A Hybrid Approach to Content Based Image Retrieval Using Computational Intelligence Techniques

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Abstract

Objectives: Improvement in the retrieval performance of the system can be brought by fusion of image features with different similarity measures. Performance of the system can be further improved by incorporating user’s feedback into the system. Method: An extensive system is proposed based on one of the computational intelligence techniques for the effective retrieval of required images from systems. The proposed technique consists of two main modules, namely: feature vector processing and result enhancement. Feature fusion is performed by application of genetic operators to find the final distance between probe and stored images. Subsequently estimated retrieved images are presented to the user; first k-images will be selected by the user as K-NN query images and are ranked according to their relevance values provided by the user. Optimization of retrieved images is done by iteratively providing user’s feedback to the system. Findings: Feature fusion and effective relevance feedback methods can contribute extensive benefits to content based image retrieval. Feature fusion combines different image features in such a way to get a single feature vector for all of them but combination of different image features however is not always beneficial. Semantic gap is reduced by providing user’s feedback after the retrieval of images. This is an iterative process and it defines a set of relevant images in the end. Genetic algorithm based search is applied for a series of weighting functions which helps to maximize the fitness function. Applications/Improvements: Multifarious features are introduced where different image features are combined with different similarity measures and the final distance is drawn by employing genetic programming technique.

Keywords: Feature Extraction, Image Descriptor, Multifarious Features, Relevance Feedback, Similarity Measure

1. Introduction

Image digitization has increased the requirement of creating image repository where images can be retained and retrieved workwise. Initially text based systems were developed for image retrieval. Keywords created by human operators were used to represent images. These systems were not very efficient as the keywords were entered manually and each keyword may not describe the image well. Therefore content based image retrieval (CBIR) systems were introduced to overcome the drawbacks of text based systems¹.

Content based retrieval of images considers the visual content of an image such as its color, shape and texture which are low level image features²,³. Low level image features are extracted from all the images in the database and a feature vector is created for all these images. Query image is also subject to the feature extraction and feature vector construction process. Distance measure is then used to find the comparison between low level features of query image and data base images⁴. The system then retrieves the most similar image based on the distance between feature vectors of query image and database images. Retrieved image as a result of content comparison between the feature vectors of two images might not give accurate result because of the semantic gap. The semantic gap can be overcome by adding a correspondence between low level image features and high level user’s expectations⁵. Semantic gap is created by assuming that all the image features are related irrespective of retrieval
of the image. Therefore some image features can better represent some query images compared to other queries. The mentioned semantic gap can be reduced by providing a mechanism to the retrieval system to learn which feature is of more interest to user. Such methods are known as Relevance Feedback (RF) techniques5,6. RF techniques have been proposed to allow the user to evaluate the images retrieved by assigning those values according to their relevance with the query in terms of semantics. User’s evaluations are interpreted to reformulate the foregoing query for improvement in its results7.

This paper proposes a technique that combines low level image features with high level semantics observed by the user. The proposed CBIR system is comprised of two parts. First part involves the creation of multifarious (MF) features. Image features are combined with the suitable similarity measure to form multifarious features by applying genetic programming technique. Combination of significant image features with corresponding optimal similarity measures form multifarious features which gives superior performance than the existing state of the art CBIR techniques. The other part involves the reduction of semantic gap by incorporating user’s feedback. The two procedures are joined to form a complete CBIR system for optimal retrieval results.

Most CBIR systems find solutions that combine image features utilizes the single similarity measure for all the features during retrieval process. However, similarity function has an important role in making descriptors as invariant as possible to change image scale and alternation.

Images in the database are catalogued by means of various pairs of feature mining algorithms and corresponding functions. Each pair is called a database descriptor as it tells how the images are distributed in the database. Feature vector is considered here as a pair of feature extraction algorithm and a similarity function8,9.

Relevance feedback is a process where user interacts with the system to tell about the relevant images for optimal retrieval. A survey of relevance feedback technologies for image retrieval until 2002 is presented in10. Most approaches have the marked images as individual queries. Recent approach however is a query-instance-based approach11 or use support vector machine to use a two class classifier12. This approach is similar to the one presented in12 as both follows a nearest neighbor approach but instead of using only the best matching query/database image combination, all query images are considered jointly.

Relevance feedback is employed to narrow down the gap between low level feature representation and user’s high level semantic concepts. A framework is proposed in which one class SVMs are ensemble13. Genetic algorithm is incorporated into relevance feedback methods. 14To properly assign weights on image features and image sections. However an effective model is not provided by the authors to learn user’s request. Nonlinear combination of different image similarities using genetic programming was proposed15 but they did not incorporate user’s feedback in the learning process.

