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An Optimal Image Retrieval System Using Content Based Image Retrieval Techniques

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ABSTRACT

Background: Semantic Image Retrieval is a challenging and promising technology which motivates to develop efficient image search techniques in large database. **Objective:** The paper proposes an Optimal Image Recovery System (OIRS), aims to bond the semantic gap between human and machine which mimics the user desires. OIRS enables to retrieve relevant images. For extracting the meaningful relevance, OIRS is demonstrated in two levels. In the first level of pre-processing, visual contents of the image are depicted as feature vector. The second level is fuzzy label and the corresponding semantic label generation and thus enabled two level classification model which reduces the search space, followed by similarity measurement with proper ranking to produce relevant images for given query image. **Results:** The experimental result ensures the relevancy and accuracy of the retrieved images. **Conclusion:** Finally, we found that two level classification based OIRS has a much better performance than the other techniques in image retrieval system.

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INTRODUCTION

Visual Image Retrieval (VIS) works with the visual properties of an image which are compared for its matching. Imagery database maintenance and indexing is in significant egress, when images and their pertinent information are retrieved over demand. Human-machine interaction in image understanding and problem defining in any field has become the emerging issue in real world applications. Tracking over the semantic similarities has become an inseparable issue in the field of computer vision. The speed of technological advances stands in contrast to the requirement for a reliable computer vision and machine learning in relevancy retrieval and analysis. As the vision of human perception embedded along with expert system extends over public networks helps to bring out efficient and accurate results by working with the exact contents of the image which are close to the man mind thoughts, rather than depending on metadata of image repositories. Traditional expert systems are not sufficient to guarantee the metrics such as Quality (resolution and color depth), Nature (dimensionality), Throughput (rate of retrieval), and accuracy (matching of human and machine perceptions). Evaluation on the results with respect to the user semantics had not been compromised during indexing and sustainment.

The research focuses in two levels. First level is the construction of feature vector for the given query image. The same process has to be carried out for image database in prior. Second, fuzzy labels generation based on fuzzy-rules and conversion into semantic labels with the help of in-built semantic label library respectively. The proposed scheme handles two techniques such as vector construction and semantic tagging for hidden properties of an image.

First, vector construction used to transform the visual low level features of the image into numerical measurements. After extracting the low level features, conversion of class labels into semantic labels helps to generate semantic classes which act as an additional feature along with extracted geometric local features.

The organization of this paper is as follows. Section 2 reviews some conventional CBIR techniques in image retrieval. In Section 3, complete details of the proposed OIRS for different images are discussed. Next, in Section 4 shows the experimental results of the proposed method. Finally, Section 5 concludes the paper.

Related Work:

Kato *et al*. (1992) stated that, Content Based Visual Image Retrieval (CBVIR) is an effective Image retrieval technique for automatized retrieval of

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images from databases (local or remote). The work in visual interception for trade mark and art museum database shows a way for automatic image retrieval close to human view. CBIR techniques provide maximum support in bridging the semantic gap between the simplicity of available visual features and the richness of the user semantics. Generally a feature frequent in an image describes this image well but a feature frequent in the collection is a weak indicator to distinguish image from each other.

CBVIR technique uses the image features instead of image itself. The first use of the concept content-based image retrieval (Kato, 1992) to describe his experiments for retrieving images from a database using colour and shape features. CBIR systems have become a reliable tool for many image database applications. Chuen *et al*. (2009), works to reduce the number of features to be extracted by constructing common color palette. The idea behind their work is computation of occurrence of same pixel color between each pixel and adjacent, gives the probability of attribute of the image and thus it supports to quickly classify pixels of an image into clusters. This optimal less feature extraction model reduces the computation complexity to some range. Hossein Pourghassem (2010) combines relevance feedback with PSO. He worked with X-ray with clinical view on shape edge and texture. Similarity measurement is found to be improved with PSO, where each particle (individual swarm) remembers best solution by itself. Kashif *et al*. (2012) developed CBIR for biometric security, where feature extraction done as color histogram for color, Gabor filter for texture, and moment invariant for shape followed by wavelet transformation to give multi resolution of images for image classification. Finally Euclidean distance for similarity measure and fuzzy rules to control the result based on fuzzy heuristics. Fig. 1 shows the general block structure of existing system.

