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Content-based Image Retrieval Systems: A Survey

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Abstract

Image retrieval system is one of the important computer systems for browsing and retrieving images from a large database. There are two approaches for image retrieval, Text based image retrieval (TBIR) and Content based image retrieval (CBIR). The drawback of TBIR is manual annotation, which is impossible and expensive task for large database. The problems in TBIR have risen the interest of researchers to come up with techniques for retrieving images on the basis of automatically derived features such as color, shape and texture – a technique generally referred as content based image retrieval (CBIR). Recently, the research focus in CBIR has been in reducing the semantic gap, between the low level visual features and the high level image semantics. In this paper a comprehensive survey of all these aspects is provided. This survey covers approaches used for extracting low level features; various distance measures for measuring the similarity of images, the mechanisms for reducing the semantic gap.

Keywords: Content based image retrieval, Image retrieval, Low level feature, Semantic gap, Text based image retrieval

I. INTRODUCTION

Images are very important in the field of image processing, database applications and multimedia databases for sorting images. Image retrieval aims to search and browse images from the database collection or in other words, when retrieved information is a collection of image, this field of knowledge is also referred as image retrieval [1]. In today's modern age, images are used for efficient service in various areas like commerce, architecture, journalism, crime prevention, fashion and historical research. A large collection of these images is referred to as image database.

The prior methods of image retrieval were only dependent on text based searching instead of its visual feature. In text based image retrieval technique image is represented by keyword and these keywords for the image was created by human operators. But, manual annotation of images in large database can be inefficient and expensive task. To restrict the text based image retrieval researchers come up with content based image retrieval technique (CBIR). In CBIR instead of manual annotations by text keywords, images are indexed by their own visual features such as color, texture, shape, etc.

The CBIR has various applications in different areas, which are as follows:

1. Crime Prevention: The police maintain an image database of criminals, crime scenes and stolen items.
2. Medical Diagnosis: In the medical profession, mammographic images and scanned image database are kept for diagnosis, monitoring, and research purposes.
3. Journalism: In publishing and advertising, journalists create image databases for various events and activities such as sports, buildings, personalities, national and international events, and product advertisements.
4. Historical Research: In historical research, image databases are created for archives in areas that include arts, sociology, and medicine. They use visual data to carry their research activities.
5. Radar engineering: detection and identification of targets, guidance of aircraft and missiles
6. Robotics: motion control through visual feedback, recognition of objects in a scene.

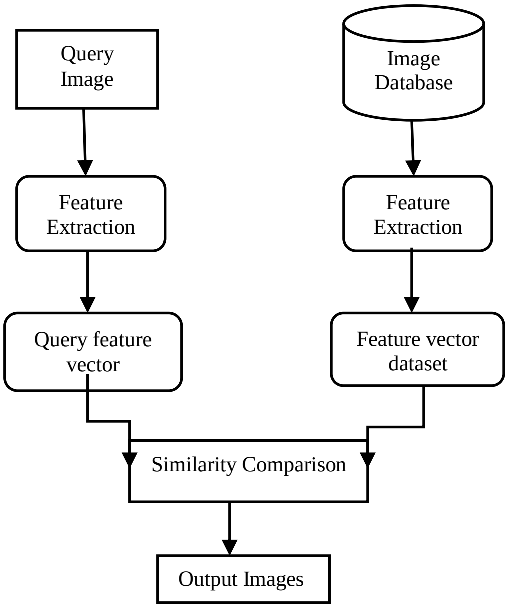

Fig. 1 Block Diagram of Content-based Image Retrieval

In typical content based image retrieval system the visual features of images in database are extracted and described by multi-dimensional feature vectors are stored in feature dataset. To retrieve the images, user will provide a query image to the retrieval system. The system then extracts the features of query image and describe it by a query feature vector. The similarity between the feature vectors of query image and images in the database are then calculated and retrieval is performed with help of indexing scheme. The block diagram of CBIR is shown in Fig.1.