2. Proposed Technique

Various CBIR systems exploit a single similarity measure for all the features used in the relevance procedure. Nevertheless, similarity function changes image measure and repetition in a significant way by comparing different image features. Hence multifarious (MF) features are proposed with diverse similarity measure for each group of descriptors. Adeptness of CBIR can also be improved by inferring active relevance feedback procedures, where response from the user is provided to the system for retrieval of enquiry image. Proposed technique consists of two main modules namely: feature vector processing and result enhancement as shown in [Figure 1].

![Diagrammatic representation of proposed method.](image)

**Algorithm**

**Step 1:** An image Ī is considered as a pair (f, Î), where:

f is a predetermined set of pixels,

 Î: f → Î is the function that assigns a vector Î(P) to each pixel in f.

**Step 2:** A simple MF feature is given by a pair (V, δj)

where:

Where Vj is a function to extract feature vector from
image and
\( \delta \) is the similarity measure. \( \mathcal{H} \) with Quadratic distance
\( \mathcal{QD}(x, y) \), \( C(i, j) \) with Manhattan dist \( (x, y) \) and DFT with
Euclidean dist \( (x, y) \)

**Step 3:** Genetic programming GP is implemented on the
distances from the comparison of MF features.

**Step 4:** Let \( d = \{ d_i \} \) be a sequence of similarities in any of
the three feature spaces. Gaussian normalization results
in the mapping \( d_i \rightarrow d_i - \mu \), where \( \mu \) and \( \sigma \) are mean and
standard deviation.

**Step 5:** The three similarities are then combined after
normalization denoted by simicom

\[
\text{SimiCom} = p_1 . \text{Simi1} + p_2 . \text{Simi2}
\]

Where \( p_1, p_2, \) and \( p_3 \) are the combining parameters

**Step 6:** Images retrieved from the system are then
presented to the user and user evaluates the first \( K \) images
by ranking according to their relevance with the query
image.

Three different values are used to acquire user’s
response. Relevant: \( \gamma(q_i) = 1 \), Irrelevant : \( \gamma(q_i) = 0 \) and not
required: \( \gamma(q_i) = -1 \)

### 2.1 Multifarious (MF) Features

The influence of simple descriptors is enhanced by
combining each descriptor with its respective similarity
function. This grouping of image feature with its
corresponding similarity measure creates MF feature.
Below is the description of the MF features utilized in the
proposed system.

#### 2.1.1 Color Histogram with Quadratic Form

Distance

Color is the most vital and extensively used characteristic
of an image. Color histogram is a multi-aspect feature
vector and is computationally demanding as they are well
appropriate for global color regions. A color histogram
represents the combined probabilities of three color
channels and is given by an equation.

\[
h_{R,G,B}(r,g,b) = N. \text{Prob}\{R = r, G = g, B = b\}
\]

The transformation of RGB is calculated by \( m =\)
\( r + Nr + NrG \) where \( Nr, Ng \) and \( Nb \) are the numbers of
bins representing three color channels. It gives the single
variable histogram.

\[
H[m] = N. \text{Prob}\{M = m\}
\]

Proposed technique extracts color feature by finding
mean, mode, median and standard deviation for each
color channel. [Table 1] shows a list of color features used
by the proposed technique along with their equations.

| Image feature | Equation with symbol definition |
|---------------|--------------------------------|
| Mean          | \( \text{Mean} = m = \frac{\sum_{i=1}^{n} X_i}{n} \) |
| Median        | \( \text{Median} = \frac{n + 1}{2} \) |
| Mode          | \( \text{Mode} = \max(X) \) |
| Standard deviation | \( \text{Standarddeviation} = \sigma = \sqrt{\frac{\sum(X - m)^2}{n - 1}} \) |

Quadratic form distance gives more desired results
compared to other distance measuring techniques. Histogram
comparison for retrieval of images based on color content
has been tried with a number of distance
measures; quadratic form distance showed better results
compared to other distance such as example Euclidean
distance, histogram intersection and Minkowski
distance.

\[
d^2(Q,I) = (H_Q - H_I)^t A (H_Q - H_I)
\]

where \( d \) represents distance between two color images
i.e. the query image and database image. \( H_Q \) and \( H_I \) are
the histograms for query image and database image
respectively.