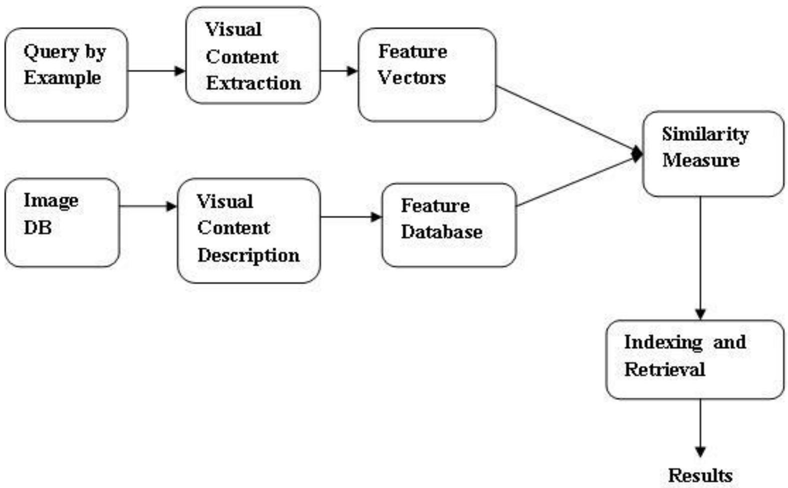

Fig. 1: General Structure of CBIR System

The Proposed Image Retrieval Scheme:

This section presents a detailed explanation of Semantic Image Retrieval for complex images, how the global features (low-level features) such as color, shape, texture and local features (high-level features) human perception level description about objects of interest (OOI) are involved in effective retrieval process. The proposed OIRS is demonstrated as in Fig 2.

A. Feature extraction:

The feature vector is necessary since the images are retrieved based on these numerical values. The relevancy of the retrieval can be improved by high precision of the features extracted. The color features extraction is done by using the color histogram techniques. While comparison the histogram of the query image and database images are compared. The main idea in indexing is to extract features from an image, map the features into points in multidimensional space, and then employ access structures to retrieve matches efficiently. The key issue here is to use access structures that are proven to be efficient in high dimensional spaces. Fig.3 shows the detailed process involved in feature extraction phase.

Color:

For color information, this is straightforward since the three color components defining the pixel's color intensity are usually used as its color features. For groups of pixels, (Suhasini *et al*., 2009) the color features are represented by the average and standard deviation of the components color values.

