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Interactive Image Retrival using Semisupervised SVM

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Abstract: An image database system is divided into two categories by their indexing and retrieval techniques one is based on the text based approach and another is based on the content based approach. In text based approach, it uses keyword or a sentence to index and retrieve the images and it is used to find "semantically" annotated images. The textual information often fails for a large collection images because enormous amount of labour is required for manual image annotation and the perception subjectivity and annotation impreciseness may cause unrecoverable mismatches. To overcome this difficulty Content-based image retrieval is used. In this paper CBIR is used for efficient retrieval of relevant images from a large image database based on automatically derived from the image feature. The features are extracted based on color, shape and texture. One fundamental problem in CBIR is the semantic gap between low level visual features and the high level semantic concepts. To reduce this semantic gap relevance feedback was introduced. Typical relevance feedback approaches by SVMs are based on strict binary classification and two–class classifications. It is used to discriminate the positive and negative samples by a maximum margin hyperplane. Various similarity measures are considered to measure the similarity between the query image and image database. Precision and Recalls are calculated to improve the performances of the CBIR.

Keywords: Content-Based Image Retrieval, Support Vector Machine, Relevance Feedback.

I. INTRODUCTION

Content-based image retrieval has been extensively used nowadays. CBIR is a technique which uses a visual content of an image to search images from a large scale image database. It employs the visual content of an image such as color, shape and texture features to index the images and it is desirable because most of the web based image search engine rely purely on metadata and this produces a lot of garbage's in the result. Thus the CBIR system filters the images based on their content and provides enhanced indexing and returns the exact results. [10]

Even though the CBIR, has some the semantic gap problem exists between low level visual features and the high level semantic concepts and the subjectivity of human perception. To reduce this semantic gap a relevance feedback was introduced as a powerful tool to enhance the performance of the CBIR. CBIR has many applications such as

- Web searching
- Crime prevention
- Biomedical etc

Relevance feedback is to take the outcome that is originally returned from a given query and to use information about whether or not those results are relevant to perform a new query [2] [3]

Fig 1.1 shows that the user gives the query image and the features are extracted based on color, shape and texture. Likewise, features are extracted from the image database and measure the similarity between them using Euclidean distance.

Future, CBIR performs indexing and retrieves the image. If the retrieved results are not satisfactory then the relevance feedback process takes place until the user is satisfied with the outcome.

The rest of this paper is organized as follows: In Section II, the CBIR techniques are discussed. In Section III, conclusion and future work are presented. Reference is given.

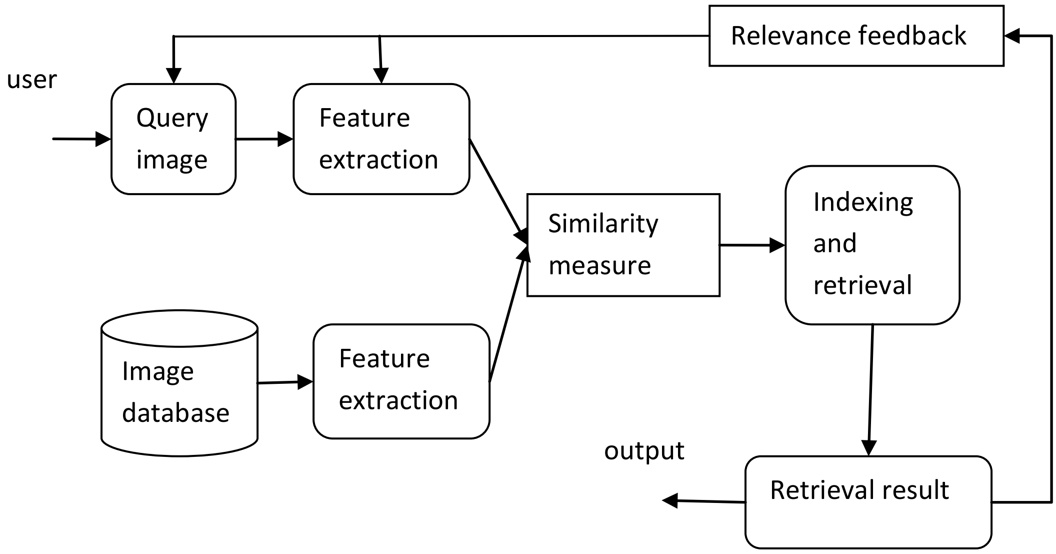

Fig 1.1Content-based Image Retrieval using RF

II. CBIR TECHNIQUES

A. Support Vector Machine

Support vector machine is used to constructs a hyperplane or set of hyperplane in a high or infinite- dimensional space, which can be worn for classification, regression. A good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (functional margin), given that in general the larger the margin the lower the generalization error of the classifier. There are many hyperplane that might classify the data. The best hyperplane is the one that represents the largest separation or margin between the two classes. In hyperplane, the distance from it to the nearest data point on each side is maximized [17]. If such a hyperplane exists, it is known as a maximum margin hyperplane and the vectors closest to the hyperplane are called support vectors [17].