In this paper section II discusses the various possible low level features available in the literature. The various distance measures are reported in the literature are presented in Section III. The main drawback of CBIR is semantic gap. Hence, to reduce the semantic gap between the low level image features and the high level semantics, became a very interesting and challenging area of research. It is called as Semantic Content Based Image Retrieval (SCBIR) and the various techniques available in SCBIR are presented in Section IV. Section V presents the performance measures to analyze the CBIR system.

II. LOW LEVEL IMAGE FEATURES

The CBIR system depends upon the low level image features which are color, texture and shape. The following subsection addresses the color, texture and shape features used in CBIR

I. Color Feature Extraction

Color feature extraction is done by using color histogram and color moment. These methods are explained in following section.

1) Color Histogram

Color histogram is most widely used method for color feature extraction from an image [2]. It shows the intensity of color pixels distributed in an image. It counts the similar pixels and stores it. Color histogram can be built in various color spaces like RGB, HSV, Lab color space, etc. For true color image, the number of different color regions is up to 2^{24} = 16777216. A histogram containing 2^{24} bins leads to a large computation. To reduce the large computation and to enhance the speed of the process, we quantize the color space without affecting the image quality. Many authors [3],[4]and [5] reported with effect of color quantization on performance of image retrieval, with different quantization schemes like RGB (8X8X8), Lab (4X8X8), HSV (16X4X4).

2) Color Moments

In this method color features are extracted using three moments of each color channel of an image, which are mean, standard deviation and skewness [6]. The first moment mean (E_i) is given by equation (1). The second moment standard deviation (σ_i) is given by equation (2). The third moment skewness (α_i) is given by equation (3).

$$E_i = \frac{1}{m.n}\sum_{j=1}^{m.n} P_{ij} \qquad \text{……………} (1)$$

$$\sigma_i = \left[\frac{1}{m.n}\sum_{j=1}^{m.n}\left(P_{ij} - E_i\right)^2\right]^{1/2} \qquad \text{………….. } (2)$$

$$\alpha_i = \left[\frac{1}{m.n}\sum_{j=1}^{m.n}\left(P_{ij} - E_i\right)^3\right]^{1/3} \qquad \text{……………} (3)$$

Where, P_{ij} is a value of each color channel at j^{th} image pixel and (m.n) are the total number of pixels per image.

II. Texture Feature Extraction

Texture feature extraction done by using Gray-level co-occurrence matrix (GLCM), Tamura features.

1) Gray-level Co-occurrence Matrix (GLCM)

To create the GLCM we have to convert RGB query image into a gray-scale image. GLCM depends upon the orientation and distance between the pixels. The GLCM matrix finds how often a pixel with the intensity value i occurs in a specific spatial relationship to a pixel with the value j. Haralick [7] proposed 28 kinds of textural features each extracted from the Gray Level Co-occurrence Matrix. The most common texture features extracted from GLCM are Contrast, Correlation, Entropy, Energy and Homogeneity [8-11].

a. Contrast

The contrast measures intensity between a pixel and its neighbor over the whole image and it is considered zero for constant image and it is also known as variance and moment of inertia.

$$\text{Contrast} = \sum_{i,j}(i-j)^2 p(i,j) \qquad \ldots\ldots\ldots\ldots (4)$$

b. Correlation

Correlation measures how pixel is correlated to its neighbor over the whole image.

$$\text{Correlation} = \sum_{i,j}\frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\delta_i\delta_j} \ldots\ldots\ldots\ldots (5)$$

c. Entropy

Entropy gives measures of complexity of the image and this complex texture tends to higher entropy.

$$\text{Entropy} = \sum_i \sum_j p(i,j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

d. Energy

Energy is the sum of squared elements in the GLCM and it is by default one for constant image.

$$\text{Energy} = \sum_{i,j}(i,j)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

2) Tamura Texture Feature

Tamura [12] in 1973, proposed texture representations that were based on psychological studies of human perception, and these representations consists of six statistical features, including coarseness, contrast, directionality, regularity, line-likeness, roughness to describe various texture properties.