#### 2.1.2 Co-occurrence Matrix with Manhattan

Distance

One of the major contents of image used for categorization
in CBIR is texture. Proposed technique considers set
of important texture feature because they represent
structural and statistical important characteristics which
do not exist in other type of features namely color and
shape. Ten different features are extracted and given
with their formulas in [Table 2].
Table 2. Texture features used in the proposed technique

| Image feature | Equation with symbol definition |
|---------------|---------------------------------|
| Skewness      | \[
\begin{align*}
SK &= \frac{1}{n} \sum_{i=1}^{n} \left( \frac{X_i - m}{\sigma} \right)^3 \\
\end{align*}
\] (8) where \( m \) = mean, \( \sigma \) = standard deviation |
| Correlation   | \[
\begin{align*}
CORR &= \frac{\sum_{i,j} (ij)C(i,j) - \mu_i \mu_j}{\sigma_i \sigma_j} \\
\end{align*}
\] (9) where, \( \mu_i = \sum_{j} C(i,j) \)
| Correlation   | \[
\begin{align*}
\mu_i &= \sum_{j} C(i,j) \\
\sigma_i &= \sqrt{\sum_{j} (i - \mu_i)^2 \sum_{j} C(i,j)} \\
\end{align*}
\] and \[
\begin{align*}
\sigma_j &= \sum_{i} (j - \mu_j)^2 \sum_{i} C(i,j) \\
C(i,j) &= \text{gray level co-occurrence matrix} \\
\end{align*}
\] |
| Maximum probability | \[
\begin{align*}
MAXP &= \max \left( \frac{n(A)}{n} \right) \\
\end{align*}
\] (10) where \( A \) = probability |
| Uniformity    | \[
\begin{align*}
UNI &= \left( 1 - \frac{\sigma}{m} \right) \times 100 \\
\end{align*}
\] (11) where \( \sigma \) = standard deviation, \( m \) = mean |
| Entropy       | \[
\begin{align*}
ENT &= -\sum_{i,j} C(i,j) \log C(i,j) \\
\end{align*}
\] (12) |
| Contrast      | \[
\begin{align*}
CONT &= \frac{1}{\sqrt{MN}} \sum_{i=1}^{N} \sum_{j=1}^{M} \left( I_i - I \right)^2 \\
\end{align*}
\] (13) where \( M \) by \( N \) = size of 2 dimensional image, \( I \) = average intensity of all pixels in the image, \( I_{ij} = i\text{-th and } j\text{-th element of an image} \) |
| Homogeneity   | \[
\begin{align*}
IKMOM &= \sum_{i,j} \frac{1}{1 + (i-j)^2} C(i,j) \\
\end{align*}
\] (14) where \( C(i,j) = \text{gray level co-occurrence matrix} \) |
| Difference Moment | \[
\begin{align*}
IKMOM &= \sum_{i,j} \frac{1}{1 + (i-j)^2} C(i,j) \\
\end{align*}
\] (15) where \( C(i,j) = \text{gray level co-occurrence matrix} \) |

Among all the distance measures tried with texture features, Manhattan distance (MD) appeared to have best similarity measure\(^{19}\) and is represented by the following formula.

\[
\begin{align*}
\text{Manhattan dist} &= \sum_{i=1}^{n} \left| X_i - Y_i \right| \\
\end{align*}
\] (4)

Where \( X \) and \( Y \) are the query image and database image respectively.

2.1.3. Fourier Descriptors with Euclidean Distance

Methods used for boundary-based recovery of shape characteristics are Fourier descriptors, Wavelet descriptors, Curvature scale space descriptors, Shape signatures, etc. Among all these methods, Fourier descriptor method is the most basic one\(^{20,21}\). Fourier descriptor method computes shape signature functions by using shape boundary coordinates. These shape signatures utilizes Fourier transform for computation of Fourier descriptor\(^{22,23}\). Let \( x|k| \) and \( y|k| \) be the coordinates of the \( k\)th pixel on the boundary of a given 2D shape containing \( n \) pixels, a complex number can be formed as \( z|k| = x|k| + py|k| \), and the Fourier Descriptor (FD) of this shape is defined as the DFT of \( Z|k| \)

\[
\begin{align*}
\text{DFT}[Z]|k| &= \sum_{k=0}^{N-1} z|k| e^{-2\pi i N k} (N = 0,...,n-1) \\
\end{align*}
\]

Fourier transformed coefficients which are used as Fourier descriptors. Fourier descriptors are finest measured through Euclidean distance (ED)\(^{15}\). Euclidean distance is given by the formula:

\[
\begin{align*}
\text{Euclidean distance} &= d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)} \\
\end{align*}
\] (5)

Where \( d \) calculates distance \( x \) is the query image and \( y \) is the database image for all the shape features \((i = 1,2,3..n)\).

In one of the recent works presented in\(^{24}\) on image retrieval tried 7 different distance measures on more than 100 image features to find the relation between query image and database images. They have also proposed fusion of features for better results. Similar research is done in\(^{25}\) where different similarity measures are tried for retrieval of medical images.

