Research Journal of Information Technology

ISSN 1815-7432

Academic Journals Inc.

www.academicjournals.com

Research Journal of Information Technology 3 (2): 114-122, 2011
ISSN 1815-7432 / DOI: 10.3923/rjit.2011.114.122

Effective Semantics Intensive Image Retrieval using Fast Indexing Technique

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ABSTRACT

This study attempts to provide fast indexing technique which will help to retrieve images from the database quickly and focuses on how to retrieve most relevant images from the database. The need for efficient Content-based Image Retrieval (CBIR) has increased tremendously in many application areas such as biomedicine, military, commerce, education and web image classification and searching. The semantic gap is the greatest challenge in the CBIR. The semantic gap is the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation. The CBIR uses the visual contents of an image such as color, shape, texture and spatial layout to represent and index the image. In typical content-based image retrieval systems, the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The similarities/distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database.

Key words: Content-based image retrieval, image indexing, gaussian mixture model, image databases, grouping of objects

INTRODUCTION

Interest in the potential of digital images has increased enormously over the last few years, fuelled at least in part by the rapid growth of imaging on the World-Wide Web. The problems of image retrieval are becoming widely recognized and the search for solutions an increasingly active area for research and development. There are two types of approaches for image retrieval:

- Text-based approach
- Content-based approach

Text-based approach: Images were first annotated with text and then searched using a text-based approach (Mueen *et al.*, 2007) from traditional database management systems.

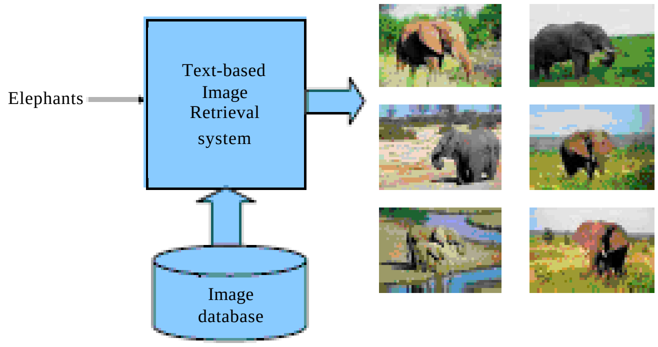

Fig. 1: Example for text-based approach

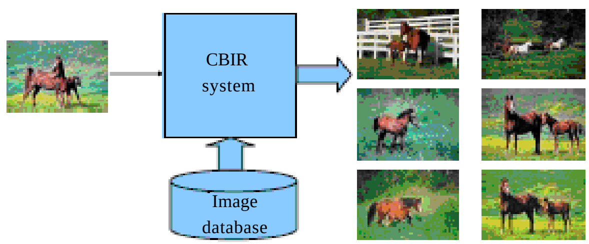

Fig. 2: Example for content-based approach

Text-based image retrieval uses traditional database techniques to manage images. The example for text based approach is shown in the Fig. 1.

Content based approach: Content-based Image Retrieval (CBIR) is the set of techniques for retrieving semantically relevant images from an image database based on automatically-derived image features such as colour, texture and shape. The example for content based approach is shown in the Fig. 2. In order to improve the retrieval accuracy of content-based image retrieval systems and research focus has been shifted from designing sophisticated low-level feature extraction algorithms to reducing the semantic gap between the visual features and the richness of human semantics.

CBIR (Smeulders *et al.*, 2000) differs from classical information retrieval in that image databases are essentially unstructured, since digitized images consist purely of arrays of pixel intensities, with no inherent meaning. The imagery features are typically extracted from shape, texture, or color properties of query image and images in the database (Flickner *et al.*, 1995). The relevance between a query image and any target image is ranked according to a similarity measure computed from the features.

AN OUTLOOK OF CBIR

Simplicity: Simplicity introduces Integrated Region Matching (IRM) scheme for CBIR. In order to reduce the influence of inaccurate segmentation, the IRM measure allows for matching a region of one image to several regions of another image. That is, the region mapping between any two

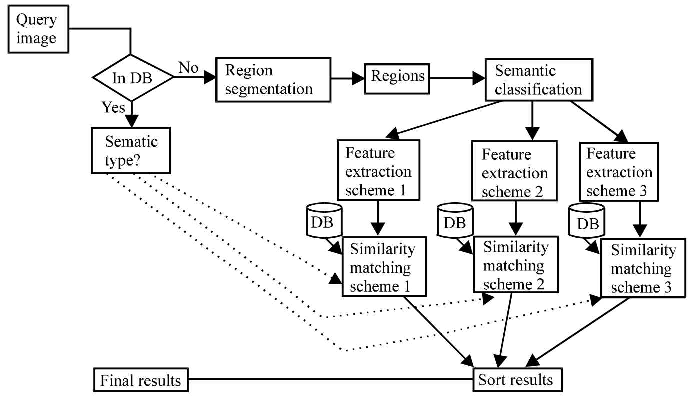

Fig. 3: Architecture for simplicity

images is a many-to-many relationship. As a result, the similarity between two images is defined as the weighted sum of distances, in the feature space, between all regions from different images (Wang *et al.*, 2001).