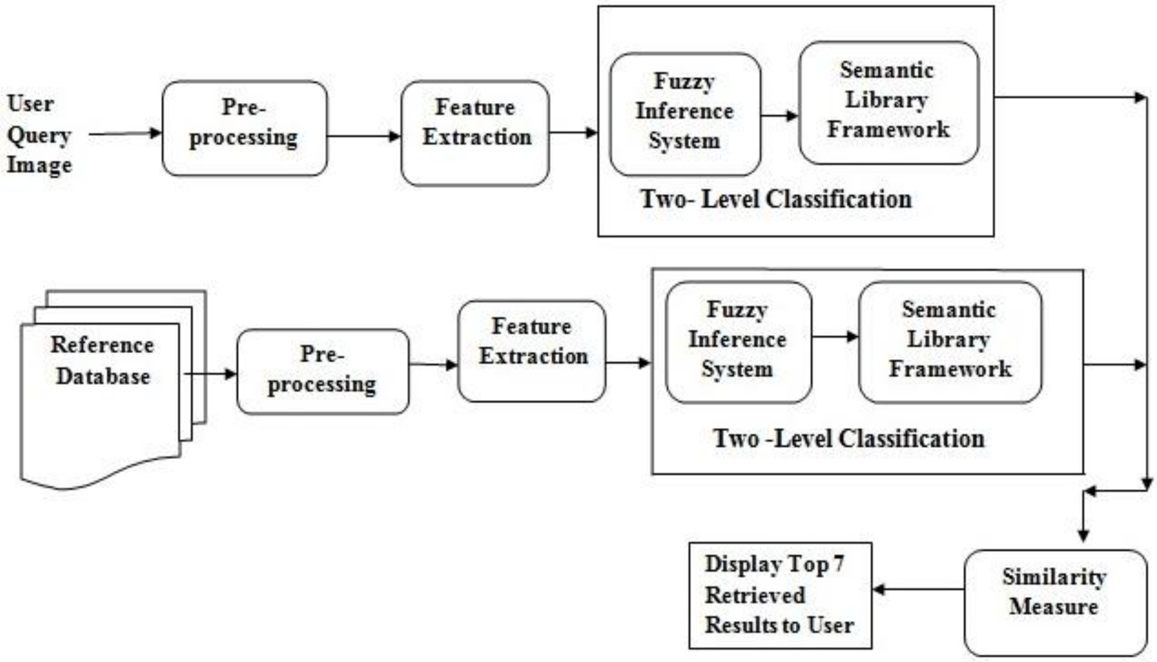

Fig. 2: Proposed Image Retrieval System

Texture:

The wavelet analysis function returns the wavelet decomposition of the matrix M at level N. The decomposition in low-pass filter and Gabor filter are taken (Naresh babu *et al*., 2010) along with the given image and level of the matrix N (positive integer). The four components such as horizontal coefficients, vertical coefficients, diagonal coefficients, approximation coefficients are analyzed.

Shape:

Shape features of objects in an image, are usually described after images have been segmented into regions or objects. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to special applications where objects or regions are readily available. A simple yet effective shape feature can be derived by describing edge direction information. Following an edge detection step using the canny edge detector (Manesh *et al*., 2011), a histogram of edge directions (typically in 5 degree steps) is generated, and then smoothed. Since it is a histogram feature, it can be compared using histogram intersection.

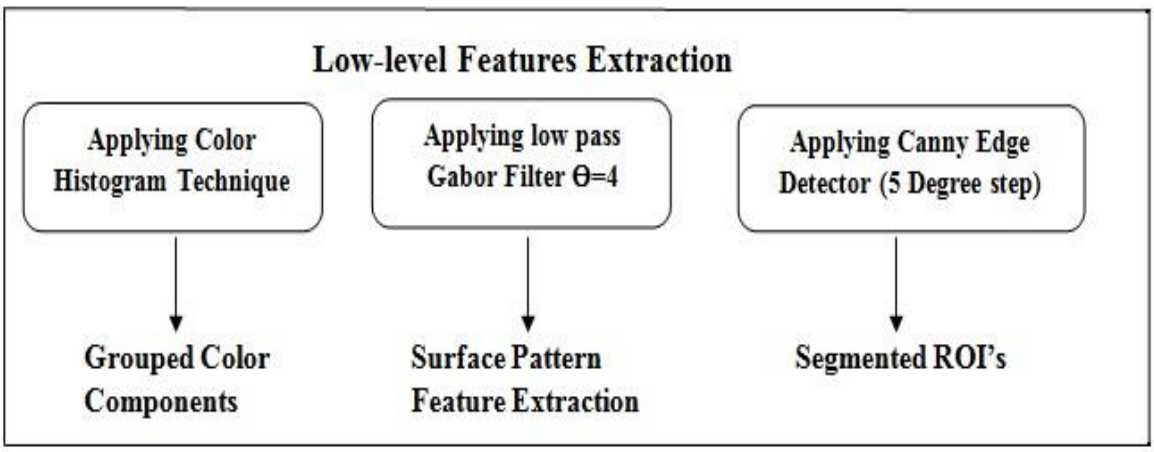

Fig. 3: Block Diagram of Feature Extraction Phase.

B. Generation of Fuzzy and semantic labels for two-level Classification:

This section describes in detail how to generate the class labels predicted by fuzzy logic and convert into semantic labels referred from inbuilt optimum human memory based perception library.