2.2 Image Retrieval Based on Genetic Operations

The process of creation of MF features and calculating the final distance through GP is shown in Figure 2. In [Figure
image feature are represented by $I_f^i$ where $i = 1, 2, 3 \ldots n$ for $n$ different image features, similarity measures are given by $\delta m^i$ where $i = 1, 2, 3 \ldots m$ form different distance measures. They are paired together to form MF features. Distance from MF features is represented by $\partial_1, \partial_2, \partial_3, \ldots \partial_d$. GP combines these distances to calculate $F_\partial$, where $F_\partial$ is a mathematical expression represented as expression tree. Non-leaf nodes of this tree are numerical operators and leaf nodes are distance values $\partial_i$, $i=1, 2, 3, \ldots, d$. In a GP based retrieval framework the population starts with random creation of individuals and this population evolves generation by generation through genetic operations. Each individual in a population is assigned a fitness value by using certain fitness functions. Fitness functions used in the experiments are FFP1, FFP2 and FFP3.

**Figure 2.** Calculation of final distance measure from MF features.

### 2.2.1 Functions and Operators of GP Method

GP uses more complex data structures compared to genetic algorithm techniques. GP tree structure is used by the proposed method for the evolution of population by application of different genetic transformations. An image $I$ is considered as a pair $(f_1, I)$, where $f_1$ is a predetermined set of pixels, $I$: $f_1 \rightarrow f'$ is the function that assigns a vector $I(P)$ to each pixel in $f_1$. A simple MF feature is given by a pair of feature vector of an image and its similarity function which calculates similarity between two images. It is given as $(V_f, \delta_f)$ where: $V_f$ is a function to extract feature vector from image and $\delta_f$ is the similarity measure.

Multifarious feature will result in the creation of composite feature and is given by $(D, \delta_D)$ where: $D$ is a set of simple descriptors and $\delta_D$ is the similarity function.

**Fitness Function:** A good fitness function is required to avoid local optimum and to efficiently explore the search space. Below are the formulas of fitness functions used with a brief description.

\[
\text{funcFFP1} = \sum_{i=1}^{N} x(i) \times s_{f_1} \times \ln^{-1}(i + s_{f_2})
\]

(6)

Where $i$ is the position of image after it has been retrieved by the system. $x(I)$ is the degree of relevance of an image. Total number of images retrieved is given by $|N|$. $s_{f_1}$ and $s_{f_2}$ are the scaling factors and are given values as follows for our experiments, $s_{f_1} = 6$, $s_{f_2} = 1.2$.

\[
\text{funcFFP2} = \sum_{i=1}^{N} x(i) \times s_{f_3} \times \log\left(\frac{1000}{i}\right)
\]

(7)

where $(x(I))$ and $|N|$ are the same as in Equation (2). $s_{f_3}$ is a scaling factor and is set to $s_{f_3} = 2$ in our experiment.

\[
\text{funcFFP3} = \sum_{i=1}^{N} x(i) \times s_{f_4}^{-1} \times e^{-s_{f_5} \times \ln(i) + s_{f_6} - s_{f_7}}
\]

(8)

where $(x(I))$ and $|N|$ are the same as in Equation (2). $s_{f_4}$, $s_{f_5}$, and $s_{f_6}$ are scaling factors. Their values are set as 3.65, 0.1, 4, and 27.32, respectively.

### 2.3 Relevance Feedback

Semantic gap is reduced by the implementation of relevance feedback (RF) provided by the user. RF methods are very useful for the CBIR systems that lets the system learn the best features to be considered for effective retrieval. A technique based on relevance feedback was proposed in where weight correction of features is done by a set of rules using mean and standard deviation of feature vector of relevant and irrelevant images. Images retrieved from the system are then presented to the user and user evaluates the first K images by ranking according to their relevance with the query image. This is an iterative process which gives a set of relevant images $\rho_r$. The distance function is adjusted by a series of $f$ weighting functions to reflect the feedback provided by user. These values are utilized in the fitness function of GA.
2.3.1 GA Framework for Optimized Results

An integer value is assigned to code a chromosome having \( n \) different points where each point matches an individual of a function in the feature space. These chromosomes provide a new transformed feature space.

Fitness function employed from the measure of ranking quality \( P \) that has been calculated in after KNN query images \( k_{NN}i \) are retrieved and is given as follows.

\[
funcFFP4[\varphi(P_i,\rho_i)] = \sum_{i=1}^{n} \gamma(q_i) \left( \frac{(P - 1)}{P} \right)^{k-1}
\]  

Where \( \rho_{a} \) is the set of objects that are relevant to the set of feature vector taken out from the query image. If \( q_k \) is a subset of \( \rho_{a} \) then \( \gamma(q_k) = 1 \), otherwise \( \gamma(q_k) = 0 \).