III. Shape Feature Extraction

Shape is an important visual feature, which contains all the geometrical information of an object in the image which does not change generally change even when orientation or location of the object are changed. Some simple shape features are the perimeter, area, eccentricity, symmetry, etc. Selecting an appropriate shape feature depends upon the situation and the nature of the image [13]. Some of the shape features are discussed in this section.

1) Histogram of Edge Directions

The general shape information in the image is captured by the edge histogram. The edge information is obtained by using various edge detection algorithms like Canny, Sobel, Prewitt etc. [39], [40]. The edge directions are quantized into a number of bins [14-17] and histogram is normalized with respect to the number of pixels in the image for achieving scale invariance.

2) Hu-Monents Feature Extraction

Hu-moments are the simplest moment function. In 1962 author Hu [18] proposed seven properties related to connected region that are invariant to rotation, scaling, and translation (RTS) and are also known as Algebraic Moment Invariants. Moment invariants that are computed from each of the windows are used to form feature vectors.

Assume R is the image, p+q central moments or R forms as

$$\mu_{p,q} = \sum_{x,y}(x - x_c)^p (y - y_c)^q \quad \ldots\ldots\ldots\ldots\ldots (8)$$

Where (xc, yc) is the center of the object. For scale –independent nature, central moments can be standardized as

$$\eta_{p,q} = \frac{\mu_{p,q}}{\mu_0^2{,}0}$$

$$\gamma = \frac{p+q+2}{2}$$

Based on these moments, Hu brings forward seven moments independence of translation, rotation and scaling.

$\emptyset_1 = \mu_{2,0} + \mu_{0,2}$ . ...(9)

$\emptyset_2 = (\mu_{2,0} - \mu_{0,2})^2 + 4\mu_{1,1}^{1}$ .... (10)

$\emptyset_3 = (\mu_{3,0} - 3\mu_{1,2})^2 + (\mu_{3,0} - 3\mu_{2,1})^2$ .... (11)

$\emptyset_4 = (\mu_{3,0} + \mu_{1,2})^2 + (\mu_{0,3} + \mu_{2,1})^2$ .... (12)

$\emptyset_5 = (\mu_{3,0} - \mu_{1,2})(\mu_{3,0} + \mu_{1,2})[(\mu_{3,0} + \mu_{1,2})^2 - 3(\mu_{2,1} + \mu_{0,3})^2] +$
$(3\mu_{2,1} - \mu_{0,3})(\mu_{2,1} + \mu_{0,3}).[3(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2]$ ....(13)

$\emptyset_6 = (\mu_{2,0} - \mu_{0,2})[(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2] + 4\mu_{1,1}(\mu)(\mu_{2,1} + \mu_{0,3})$ ....(14)

3) Zernike Moments

Zernike moments are also called as orthogonal moments because it derived from the orthogonal Zernike polynomials. The Zernike moments are given by the equation

$$V_{nm}(x,y) = V_{nm}(rcos\theta, rsin\theta) = R_{mn}(r)exp(jm\theta)$$

……..….(15)

Where R_{mn} (r) is the orthogonal radial polynomial. The Zernike moments for the image f(x,y) are defined by the equation

$$Z_{nm} = \frac{n+1}{\pi} \sum_j \sum_\theta f(rcos\theta, rsin\theta) \,.\, R_{mn}(r)\exp(jm\theta) \,.$$

………….(16)

Zernike moments have high computational complexity [19], [20].

III. DISTANCE MEASURES

To compare the similarity of two images, different kinds of similarity measurements are present like Euclidean distance, Manhattan distance, Minkowski-Form distance and Histogram intersection. Many distance measures can be applied to evaluate the similarity of two images according to their features [21].

