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Quality Assessment and Simulative Performance Measures of Content Based Image Retrieval System

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***Abstract*—** Content based image retrieval (CBIR) from large resources has become a dominant research field and found wide interest nowadays in many applications. In this thesis work, we design and implement a content based image retrieval system that uses color and texture as visual features to describe the content of an image region. We use k-nearest neighbor (knn) and HSV color model to extract feature of images. Our contribution is to design 'knn' feature vectors. We feature of images used to create database are color correlogram, color moments, gabor filter for mean amplitude & energy calculation, wavelet moments and histogram. The similarity measures used in this thesis to find similarity between query image & database images are Manhattan distance, Euclidean distance and Relative deviation. We segment the images into five classes consist images of Dinosaur, Bus, Beach, Flower and Sunset. We combine various features of images to construct 'knn' feature vector. The proposed CBIR system using various feature of 'knn' has the advantage of increasing the retrieval accuracy in form of Precision and Recall. The experimental evaluation of the system is based on a 250 color image database. From the experimental results, it is evident that developed system performs significantly better and faster compared with other existing systems like HSV.

***Keywords*—** CBIR; HSV; KNN; manhattan distance; euclidean distance.

I. INTRODUCTION

The need for efficient technique to retrieve images from large dataset becomes essential due to tremendous growth in volume of images as well as the widespread use of World Wide Web (www). The increasing use of images in miscellaneous application areas such as medicine, education, remote sensing and entertainment has led to vast image archives that require management and retrieval of effective image data [1]. In early time, image retrieval was based on the textual annotation of images; i.e. images were manually annotated by keywords/text and organized by topical/semantic hierarchies in traditional Database management Systems (DBMSs) to facilitate easy access based on standard Boolean queries. The text based methods has significant limitations on image retrieval. Manual annotation is subjective, time-consuming, and prohibitively expensive. Also, various visual features in images, such as irregular shapes and jumbled textures are very difficult to describe in text. In comparison to traditional text-based approaches that performed retrieval only at a conceptual level, the automatic CBIR techniques support full retrieval by visual content or properties of images. The developed CBIR system, retrieved image data at a perceptual level with objective and quantitative measurements of the visual content and integration of image processing, pattern recognition & computer vision [2], [3].

Content based means that the search analyzes the contents of the image rather than the meta-data like keywords, tags, or descriptions associated with the image. It might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is required because most internet image search engines works on metadata & hence produces irrelevant images in the results. For large database, manually enter keywords for images can be inefficient, expensive and may not capture every keyword that describes the image. Therefore an efficient tool is required that can filter images based on their content, provide better indexing and return more accurate results.

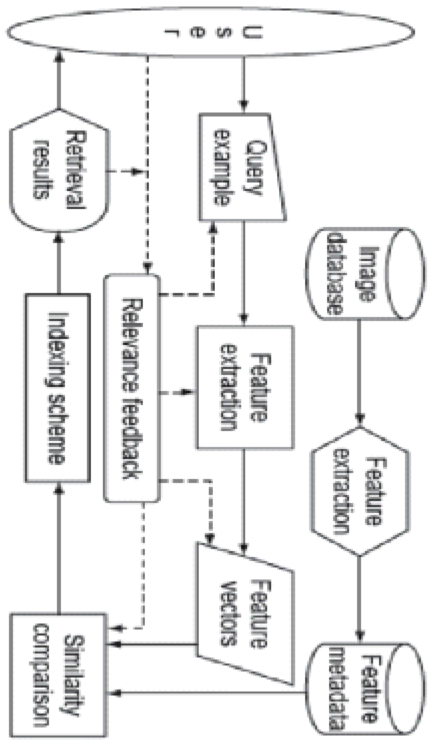

Fig. 1. General architecture of the CBIR system.

- Feature extraction and indexing of image database with chosen visual features like color, shape, texture or any combination of the above.

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- Feature extraction of query image.
- Matching the query image to the most similar images in the database according to some similarity metric/measure. This forms the search part of the CBIR.
- User interface/feedback which display the results, their ranking, type of the user interaction with possibility of refining the search through some automatic or manual preference scheme.

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II. Feature Extraction & Indexing

The key to the CBIR tool lies in feature extraction in which the image features are used to characterize image content. Image features can be classified into (1) general visual features and (2) domain specific semantic features. General visual features include primitive image information that refers to the constituents and composition of an image, such as color, texture, shape, and spatial relationships. However domain specific semantic features, are application dependent and consist mainly of abstract information that refers to the ‘‘meaning’’ of an image, describing high-level image semantic content in specialized domains. General visual features can be further classified into (a) physical visual features, including color and texture, and (b) geometric spatial features, such as shape and spatial relationships.