The architecture for SIMPLIcity is given in the Fig. 3. The concept in the figure is explained as follows:

The image segmentation method: To segment an image, simplicity partitions the image into blocks with 4×4 pixels and extracts a feature vector for each block. The k-means algorithm is used to cluster the feature vectors into several classes with every class corresponding to one region in the segmented image (Hartigan and Wong, 1979). Since the block size is small and boundary blockness has little effect on retrieval, choose block wise segmentation rather than pixel wise segmentation to lower computational cost significant.

The image classification methods: The image classification methods have been developed mainly for searching picture libraries such as Web images:

- Textured versus non textured classification
- Graph versus photograph classification

A textured image is defined as an image of a surface, a pattern of similarly-shaped objects, or an essential element of an object. Non textured images are usually partitioned into clumped regions (Vailaya *et al.*, 1998). An image is a photograph if it is a continuous-tone image. A graph image is an image containing mainly text, graph and overlays.

The IRM similarity measure: The principle of matching is that the most similar region pair is matched first. This matching scheme (Jain *et al.*, 1995) is called Integrated Region Matching (IRM) to stress the incorporation of regions in the retrieval process. After regions are matched, the similarity measure (Natsev *et al.*, 1999) is computed as a weighted sum of the similarity between region pairs, with weights determined by the matching scheme.

FUZZY FEATURE MATCHING

Image segmentation and representation: The building blocks for the UFM approach are segmented regions and the corresponding fuzzy features. In this system, the query image and all images in the database are first segmented into regions. Regions are then represented by multidimensional fuzzy sets in the feature space (Li *et al*., 2000). The collection of fuzzy sets for all regions of an image constitutes the signature of the image. To segment an image, the system first partitions the image into small blocks (Ma and Manjunath, 2000).

Representing regions by fuzzy features combines the advantages and avoids the drawbacks of both region representation forms. In this representation form, each region is associated with a fuzzy feature that assigns a value (between 0 and 1) to each feature vector in the feature space (Wiederhold *et al*., 2000). The value, named degree of membership, illustrates the degree of wellness that a corresponding feature vector characterizes the region and thus models the segmentation-related uncertainties.

Unified feature matching: The unified feature-matching scheme which characterizes the resemblance between, images by integrating properties of all regions in the images. Based upon fuzzy feature representation of images, characterizing the similarity between images becomes an issue of finding similarities between fuzzy features. Fuzzy similarity measure is introduced for two regions (Chen and Wang, 2002). The result is then extended to construct a similarity vector which includes the region-level similarities for all regions in two images.

An algorithmic summarization of the system: To generate the codebook for an image database, signatures for all images in the database are extracted by Image Segmentation (Greenspan *et al*., 2002) and Fuzzy Features Extraction. Each image is classified as either a textured or a non-textured image. Consider two scenarios, namely inside query and outside query. For inside query, the query image is in the database. Therefore, the fuzzy features and semantic types can be directly loaded from the codebook (Figueiredo *et al*., 2001). If a query image is not in the database, the image is first expanded or contracted so that the maximum value of the resulting width and height is 384 and the aspect ratio of the image is preserved. Fuzzy features are then computed for the resized query image. Finally, the query image is classified as textured or non-textured image.

Using Unified Feature Matching Algorithm, the UFM measures are evaluated for the query image and all images in the database which have semantic types identical to that of the query image. Images in the database are sorted in a descending order according to the UFM measures obtained from the previous step. Depending on a user specified number n, the system returns the first n images. The quick sort algorithm is applied here (Yang, 2004).

Content-based image retrieval by clustering: The retrieval process starts with feature extraction for a query image. The features for target images (images in the database) are usually precomputed and stored as feature files. Using these features together with an image similarity measure, the resemblance between the query image and target images are evaluated and sorted. Next, collections of target images that are close to the query image are selected as the neighborhood of the query image. A clustering algorithm is then applied to these target images. Finally, the system displays the image clusters and adjusts the similarity model according to user feedback (Chen *et al*., 2003). This concept is explained diagrammatically in the Fig. 4.