Larger value of \( P \) will not be considered strongly as it gives relative status of the position of the images in ranking. Smaller values for \( P \) show importance of relevant images.

Variation is brought by crossover and mutation. A mask is generated randomly to indicate the use of chromosome that will provide gene for the first generation. Compliment of the mask is then used to produce second generation. Offspring chromosome is subject to mutation where probable genes are selected and their values are replaced by a randomly generated valid value.

3. Experimental Results and Discussion

Experiments were conducted to find the accuracy of the proposed technique. Different fitness functions were tried in the GP process to find the final distance value for the comparison of query image and database images. Results of the proposed technique were then compared with five different techniques from the literature. Precision is used as a performance measure for all the experiments. Proposed technique is tested on a database of 1,000 natural images from COREL image database available free on the internet. COREL images are stored in JPEG format with size \( 384 \times 256 \) or \( 256 \times 384 \). The entire database has 10 different image categories, where each category contains 100 images. GP has been tried for extraction of MF features. [Table 3] shows average retrieval precision of each feature with a distinct fitness function. Results revealed that \( func3 \) gives better result with GP for all the three features in comparison with other fitness functions.

| Multifarious features | GP with \( func1 \) | GP with \( func2 \) | GP with \( func3 \) |
|-----------------------|-------------------|-------------------|-------------------|
| Color with QD         | 80.4              | 81.0              | 85.3              |
| Co-occurrence         | 70.5              | 78.4              | 82.6              |
| matrix MD             |                   |                   |                   |
| Fourier descriptor    | 81.2              | 82.5              | 83.0              |

3.1 Results

Two different methods were used to perform experiments: Direct weight generator (WG) and weighting method (WM). Fitness function defined for GA was employed by these functions. Parameter \( P \) is tested with 10 and 20.

Regarding KNN 30 nearest neighbor images to the query were selected and 10 cycles were given to the relevance feedback process. Results were analyzed by finding the precision and recall for the two different methods selected for experimentation. [Figure 3] shows the number of relevant images retrieved using WG and the proposed WM. It shows that WM outperforms WG for both the values of \( P \) of the fitness function. Maximum number of relevant images are retrieved for \( P = 20 \) in our experiments. [Figure 4] shows the graph for number of relevant number of images retrieved for 5 different categories of images. These different categories are selected from the database because of their diverse nature. Content for each category of images is different from the other. These various image types are selected for the better analysis of results given by the proposed system.

![Figure 3. Number of relevant images retrieved for each image category using WM and WG.](image-url)
3.2 Comparison of Overall Retrieval Performance

Fair comparisons are ensured by using the same image database as a tester and alike 50 images as queries. Average retrieval of the selected 3 image groups from top 10, 20, 30, 40 and 50 is calculated. [Table 4] compares different image categories and techniques in terms of average retrieval precision. It is obvious from the results that the proposed method outperforms all eight techniques in approximately all image categories.

Table 4. Comparison of average retrieval precision of five distinct image categories by using eight different methods

| Image Category | Proposed | NFA | UFM | IRM | EHD | Color Indexing |
|----------------|----------|-----|-----|-----|-----|----------------|
| Beach          | 0.3670   | 0.2800 | 0.2533 | 0.2800 | 0.1067 | 0.2233 |
| Vehicle        | 0.4267   | 0.5600 | 0.3167 | 0.1367 | 0.4700 | 0.1633 |
| People         | 0.3940   | 0.2433 | 0.2233 | 0.1433 | 0.1400 | 0.1467 |
| Average        | 0.39     | 0.36  | 0.26  | 0.1833 | 0.2366 | 0.1733 |

NEAs results for vehicle are better as compared to our proposed technique but overall retrieval accuracy of our proposed technique is greater than NFA. For all the other four methods UFM method, IRM method, EHD method and color indexing method, our proposed method has improved results and better image retrieval accuracy in all types of pictures.

4. Conclusion

The problem of image feature combination with similarity measure is addressed in the proposed method. Multifarious features are introduced and their resultant distances are combined through genetic programming. Retrieved images are subject to relevance feedback and images are ranked based on user's input to the system. Feature space thus obtained by the k-nearest neighbor query images is transformed through genetic algorithm to get optimized retrieved images from the system. The transformation functions used can be further investigated in future. Also different image features in combination with similarity measure can be analyzed for a wide range of multifarious features.

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