors in three dimen-

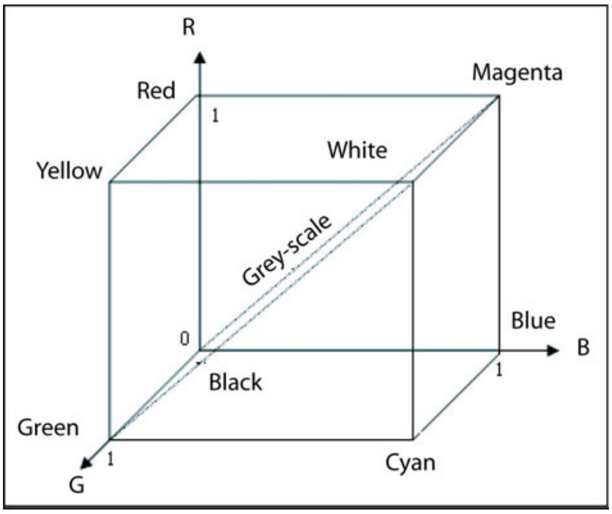

Fig. 1. RGB coordinates system.

sions, such that each color is represented by three coordinates.

Furthermore, the color models are classified as uniform/non-uniform depending upon the difference in color space, as perceived by an observer. The difference between any two colors is approximated to be the Euclidean distance in a uniform color space [9]. RGB (Red, Green, and Blue) is the most commonly used color space model, and is composed of three primary colors – Red, Green, and Blue [10]. The primary colors are additive, that is by varying their combinations, other colors can be obtained [9]. The model is visualized as a unit cube.

The RGB model uses the cartesian coordinate system as shown in **Fig. 1**, with corners of black, white, the three primary colors (red, green, blue), and the three secondary colors (cyan, magenta, yellow). The color model however bears the limitation that it is not perceptually uniform, meaning that the calculated distance in the RGB space does not truly correspond to the perceptual color difference [9]. Notice the diagonal from (0,0,0) black to (1,1,1) white which represents the grey-scale.

The RGB color model is composed of the primary colors Red, Green, and Blue. They are considered the "additive primaries" since the colors are added together to produce the desired color. The RGB model uses the cartesian coordinate system as shown in **Fig. 1**. Notice the diagonal from (0,0,0) black to (1,1,1) white which represents the grey-scale.

In this research, color feature defines 12 colors. Itten color-wheel consisted of 12 fundamental colors or hue, as can be seen at **Fig. 2**.

Twelve hues are as long as meridian from color-wheel, where saturation mounts along with increasing radius. Hues are red, purple red, purple, blue purple, blue, green blue, green, yellow green, yellow, orange yellow, orange, and red orange [11].

Fig. 2. Itten *color-wheel.*

3. Relevance Feedback Method

Content-based image retrieval is a technique which uses visual contents to search images from large scale image databases according to user interest, has been an active and fast advancing research area since the 1990 [1–5]. During the past decade, remarkable progress has been made in both theoretical research and system development. However, there remain many challenging research problems that continue to attract researchers from multiple disciplines.

Relevance feedback (RF) is a commonly accepted method to improve the effectiveness of retrieval system interactively [6, 7, 12]. Basically, it is composed of three steps: (a) an initial search is made by the system for a user-supplied query pattern, returning a small number of images: (b) the user then indicates which of the retrieved images: (c) finally, the system automatically reformulates the original query based upon user relevance judgments. This process can continue to iterate until the user is satisfied. Relevance feedback strategies help to alleviate the semantic gap problem, since it allows the CBIR system to learn user image perceptions. Flowchart of relevance feedback method showed in **Fig. 3**.