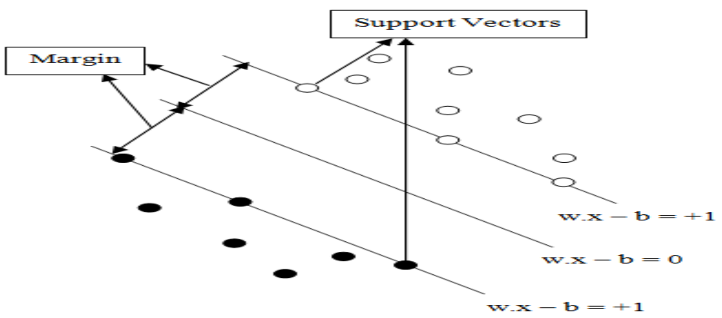

Fig 2.1 SVM Model

Fig 2.1 shows, [17] the line w. X –b =0 is known as the margin of separation or marginal line. The circle and the shaded circle represent the positive and negative instances. One-class SVM [1] is used to estimated the density of positive feedback samples. The density estimation method ignores any information contained in the negative feedback samples. Plagiaristic from one-class SVM, a biased SVM innate the qualities of one-class SVM but incorporated the negative feedback samples.

Biased Support Vector Machine

Relevance feedback approaches by SVMs are based on strict binary classification or one class classification. The strict binary classification [7] does not support the imbalanced data set problem in relevance feedback because the imbalanced data set the negative instance largely outnumbers the positive instances. Without the negative information the relevance feedback cannot work properly. To avoid this problem a modified SVM called Biased SVM is used. Biased SVM is derived from the one class SVM. It is used to construct the relevance feedback technique in CBIR. [7]

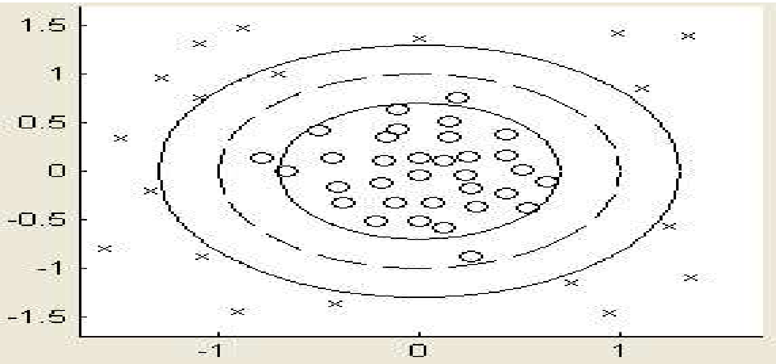

Fig 2.2 [7] the sphere hyperplane of BSVM.

The circles and the crosses represent the positive instances and the negative instances, respectively. The dashed Sphere is the decision hyperplane.The optimal sphere hyperplane contain not only the positive data it also include the negative data .Most of the negative data pushed out of the sphere.

B. Clustering Techniques

Clustering is an unsupervised learning task that aims at decomposing a given set of objects into subgroups or clusters based on similarity, like discriminant analysis. It is divided into two types they are hierarchical and non hierarchical clustering techniques. Hierarchical clustering techniques proceed by either a series of successive mergers or a series of successive divisions. Examples are single linkage, complete linkage etc. Non hierarchical clustering techniques proceed as a monotonically increasing ranking in strength as cluster themselves progressively become members of large clusters. Examples are K- mean, Fuzzy clustering etc. One of the non hierarchical clustering methods is the partitioning method. The partitioning method constructs K clusters from data as follows.

- Each cluster consists of at least one object n and each object K must be belonging to one cluster. This condition implies that$K \leq n$.
- Dissimilar clusters cannot have the same object and construct K groups up to the full data set.

Fuzzy clustering

It is also known as soft clustering. The data elements can belong to more than one cluster and associated with each element .It is a process of assigning these membership levels and using them to assign data element to one or more cluster.

C. Image Feature Extraction

Feature extraction done by low level visual feature such as color, shape and texture. [6]

Color

Examining images based on color , it is one of the most widely used techniques .Color search usually involve by comparing color histograms .Color histogram is a kind of bar graph, where each one bar represents an exact color of the color space being worn. RGB or HSV colors are worn. Quantization in terms of color histograms refers to the process of reducing the number of bins by taking color that is very similar to each other and putting them in the same bin. The maximum number of bins one can obtain using the histogram function is 256. There are two types of color histograms, Global Color Histograms (GCHs) and Local Color Histograms (LCHs).

Texture

Texture is an innate property of all surfaces that describes visual patterns, each has homogeneity. Texture images are stored and trained in the database. And all the images are retrieved using the feature texture by using the texture correlogram adaptive hierarchical multi class SVM classifier for texture based image classification Texture feature include directionality, periodicity, coarseness, color distribution, contrast etc. Wavelets are used for texture representation. The co-occurrence matrix method of texture description based on the repeated occurrence of gray level configuration is described by a matrix of relative frequencies [4].