By submitting the query by example, process has to find the class and return images within that class. Exact categorizations of class labels are not possible for complex images with different object features. Fuzzy based rule classifier helps to depict the nature of image with their composition of percentage of presence to each cluster. Each image can gain the membership on different classes and so proposed dynamic label classifier supports to identify exact proposition of image among different classes. For example, "tall tree that is dark green and has fine gray texture". With a simple n-dimensional feature vector representation where each element of the vector corresponds to the value of a feature in the image, fuzzy values for each element is stored.

Let f_i, i= 1… n., denote the i_{th} attribute (e.g., "green").By defining a set of linguistic labels (with corresponding membership functions) for attribute f_i. Let the set of linguistic labels be $\{L_1; L_2; . . . ; L_n\}$ where n is the number linguistic labels for attribute f_i. The membership degrees in all labels using the membership functions are assigned. The value of attribute which is a fuzzy set defined over the domain of linguistic labels. This process can be repeated for all attributes. This method is fairly simple to represent a linguistic representation for all the images.

Most existing image retrieval methods assume that images have binary memberships in semantic classes. Therefore, they assign a single semantic or a crisp label to each image, while images may belong to many classes with different degrees of relevance. Hence, a novel fuzzy relevance feedback is proposed for user feedback which enables the user to make a fuzzy judgment. The fuzzy labeling has more flexibility for users, especially when the queries or images are semantically rich; it provides a natural and flexible way in expressing the user's preferences. Five types of fuzzy labels are considered as full irrelevant, irrelevant, full relevant, relevant, and Don't Care (DC). The four primary membership functions are defined by a trapezoidal membership function, while the DC is defined by a triangular one. Users judge the relevance degree of the retrieved images. When the image does not retrieve in any iteration, then those elements are called missing values. If the number of missing values is few, instances with missing values can be discarded, while, there are many images of this form, especially in the first query sessions. Therefore, the DC membership function is used to solve the missing value problem in the transaction logs' data.

Generation of fuzzy label with the designed fuzzy inference system brings out the first level of classification. Here, five linguistic labels and nine fuzzy rules are stated for the fuzzy logic system which helps to categorize the shuffled database into initial level of classification. To still converge into optimal search space, we suggest the conversion of fuzzy linguistic label into semantic labels enables the second level of classification with the help of inbuilt semantic library which mimics the optimum human memory perception system. Thus the vagueness and uncertainty with crispy systems can be eradicated by adopting fuzzy linguistic variables to demonstrate the degree of similarity among image features. This logic system helps to retrieve the hidden features through their inference of assigning weights to extracted human perception are approximately applied through fuzzy. Breaking an image into semantic cues such as face, sky, etc. combining all these cues helps to interpret the query image correctly and thus minimizes the semantic gap between human and machine interception.

Algorithm

Purpose: The algorithm is to retrieve images similar to the input image.

Input: An RGB image from the user.

Output: **N** images similar to the given input image.

Method:

1. Get the input color image in RGB color space.
2. Generating histogram for color components where average and standard deviation gives the color features.
3. Apply the Wavelet Transform using Gabor filter for each image layer (R, G, and B). The output images will be in four orientations (vertical, horizontal, approximation and diagonal).
4. Construct the feature vector that will represent the geometric measures of the image in numerical values.
5. Cluster the images in the database using fuzzy based labelling technique for different and merged categories to have linguistic values for crisp data.
6. Convert the linguistic labels into semantic labels with the help of semantic library, built on the basis of optimum perception knowledge of human memory.
7. Calculate the distance between the input image and the images in the cluster that has the smallest distance with the input image.
8. Retrieve the first n images that are similar to the input image and rule database is updated with retrieval updates.

Along with the low-level features, this inbuilt semantic library helps to combine the visual information from high level features from an image. The previous section helps to narrow down the search space, so that the human level understanding of the images can be predicted by means accuracy.

C. Similarity Measure:

The Euclidean distance related to the variances of the components of the feature vectors. The distance between the images are measured by using,

$$D(x,y) = \sum_{i=1}^{n} \sqrt{f_{x_i}^2 - f_{y_i}^2} \tag{1}$$

The distance measure helps to rank the images based on the computed distance value. A smaller distance indicates a higher degree of similarity between the query image and reference images. From the distance of zero as top ranked, similarly ascending order of ranking is done.