4. Query Vector Modification Method

Query Vector Modification (QVM) method approach repeatedly reformulates the query vector through user's feedback so it moves the query toward relevant images and away from non relevant ones, in an attempt to redirect the query vector toward a more desired area [6]. Let a user submit the i^{th} database image as the query and have experienced j relevance feedback iterations, and let $x_i^{(j)}$ denote the current query formulation. Also, let the set of relevant images identified at the j^{th} iteration be R, and the set of identified non relevant images be N. For the $(j+1)^{\text{th}}$ relevance feedback iteration, the reformulated query vector [6, 7], is calculated as

$$X_i^{(j+1)} = \alpha\, X_i^{(j)} + \beta \sum_{Y_k \in R} \frac{Y_k}{|R|} - \gamma \sum_{Y_k \in N} \frac{Y_k}{|N|} \quad . \; . \; . \quad (1)$$

where Y_R and Y_N are images that belong to region R or N,and α, β, *and* γ are the parameters controlling the relative contribution of each component.

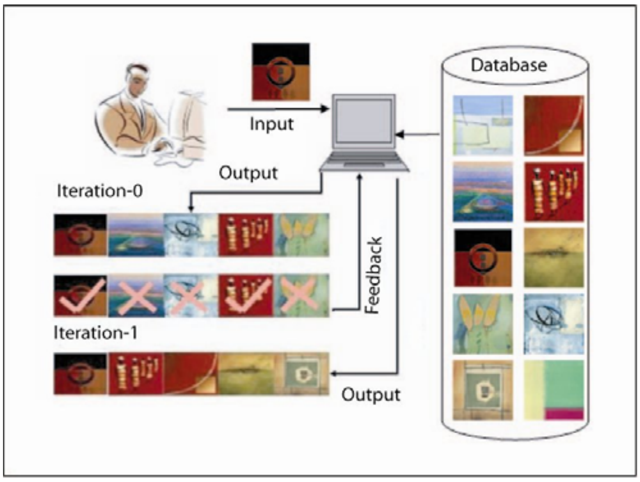

Fig. 3. Flowchart of relevance feedback method.

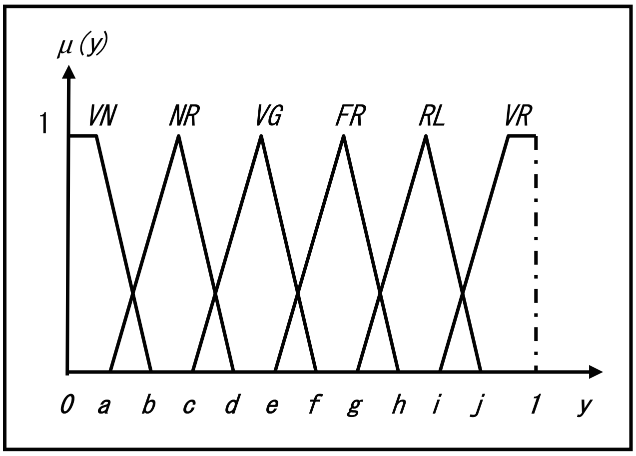

Fig. 4. Membership function for six relevance levels.

5. Fuzzy Relevance Feedback Using Query Vector Modification Method

Basically, Fuzzy Logic is a multi valued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc [13, 14]. The binary logic variables may have value only 0 and 1. In contrast with binary sets having binary logic, also known as crisp logic, the fuzzy logic variables may have a membership value that is not only 0 or 1. Just as in fuzzy set theory with fuzzy logic, the set of membership value is in range between 0 and 1 and is not constrained to the two truth value (true (1), false (0)) as in classic propositional logic.

The membership function of a fuzzy set is a generalization of the indicator function in classical sets. In fuzzy logic, it represents the degree of truth as an extension of valuation. Degrees of truth are often confused with probabilities, although they are conceptually distinct, because fuzzy truth represents membership in vaguely defined sets, not likelihood of some event or condition. The membership function of relevance feedback in this research is shown in **Fig. 4**.