Shape

Shape feature is an important feature to describe the image. Shapes often link to the target which has a certain semantic meaning. So shape feature can be seen higher level feature than color and texture feature. The description of the target shape is very complex issues. Shape feature extraction widely used in medical image analysis. There are two types of shape feature extraction one is based on the boundary and another is based on region. There are many invariant moments used to describe the shape which is the arithmetic invariant moment, Legendre moment, Zerrnike moment etc. [5]

D. Similarity Measure

The system compares the similarity between the query image and the database images according to the aforementioned low-level visual features (color, shape and texture) [8] [9]. The similarity measure can be

- Distance-Based Similarity Measures
- Feature-Based Similarity Measures

Distance-Based Similarity Measures

The two most popular distance measures in Multidimensional Scaling are

- Euclidean distance
- City-block distance
- Histogram intersection
- Quadratic form distance
- Mahalanobis distance

Euclidean distance

If the coordinates of some stimulus A in an n-dimensional psychological space are (x_{A1}, x_{A2}… x_{An}) then the Euclidean distance from stimulus A to some other stimulus B is

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(x_{Ai} - x_{Bi})^2} \quad (1)$$

A significant hypothesis has been that Euclidean distance is valid when stimulus dimensions are perceptually integral.

City block distance

The city-block distance connecting two stimuli is defined as

$$d(A,B) = \sum_{i=1}^{n} |x_{Ai} - x_{Bi}| \quad (2)$$

City-block distance is so-named because it is the distance in blocks between any two points in a city.City-block distance is appropriate when stimulus dimensions are perceptually separable.

Histogram intersection

It is used to compute the similarity between color images. The intersection of the two histograms of I and J is defined as

$$S(I,J) = \frac{\sum_{i=1}^{N} \min(f_i(I), f_i(J))}{\sum_{i=1}^{N} f_i(J)} \quad (3)$$

It is comparatively tactless to changes in image resolution, histogram size, occlusion and depth.

Quadratic form distance

The quadratic form distance is given as

$$D(I,J) = \sqrt{(F_I - F_J)^T A(F_I - F_J)} \quad (4)$$

Quadratic form distance can lead to perceptually more desirable results than Euclidean distance and histogram intersection [16].

Mahalanobis distance

Mahalanobis Distance is a distance measuring metric in statistics. It is based on the relationship between variables and can be used to analyze various patterns. It is suitable when each dimension of the image feature vector is dependent of each other and it is defined as

$$D(I,J) = \sqrt{(F_I - F_J)^T C^{-1}(F_I - F_J)} \quad (5)$$

Where C is the covariance matrix of the image feature vectors. [16]

Feature based similarity measure

The feature contrast model suggests that the similarity between A and B is equal to

$$S(A, B) = \alpha\, g(A \cap B) - \beta\, g(A - B) - \gamma\, g(B - A) \quad (6)$$

Where α, β and γ are constants that capacity differ across individuals, context, and instructions_ Let g $(A \cap B)$ denote the salience of the features that are common to stimuli A and B and let g $(A - B)$ denote the salience of the features that are unique to stimulus A. According to this model, features in common increase similarity, whereas features that are only one of its kinds to one stimulus decrease similarity. One benefit of the feature contrast model is that it can account for violations in any of the distance axioms.

E. Performances in CBIR

The performance of the Content-based Image retrieval is improved by precision, recall, error rate and retrieval efficiency. The Average Precision is defined as the average ratio of the number of relevant images of the returned images over the total number of the returned images. [7]

$$\text{Precision} = \frac{\text{number of relevant images retrieved}}{\text{Total number of returning images}} \quad (7)$$

The average Recall is defined as the average ratio of the number of relevant images retrieved over the total number of relevant images in the collection. [18]

$$\text{Recall} = \frac{\text{number of relevant images retrieved}}{\text{total number of relevant images in the collection}} \quad (8)$$

The error rate is defined as the number of non relevant images retrieved over the total number of images retrieved

$$\text{Error rate} = \frac{\text{number of nonrelevant images retrieved}}{\text{Total number of images retrieved}} \quad (9)$$

Retrieval efficiency is defined as if the number of images retrieved is lower than or equal to the number of relevant images, then this value is precision, otherwise it is a recall of a query.

III. CONCLUSION

In this paper, CBIR is used for efficient retrieval of relevant images from a large image database based on automatically derived from the image feature. The features are extracted based on color, shape and texture. One fundamental problem in CBIR is the semantic gap between low level visual features and the high level semantic concepts. To reduce this semantic gap relevance feedback was introduced. Typical relevance feedback approaches by SVMs are based on strict binary classification or one–class classifications. It is used to discriminate the positive and negative samples by a maximum margin hyperplane. Various similarity measures are considered to measure the similarity between the query image and image database. Precision and Recalls are calculated to improve the performances of the CBIR. In future, the Semisupervised biased maximum margin analyses are used to consider the unlabeled samples.

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