Neighboring target images selection: There are two simple methods to select a collection of neighboring target images for a query image i. First one is Fixed Radius Method (FRM) takes all

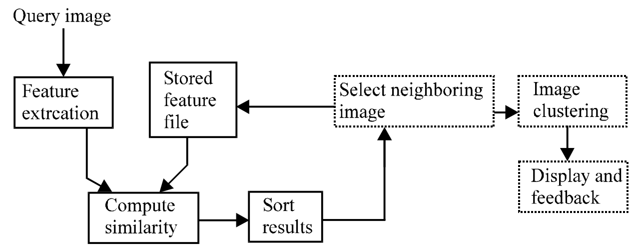

Fig. 4: A general diagram of a CBIR system using CLUE

target images within some fixed radius ϵ with respect to i. For a given query image, the number of neighboring target images is determined by ϵ .Second one is Nearest Neighbors Method (NNM) first chooses k nearest neighbors (Jose and Mythili, 2009) of i as seeds. The r nearest neighbors for each seed are then found. Finally, the neighboring target images are selected to be all the distinct target images among seeds and their r nearest neighbors. The time complexity can be reduced at the price of extra storage space (Faloutsos *et al.*, 1994).

Weighted graph representation and spectral graph partitioning: This uses the Normalized cut (Ncut) algorithm for image clustering. The process terminates when the bound on the number of clusters is reached or the Ncut alue exceeds some threshold T (Gdalyahu *et al.*, 2001). The graph representation emphasizes the pairwise relationship but is usually short of geometric interpretation. A graph representation of neighboring target images. A set of n images is represented by a weighted undirected graph G = (V, E): the nodes V = {1, 2,..., n} represent images, the edges E = {(i, j): i, j ∈, V} are formed between every pair of nodes and the non-negative weight w_{ij} of an edge (i, j) indicating the similarity between two nodes, is a function of the distance (or similarity) between nodes (images) i and j (Jianbo and Malik, 2000). The weights can be organized into a matrix W, named the affinity matrix, with the ij-th entry given by w_{ij}.

Finding representative images: Ultimately, the system needs to present the image clusters to the user. CBICR system should be able to provide an intuitive visualization of the clustered structure in addition to all the retrieved target images (Smith and Chang, 1996). For this reason, a two level display scheme is proposed. At the first level, the system shows a collection of representative images of all the clusters (one for each cluster). At the second level, the system displays all target images within the cluster specified by a user. Given a graph representation of images G = (V, E) with affinity matrix W, let the collection of image clusters {C1, C2,..., Cm} be a partition of V. Basically, for each cluster, pick the image that has the maximum sum of within cluster similarities.

Design and development of semantics intensive image retrieval: The system architecture of the proposed design is given in the Fig. 5. It is explained as follows: The query image is first segmented with the help of Gaussian mixture model method. Then, representative properties are extracted for every region by incorporating multiple semantics-related features, specifically, color properties. Then grouping of objects are done with the help of hue, saturation, value mean. The Fast indexing technique is applied to index the objects.

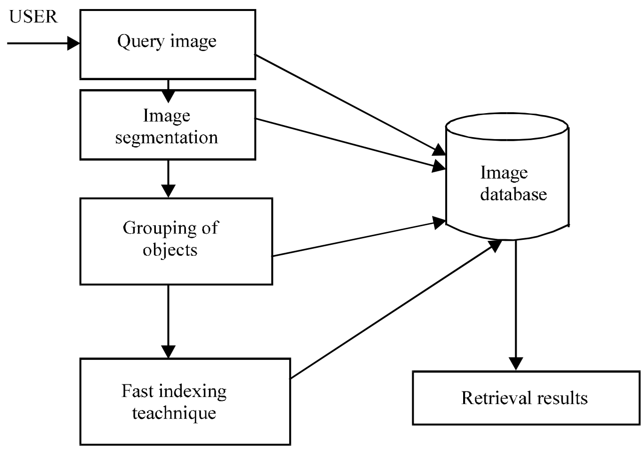

Fig. 5: System architecture

Image segmentation: Image segmentation is done by Gaussian Mixture Model (GMM). Mixture Model are a type of density model which comprise a number of component functions, usually Gaussian (Nasibov and Peker, 2011). These component functions are combined to provide a multimodal density. They can be employed to model the colours of an object in order to perform tasks such as real-time colour-based tracking and segmentation. These tasks may be made more robust by generating a mixture model corresponding to background colours in addition to a foreground model and employing Bayes theorem to perform pixel classification. Mixture models are also amenable to effective methods for on-line adaptation of models to cope with slowly-varying lighting conditions.

The image is taken to consist of pixels zn in RGB color space. As it is impractical to construct adequate color space histograms, the GMMs is used to model the color data (Lee, 2009). Each GMM, one for the background and one for the foreground, is taken to be a full covariance Gaussian mixture with K components (Premalatha and Natarajan, 2010).