QVM method approach repeatedly reformulates the query vector through user's feedback so it moves the query toward relevant images and away from non relevant ones, in an attempt to redirect the query vector toward a more desired area [6]. Let a user submit the i^{th} database image as the query and have experienced j relevance feedback iterations, and let $x_i^{(j)}$ denote the current query formulation. Also, let the set of very relevant images identified at the j^{th} iteration be VR, the set of identified relevant images be RL, the set of identified few relevant images be FR, the set of identified vague images be VG, the set of identified non relevant images be NR, and the set of identified very non relevant images be VN. For the $(j+1)^{\text{th}}$ relevance feedback iteration, conventional reformulated query vector is calculated as follow

$$X_i^{(j+1)} = \alpha\, X_i^{(j)} + \beta \sum_{i=1}^{r} \frac{R_i}{r} - \gamma \sum_{i=1}^{n} \frac{N_i}{n} \quad . \quad . \quad . \quad . \quad (2)$$

Reformulation query vector with six relevance levels is calculated as follow

$$\begin{aligned}
X^{(j+1)} &= \alpha\, X^{(j)} + \beta \sum_{i=1}^{r} \tfrac{R_i}{r} - \gamma \sum_{i=1}^{n} \tfrac{N_i}{n} \\
&= \alpha\, X^{(j)} + \tfrac{\beta}{r} \sum_{i=1}^{r} R_i - \tfrac{\gamma}{n} \sum_{i=1}^{n} N_i \\
&= \alpha\, X^{(j)} + \tfrac{\beta}{r}(R_1 + \ldots + R_o + \ldots + R_p + \ldots + R_q) \\
&\quad - \tfrac{\gamma}{n}(N_1 + \ldots + N_l + \ \ldots\ + N_m + \ldots + N_n) \\
&= \alpha\, X^{(j)} + \tfrac{\beta}{r}(R_1 + \ldots + R_o) + \tfrac{\beta}{r}(R_{o+1} + \ldots + R_p) \\
&\quad + \tfrac{\beta}{r}(R_{p+1} + \ldots + R_q) - \tfrac{\gamma}{n}(N_1 + \ \ldots\ + N_l) \\
&\quad - \tfrac{\gamma}{n}(N_{l+1} + \ldots + N_m) - \tfrac{\gamma}{n}(N_{m+1} + \ldots + N_n) \\
X^{(j+1)} &= \alpha\, X^{(j)} + \tfrac{\beta}{r}(R_1 + \ldots + R_{vr}) \\
&\quad + \tfrac{\beta}{r}(R_1 + \ldots. + R_{rl}) + \tfrac{\beta}{r}(R_1 + \ldots + R_{fr}) \\
&\quad - \tfrac{\gamma}{n}(N_1 + \ldots + N_{vg}) - \tfrac{\gamma}{n}(N_1 + \ldots. + N_{nr}) \\
&\quad - \tfrac{\gamma}{n}(N_1 + \ldots. + N_{vn}) \\
&= \alpha\, X^{(j)} + \tfrac{\beta}{r} \sum_{i=1}^{vr} R_i + \tfrac{\beta}{r} \sum_{i=1}^{rl} R_i + \tfrac{\beta}{r} \sum_{i=1}^{fr} R_i \\
&\quad - \tfrac{\gamma}{n} \sum_{i=1}^{vg} N_i - \tfrac{\gamma}{n} \sum_{i=1}^{nr} N_i - \tfrac{\gamma}{n} \sum_{i=1}^{vn} N_i \\
&= \alpha\, X^{(j)} + \tfrac{\beta_1}{vr} \sum_{i=1}^{vr} R_i + \tfrac{\beta_2}{rl} \sum_{i=1}^{rl} R_i + \tfrac{\beta_3}{fr} \sum_{i=1}^{fr} R_i \\
&\quad - \tfrac{\gamma_1}{vg} \sum_{i=1}^{vg} N_i - \tfrac{\gamma_2}{nr} \sum_{i=1}^{nr} N_i - \tfrac{\gamma_3}{vn} \sum_{i=1}^{vn} N_i
\end{aligned}$$

$$. \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (3)$$

where :

$$\begin{aligned}
& vr = o, \ \ rl = p - o, \ \ fr = q - p \\
& vg = l, \ \ nr = m - l, \ \ vn = n - m \\
& \frac{\beta}{r} = \frac{\beta_1}{vr} = \frac{\beta_2}{rl} = \frac{\beta_3}{fr} \\
& \frac{\gamma}{n} = \frac{\gamma_1}{vg} = \frac{\gamma_2}{nr} = \frac{\gamma_3}{vn}
\end{aligned}$$