I. Euclidean Distance

The Euclidean distance between the query image and the database image [22-24] is given by the equation:

$$D(q,d) = \sum_{i=1}^{n}(q - d_i)^2 \quad \ldots\ldots\ldots\ldots\ldots.. \quad (17)$$

Where q is the query image and d be the database image. The distance between query and database image is calculated and least value of distance is taken. This process is repeated until all the images in the database have been compared with the query image. After completion of this algorithm, we have an array of Euclidean distance, which is then sorted.

II. Manhattan Distance

Manhattan distance is considered as two sides of a square approach. The Manhattan distance between feature vector P = (p1, p2, ……, pn) and Q = (q1, q2, …….., qn) is given by equation:

$$D = \sum_{k=1}^{n}|p_k - q_k| \ldots\ldots\ldots\ldots.. \quad (18)$$

Where D is the distance between two vectors and n is the length of the feature vector.

III. Minkowski-Form Distance

The Minkowski- Form distance is most widely used metric for image retrieval. The distance between two feature vector f1 and f2 of N bins is given by equation:

$$D(f_1, f_2) = \left(\sum_1^N |f_1(i) - f_2(i)|^p\right)^{1/p} \ldots\ldots\ldots\ldots\ldots \quad (19)$$

In this method each dimension of the image feature vector is independent of each other and is of equal importance. When p=1, the Minkowski-Form distance corresponds to Manhattan distance (L_1) and when p=2, it corresponds to Euclidean distance (L_2).

IV. Histogram Intersection

Histogram intersection is a measure that compares histograms. It calculates the common part of two histograms. The histogram intersection of two histograms H and H' is given by equation [25]:

$D(H, H') = \sum_{m=1}^{M} min(H, H')$ …………….. (20)

IV. SEMANTIC CONTENT-BASED IMAGE RETRIEVAL

The limitation of CBIR is semantic gap. Many techniques are developed to reduce 'Semantic gap' between low level features and high level semantics. This section describes the various techniques developed for reducing the semantic gap.

I. Support Vector Machine

SVM is the supervised machine learning technique, which perform the classification process with the help of the already categorized training data. The SVM multi classifiers were developed by using SVM binary classifiers. Each binary SVM chooses one class as the positive example and the remaining all classes as a negative example. A data point is classified under a certain class, if and only if, the corresponding class SVM accepts it, and all the other SVMs rejects it. The disadvantage is that when more than one SVM may accept or all SVMs may reject, the data point cannot be classified. N*(N −1)/2 SVM binary classifiers were constructed using One-Against-one or Pair Wise Coupling. For each pair of classes, there is one classifier. The class which gets the highest vote is the class of the data point. Hence, when a query image feature vector is given to the SVM, it predicts its class [26].

II. Neural Network

Neural Network is useful supervised machine learning technique, which are trained with the known training data and it is able to generalize the new unseen data. The input of the neural network classifiers is the low level features of the segmented regions of the training set images that establish the link between the low level image features and high level semantics. The disadvantage of this method is that it requires a large amount of training data, and is computationally exhaustive [27-29].

III. Relevance Feedback

Relevance feedback (RF) is an effective scheme to bridge the gap between high-level semantics and low-level features in content based image retrieval. A relevance feedback approach allows a user to interact with the retrieval algorithm by providing the information of which images user thinks are relevant to the query [30-32]. In RF, the user states whether the retrieved results are relevant or irrelevant to the query , when the system provides the retrieval results with the help of distance measures or some of the machine learning techniques.

Liu.Y [27] (2007) discussed some relevance feedback techniques which are Query reweighting (QR) and Query Point Movement (QPM). The RF strategies QR and QPM did not completely cover the user‘s interest in the broad feature space. Query Expansion (QEX) is another RF technique which groups the similar relevant points into several clusters, and selects good representative points from these clusters to construct the multipoint query. QEX is more effective than QPM and QR [34]. Samuel Rota Bul_o [33] in 2011 proposed a novel approach to CBIR with RF, which is based on a random walk algorithm.