A. Color based Extraction

Color is the most frequently used general visual feature for CBIR tool because of its invariance to image scaling, translation, and rotation. It is represented by its three color component values like red/green/blue (RGB), hue/saturation/value (HSV), Luv/Lab (luminance/chrominance values), which make its discrimination potential superior to the single gray intensities of image. There are many color features that have been developed for CBIR, such as:

- Color histogram: Widely used and most effective color representation with the distribution of the number of pixels for each quantized color bin located in three different color components.
- Color moments: Very compact color representations, with three low-order moments (mean, variance, and skewness) for each color component.
- Color coherence vectors (CCVs): Incorporating spatial information into the color histogram.
- Color correlogram: A color descriptor characterizing both color distributions of pixels and the spatial correlation of pairs of colors.
- HDS-S (hue/diff/sum–structure): Color structure descriptor for capturing local color image structure based on MPEG-7 HMMD (hue-min-max-difference) color space.

B. Texture based Extraction

Texture is a powerful visual feature widely used in pattern recognition and computer vision. It is used for identifying visual patterns with properties of homogeneity that cannot result from the presence of only a single color or intensity. The size of the image patch and the number of distinguishable gray-level primitives and the spatial relationships between them are all interrelated elements that characterize a texture pattern. Some commonly used texture features are:

- Co-occurrence matrices, with 14 texture descriptors for capturing the spatial dependence of gray levels.
- Tamura features, with six visual texture components designed in accordance with psychological studies of the human perception of texture.
- Run-length matrices, for quantifying the coarseness of texture in specified directions.
- Wavelet transform coefficients, representing frequency properties of texture patterns, including pyramid-structured and tree-structured wavelet transform.
- Gabor filters, as orientation and scale tunable edge and bar/line detectors.
- Wold decomposition, providing perceptual properties with three components: harmonic (repetitiveness), evanescent (directionality), and in-deterministic (randomness).
- Markov random Weld (MRF).
- Fourier power spectrum.
- Fractal dimension.
- Shift-invariant principal components analysis (SPCA).

C. Shape based Extraction

Shape can be used to identify an object/region as a meaningful geometric form. Shape features in an image are normally represented after that image has been segmented into objects or regions. CBIR based on shape features is considered to be one of the most challenging tasks and has usually been limited to specific applications where objects or regions are readily available. Shape representation techniques of an object classified into two broad categories: (a) boundary based and (b) region based approaches. Boundary based approaches work on the outer boundary of the shape. The shape descriptors in this category include:

- Fourier descriptor, which describes the shape of an object with the Fourier transform of its boundary.
- Turning functions, for comparing both convex and concave polygons.
- Finite element method (FEM), with a stiffness matrix and its eigenvectors.
- Curvature scale space (CSS).
- Chord-length statistics.
- Chain encoding.
- Beam angle statistics (BAS).
- Wavelet descriptor.

Shape descriptors generally used in region based approaches are:

- Invariant moments, a set of statistical region-based moments.

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- Zernike moments.
- Generalized complex moments.
- Morphological descriptors.
- Spatial Relationships

Spatial relationships between multiple objects/regions in an image usually capture the most relevant & regular part of information in the image content. Spatial relationships are very useful for image retrieval and searching. It can be classified into (a) directional/orientation relationships and (b) topological relationships. Directional relationships capture relative positions of objects w.r.t each other like ‘‘left’’, ‘‘above’’ & ‘‘front’’. It is usually calculated through objects centroids. Topological relationships describe neighborhood & incidence between objects such as ‘‘disjoint’’, ‘‘adjacency’’ & ‘‘overlapping’’. It is calculated via objects shapes. The most commonly used approach to describe spatial relationships is the attributed relational graph (ARG) in which objects are represented by graph nodes. The relationships between objects are represented by arcs between such nodes. Another approach known as 2D strings method is based on symbolic projection theory. It allows a bi-dimensional arrangement of a set of objects into a sequential structure. Additionally spatial quad trees and symbolic images are used to represent spatial relationships.

We implement and verify the performance of developed CBIR system. The model developed used various feature extraction methods. Also the different similarity measures are used to do performance analysis.

III. Results and Discussion

The effectiveness of developed CBIR system is tested and verified by randomly select images from different classes namely Dinosaur, Buses, Flowers, Beaches and sunset. Each input query image returns the top 20 images from the database. We calculate precision and recall for each class. The accuracy of the developed system is evaluated with average value of precision and recall.

Usually precision and recall scores are not discussed in isolation. Instead either value for one metric are compared for a fixed level at the other metric (precision at a recall level of 0.68) or both are combined into a single measure, such as precision/recall graph. Precision and recall pair is a good standard of performance evaluation of any search system. It provides useful and meaningful result when the database type is known and has been effectively used in some earlier research. The experimental results are shown in figure 2 and figure 3.

The results of random images with KNN and HSV using relative deviation as similarity measure are shown in figure 2 and figure 3. The results show the topmost 20 retrieved images and contain both relevant and irrelevant images.

The results revealed that the CBIR system with KNN feature extraction using relative deviation has good retrieving results as compared to HSV over the randomly selected images as queries. However the results when compared with Manhattan distance as similarity measure are less retrieval performance. The results contain some irrelevant images. The results of KNN have 2 irrelevant images whereas HSV has 9 irrelevant images.