Fuzzy relevance feedback for six relevance levels is calculated as follow

$$
\begin{aligned}
X^{(j+1)} &= \alpha\, X^{(j)} + \tfrac{\beta_1}{vr}\sum_{i=1}^{vr} R_i + \tfrac{\beta_2}{rl}\sum_{i=1}^{rl} R_i \\
&\quad + \tfrac{\beta_3}{fr}\sum_{i=1}^{fr} R_i - \tfrac{\gamma_1}{vg}\sum_{i=1}^{vg} N_i \\
&\quad - \tfrac{\gamma_2}{nr}\sum_{i=1}^{nr} N_i - \tfrac{\gamma_3}{vn}\sum_{i=1}^{vn} N_i \\
&= \alpha X^{(j)} + \tfrac{\beta_1}{vr}\sum_{i=1}^{vr} 1.R_i + \tfrac{\beta_2}{rl}\sum_{i=1}^{rl} 1.R_i \\
&\quad + \tfrac{\beta_3}{fr}\sum_{i=1}^{fr} 1.R_i - \tfrac{\gamma_1}{vg}\sum_{i=1}^{vg} 1.N_i \\
&\quad - \tfrac{\gamma_2}{nr}\sum_{i=1}^{nr} 1.N_i - \tfrac{\gamma_3}{vn}\sum_{i=1}^{vn} 1.N_i \\
&= \alpha\, X^{(j)} + \tfrac{\beta_1}{vr}\sum_{i=1}^{vr} m_i R_i + \tfrac{\beta_2}{rl}\sum_{i=1}^{rl} m_i R_i \\
&\quad + \tfrac{\beta_3}{fr}\sum_{i=1}^{fr} m_i R_i - \tfrac{\gamma_1}{vg}\sum_{i=1}^{vg} m_i N_i \\
&\quad - \tfrac{\gamma_2}{nr}\sum_{i=1}^{nr} m_i N_i - \tfrac{\gamma_3}{vn}\sum_{i=1}^{vn} m_i N_i \qquad \ldots\ldots\ldots\ldots (4)
\end{aligned}
$$

$$
\begin{aligned}
X^{(j+1)} &= \alpha\, X^{(j)} + \tfrac{\beta_1}{vr}\sum_{i=1}^{vr} m_i VR_i + \tfrac{\beta_2}{rl}\sum_{i=1}^{rl} m_i RL_i \\
&\quad + \tfrac{\beta_3}{fr}\sum_{i=1}^{fr} m_i FR_i - \tfrac{\gamma_1}{vg}\sum_{i=1}^{vg} m_i VG_i \\
&\quad - \tfrac{\gamma_2}{nr}\sum_{i=1}^{nr} m_i NR_i - \tfrac{\gamma_3}{vn}\sum_{i=1}^{vn} m_i VN_i \qquad \ldots\ldots\ldots\ldots (5)
\end{aligned}
$$

where :

R_i is relevant identified image, that consist of *VR, RL, FR*,

N_i is non relevant identified image, that consists of *VG, NR, VN*,

α, β, δ, and γ is control parameter.

6. Experimental Results

In this section, extensive experiments to evaluate the performance are carried out. Similarity between query image and database images are calculated by using color matching. Each image taken in 12 features is selected. The system is developed using C^{++} Builder version 6.