Results:

The proposed method has been implemented using Mat lab 7.3 and tested on the Corel database containing images in JPEG format of size 384x256. The search is usually based on similarity rather than the exact match. By following the image retrieval technique, the quality of the image retrieval has been evaluated by randomly selecting 10 query images, of each category, from the image database. Each query returns the top 7 images from database, and the calculated precision and recall values are also tabulated. The improvement indicates the better retrieval results when compared to surveyed techniques. Fig.4 shows the sample output received for the demonstrated system.

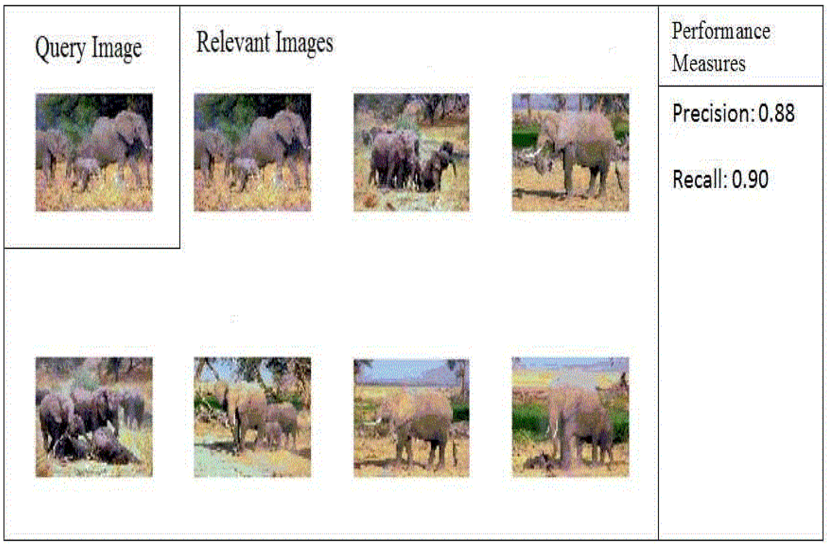

Fig. 4: Retrieved results for given sample query image.

Performance Graph:

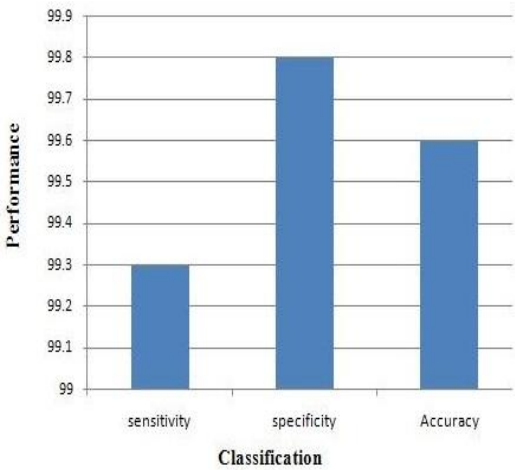

Fig. 5: Average Performance of proposed OIRS.

By comparing single level classification, the accuracy of OIRS is achieved as 99.6%.The enhancement shown in reducing search space by means of fuzzy based followed by semantic library based labelling technique helps to improve the edges of classification, so that the similarity matching process picks most relevant images to given query image in less search time. Fig. 5 shows the classification accuracy of proposed system.

Conclusion:

In this paper, a novel approach for Content Based Image Retrieval by combining the fuzzy and semantic labelling techniques. The proposed scheme improves the way of bridging between humans and machines. The advantage of the proposed scheme is the retrieval of meaningful images relevant to the request and with less computational complexity. The decomposition process reduces the size of the feature vector without increasing the retrieval time for the dominant channels. Pixel level feature extraction speed is increased and distortion of the image is reduced. The system learns the user's semantics and stores them as a rule for further references. Similarity between the images is ascertained by means of a distance function. The experimental result shows that the proposed method outperforms the other retrieval methods in terms of Precision and recall measures.

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