In GMM a parametric Gaussian distribution mathematically represents each cluster. A mixture of these distributions models the entire data set. An individual distribution used to model a specific cluster is often referred to as a component distribution. Suppose there are K components (clusters). Each component is a Gaussian distribution parameterized by μ_k, Σ_k. Denote the data by x, $x \varepsilon R^d$. The density of component k is:

$$P_k (X) = (1/(2\pi)^d |\Sigma_k|) \exp\langle \_(x\_\mu_k)^t \Sigma^1{}_k (x\_\mu_k)/2 \rangle \quad (1)$$

The prior probability (weight) of component k is πk. The mixture density is:

$$p(x) = \sum_{k=1}^{k} \pi_k p_k (x) \quad (2)$$

Grouping of objects: Grouping of objects is done according to the HSV value of the objects. HSV is the related representations of points in an RGB color space which attempt to describe perceptual color relationships more accurately than RGB while remaining computationally simple. HSV stands for hue, saturation and value.

The visualization method of the HSV model is the cone. In this representation, the hue is depicted as a three-dimensional conical formation of the color wheel. The saturation is represented by the distance from the center of a circular cross-section of the cone and the value is the distance from the pointed end of the cone. Some representations use a hexagonal cone, or hexcone, instead of a circular cone. This method is well-suited to visualizing the entire HSV color space in a single object. However, due to its three-dimensional nature, it is not well-suited to color selection in two-dimensional computer interfaces. Because HSV is the simple transformations of device-dependent RGB, the color defined by a (h, s, v) triplet depends on the particular color of red, green and blue primaries used. Each unique RGB device therefore has unique HSV spaces to accompany it. An (h, s, v) triplet can however, become definite when it is tied to a particular RGB color space, such as RGB.

The conversion from RGB to HSV is as follows : Let r, g, b ε (0,1) be the red, green and blue coordinates, respectively of a color in RGB space. Let max be the greatest of r, g and b and min the least. To find the hue angle h ε (0.360) for HSV space, compute:

$$h = \begin{cases} 0 \text{ if } \max = \min \\ 60° \times (g-b)/(\max-\min) + 0° \text{ if } \max = r \text{ and } g >= b \\ 60° \times (g-b)/(\max-\min) + 360° \text{ if } \max = r \text{ and } g < b \\ 60° \times (b-r)/(\max-\min) + 120° \text{ if } \max = g \\ 60° \times (r-g)/(\max-\min) + 240° \text{ if } \max = b \end{cases} \tag{3}$$

The value of h is generally normalized to lie between 0 and 360° and h = 0 is used when max = min (that is, for grays) though the hue has no geometric meaning there, where the saturation s is zero. The values for s and v of an HSV color are defined as follows:

$$s = \begin{cases} 0 \text{ if } \max = 0 \\ (\max-\min)/\max = 1 - (\min/\max), \text{ Otherwise} \end{cases} \tag{4}$$

$$v = \max \tag{5}$$

Fast indexing technique: Apply the same segmentation algorithm again to all the feature vectors corresponding to all the regions of all the images recursively to form the hierarchy of the indexing structure. All the nodes represent centroid feature vectors of a corresponding set of regions except for the leaf nodes which, in addition to a set of regions belonging to the corresponding cluster, also record IDs of images that share one region with the feature vectors of the regions in that set. The depth of the indexing structure is determined adaptively based on the size of the image database. The resulting indexing tree is called the hierarchical indexing structure. An optimal indexing structure is defined in the region space such that a query image only needs to be compared with those in the database that have at least one region that is most similar to a region in the query image given a specified similarity.

Typical search algorithms would traverse the tree topdown, selecting the branch that minimizes the distance between a query q and a cluster centroid zs. However, this search strategy is not optimal since it does not allow backtracking. To achieve an optimal search, apply A* search algorithm by keeping track of all nodes that have been searched and always selecting the nodes with the minimum distance to the query region. The A* search is guaranteed to select the cluster whose centroid has the minimum distance in the set of visited nodes to the query region. Hence, it is optimal.

CONCLUSION

This study addresses effective retrieval of images from the database. It contains an algorithm for separating the object from the background in which it produces objects of good quality for moderately difficult images. The algorithm used is a more powerful and iterative version of the optimization is obtained. The power of the iterative algorithm is used to simplify substantially the user interaction. Grouping of object is done effectively by taking mean value of Hue, Saturation and Value. Maintaining tables for each identical object with the help of training the system to find the similar images and Fast indexing technique, we can reduce mismatching of images while retrieving images from the database for the query image.

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