To simulate the practical situation of online users, the sequence of query images is used. The user initializes a query session by submitting an abstract image. The system then compares the query image to each image in the database and returns some images that has the nearest neighbors to the query. If the user is not satisfied with the retrieved result, user can activate relevance feedback process by identifying which image retrieved are "very relevant", "relevant", "few relevant", "vague", "non relevant", and "very non relevant".

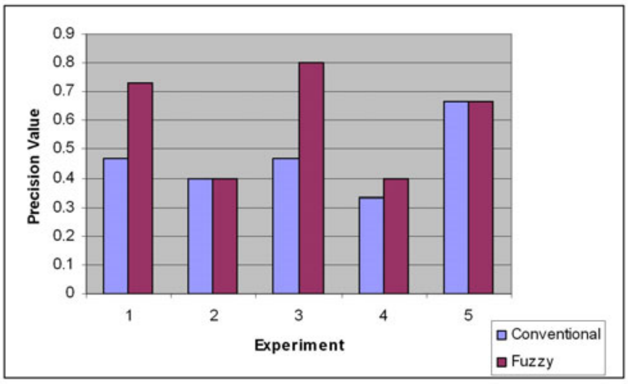

Fig. 5. Precision value for five experiments.

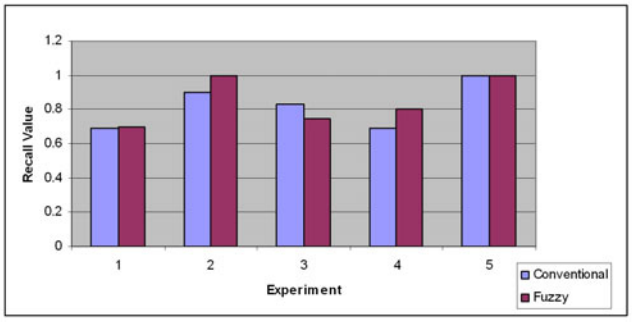

Fig. 6. Recall value for five experiments.

The system then updates the relevant information, such as the reformulated query vector to include as many user-desired images as possible in the next retrieved result. Fuzzy approach used calculation to the new query formulation. Each relevance levels is calculated using membership function, then the system updates the formulation query image using Eq. (5).

The system compares the new query image to each image in the database and returns some images that are more relevant to the new query. Retrieval result is done using calculation precision and recall value. Precision is the number of relevant retrieved divided by the number of image retrieved. Recall is the number of relevant retrieved divided by the number of image relevant. Precision and recall value are defined as follows

$$precison = \frac{a}{b} \quad \ldots\ldots\ldots\ldots (6)$$

$$recall = \frac{a}{c} \quad \ldots\ldots\ldots\ldots (7)$$

where :
a: relevant retrieved,
b: retrieved,
c: relevant.

Experiments have been done for five experiments. Each experiment computes precision value and recall value. Experiment is analyzed using conventional relevance feedback and fuzzy approach measure as shown in **Figs. 5** and **6**.

7. Conclusions

Query Vector Modification (QVM) method is one of relevance feedback method in the CBIR. The QVM method approach repeatedly reformulates the query vector through user feedback so it moves the query toward relevant images and away from non relevant ones. Then the new query formulation is calculated to similarity image.

From the research which has been done, image retrieved is identified into two relevance levels those are: "relevant" and "non relevant". The relevance levels are not yet able to representation of retrieved image. The fuzzy relevance feedback consist of six relevance levels is improved this research. Six relevance levels are: "very relevant", "relevant", "few relevant", "vague", "non relevant", and "very non relevant". Fuzzy relevance feedback using QVM method for six relevance levels is proposed.

Experimental results on image retrieval problem show fuzzy relevance feedback using QVM method can improve performance of content based image retrieval system. The improvement precision ranges from 46.67% to 60.00% and recall ranges from 82.35% to 85.00% at conventional feedback. Experimental results show that the precision value improved 60/46.67=28.56% and recall value improved 85/82.35=3.2% of conventional relevance feedback. The proposed approach can improve CBIR performance.

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