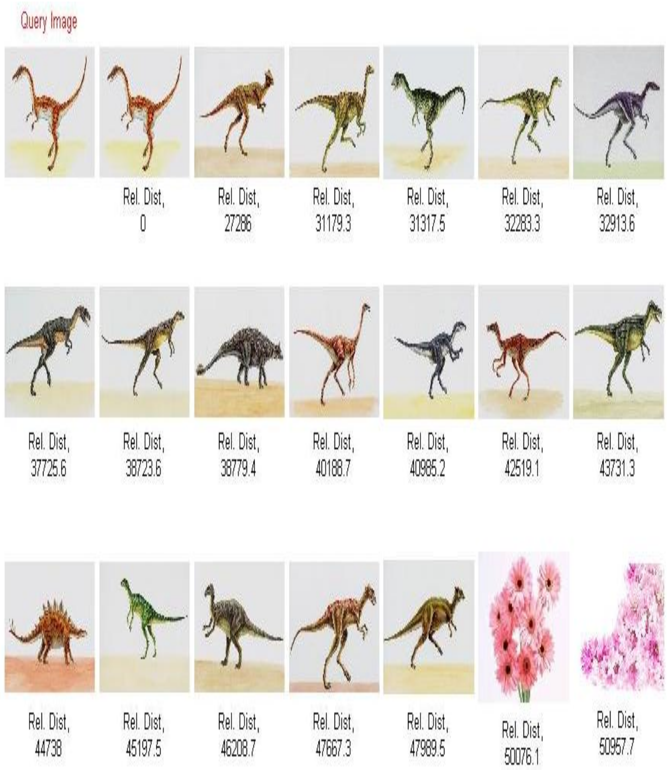

Fig. 2. Dinosaur (Class 1) query image with KNN using relative deviation.

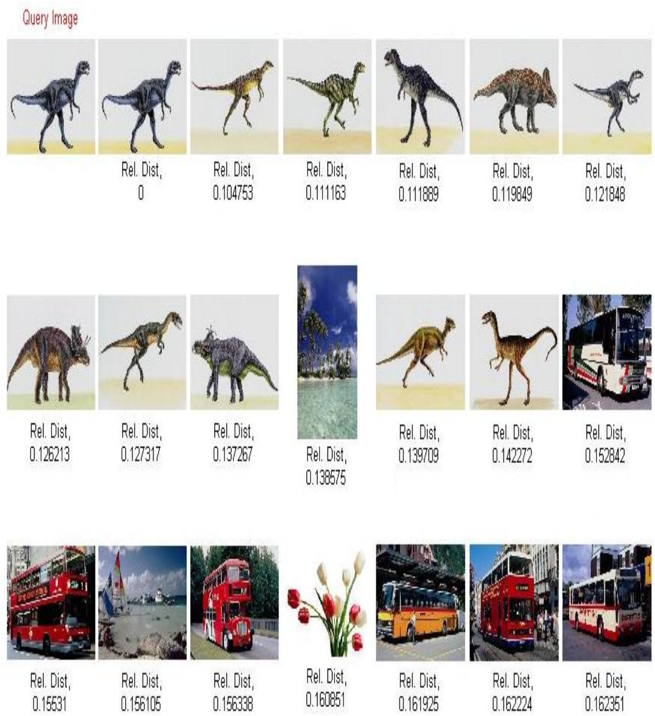

Fig. 3. Dinosaur (Class 1) query image with HSV using relative Deviation.

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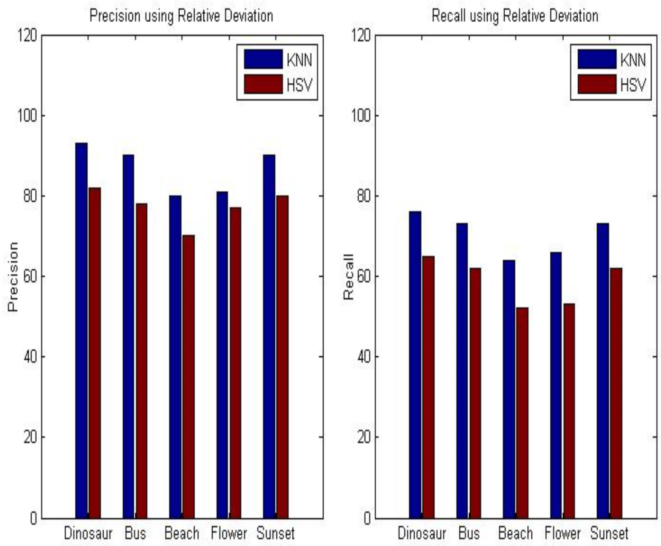

Fig. 4. Average values of precision/recall using relative deviation.

IV. Conclusion

We implement and test the CBIR system using Matlab. We design the system using KNN features and HSV features. We concluded that the CBIR system with KNN feature extraction using Euclidean distance has good retrieving results as compared to HSV over the randomly selected images as queries. However the results when compared with Manhattan distance as similarity measure are less retrieval performance. The results contain some irrelevant images.

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