IV. Clustering Techniques

In clustering, no labeled data are available [35]. The goal of clustering is to separate a finite unlabeled data set into a finite and discrete set of "natural," hidden data structures [36]. The clustering algorithms divide the given data into n clusters and give cluster centers of each cluster. When a query image features are given to the clustering algorithm, it finds the distance between the query image and all cluster centers. The query image belongs to the cluster for which the distance is a minimum.

Ncut method attempts to organize nodes into groups so that the within the group similarity is high, and/or between the group similarity is low. A set of 'n' images is represented by a weighted undirected graph and the edges are formed between every pair of nodes. The weight of an edge is a function of the distance between those two nodes (images). The system displays the image clusters and adjusts the model of similarity measure, according to user feedbacks [37].

K-means method initially takes the number of components of the population equal to the final required number of clusters. Next, it examines each component in the population and assigns it to one of the clusters depending on the minimum distance. The centroid position is recalculated every time a component is added to the cluster and this continues until all the components are grouped into the final required number of clusters. The K-means algorithm is very simple and can be easily implemented in solving many practical problems [27].

The Fuzzy c-means (FCM) clustering is the most widely used clustering algorithms. This algorithm is based on an iterative optimization of a fuzzy objective function. The degree of membership of a data item to a cluster is between [0, 1]. For a given query image, the output of the FCM is the membership value of the image with each of the K classes. The query image belongs to the class for which the membership value is high [15], [16] and [38].

V. PERFORMANCE MEASURE

Many different methods for measuring the performance of a system have been created and used by researchers. The most common evaluation measures used in CBIR are precision and recall which is defined as, [9], [11], [15] and [34].

$$Precision := \frac{\textbf{\textit{Number of relevant images retrieved}}}{\textbf{\textit{Total number of images retrieved}}} \quad \ldots\ldots (21)$$

$$Recall := \frac{\textbf{\textit{Number of relevant images retrieved}}}{\textbf{\textit{Total number of images in database}}} \quad \ldots\ldots.. (22)$$

VI. RELATED WORK

N. Puviarasan [12] in 2014 proposed CBIR technique to retrieve the images from large databases. They proposed a combination of texture and shape feature extraction methods like Haralick features and Hu-invariant moments. They first segment the image according to the Fuzzy C-means clustering and comparing with the k-means, and they extracted features according to the texture and shape and use the combination of both features. The corel image database was used for experimentation and similarity measures Euclidian distance was applied for the retrieval of images.

H. Ma [42] in 2010 , they extract four kinds of effective global features Grid color moment, Local binary pattern (LBP), Gabor wavelet texture, Edge using canny edge detector from every image, they create image similarity graph, and then form a hybrid graph with the image-tag bipartite graph. After building the hybrid graph, they propose a novel and effective random walk model that employs a fusion parameter to balance the importance between the image contents and the tags and also provide a natural solution for including the pseudo relevant feedback into image retrieval and annotation tasks. The experimental results on a large Flickr dataset show the advantage of their proposed framework.

Rehman M.H [43] in 2012, texture features is extracted using invariant Gabor Descriptor from the image and similarity measure Canberra distance was applied for retrieval of images. The Brodatz texture database and Food database were used for experimentation.

Hatice [44] in 2012, color and texture features are extracted using color moment and co-occurrence histogram respectively and similarity measure correlation distance measure is used. For reducing the semantic gap in CBIR they used SVM and nearest neighbor search. The Follicular Lymphoma and Neuroblastoma database were used for experimentation. The database contains images of more than one disease. This CBIR system is developed for microscopic images.

VII. CONCLUSIONS

This survey paper gives an overview of functionality of content based image retrieval. This paper discussed about the various methodologies used for extracting low level features, various distance measures to find similarity in images and also provide reviews of work done by researchers to reduce the semantic gap between low level features and high level semantic concept. Use of the hybrid feature including color, texture and shape as a feature vector to match images can give better results. Selecting components of CBIR in balanced manner will help to obtain an efficient CBIR framework.

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