CBIR BASED ON LEARNING OF NEURAL NETWORK WITH FEEDBACK RELEVANCE

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ABSTRACT

To achieve the knowledge and information from web there must be use of retrieval of images from web databases because of effective information in images .For more effective and efficient image retrieval, learning is most important. Learning is also most important concept for feedback method to any data mining task. Using the retrieval pattern-based learning is the most effective that aim to establish the relationship between the current and previous query sessions by analyzing retrieval patterns. User's feedback is utilized for updating the high level semantic features of query image and each database image. We propose a new feedback based and content based image retrieval system using neural network based pattern learning to achieve effective classification and with neural network we use decision tree algorithm to make less complex mining of images.

Keywords: *Pattern-based learning, Image retrieval, Neural network*.

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I. INTRODUCTION

As we know that the World Wide Web has huge amount of data, there has been an explosion in the amount and complexity of digital data being generated, stored, transmitted, analyzed, and accessed. As the visual perception is more impressive in the nature so there are increasing amount of multimedia data in the nature including the images, videos, graphics, audio and text data. Among the various media type the image has the prime importance. To retrieve the images from the image data there are two techniques, text based and content based image retrieval techniques (CBIR). In text based Retrieval where each image in the database is labeled by keywords describing the image. For searching for an image, user formulates the query using keywords which best describes his query image. Since image databases are very large, so annotating such a huge collection is a very tedious task. Also subjective description of a query image may differ from person to person due to differences in human perception. Keyword annotation is the traditional image retrieval Paradigm [1], [2]. In this approach, the images are first annotated manually by keywords. They can then be retrieved by their corresponding annotations. However, there are three main difficulties with this approach, i.e. the large amount of manual effort required in developing the annotations, the differences in interpretation of image contents, and inconsistency of the keyword assignments.

The CBIR is the technique that is proposed in 1990 to overcome these difficulties. The goal of CBIR is to retrieve images that are visually similar to the query image.CBIR uses the visual content of images like color, texture, and shape as the image index to retrieve the images from the database. These feature never changed. The CBIR is the technique to map each of the images in the database to a feature space and then retrieve based on the feature of the query image. Typical features might include pixel color histograms, gray scale histograms, texture features, and edge-content measures.

Color Feature

Color is the most popularly used features in image retrieval and indexing. On the other hand, due to its inherent nature of inaccuracy in description of the same semantic content by different color quantization and or by the uncertainty of human perception, it is important to capture this inaccuracy when defining the features.

Texture Feature

There is no precise definition for texture. However, one can define texture as the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. Texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules

Shape Feature

Shape is used as another feature in image retrieval. However, it is evident that Retrieval by shape is useful only in very restricted environments, which provide a good basis for segmentation (e.g. art items in front of a homogeneous background). Shape descriptors are diverse, e.g. turning angle functions, deformable templates, algebraic moments, and Fourier coefficient

Similarity Computation

Feature vectors, extracted from the database image and from the query, are often passed through the distance function d. The aim of any distance function (or similarity measure) is to calculate how close the feature vectors are to each other. There exist several common techniques for measuring the distance (dissimilarity) between two N-dimensional feature vector f and g. Each metric has some important characteristics related to an application. There exist several common techniques for measuring the distance (dissimilarity) between two N-dimensional feature vector f and g.

The Euclidean metric is obtained as:

$$D_{eucld}(f,g) = \sqrt{\sum_{i=1}^{N}(f_i - g_i)^2}$$

Correlation is given by

$$D_{corr}(f,g) = \frac{\Sigma(f_i - f)(g_i - g)}{\sqrt{\Sigma(f_i - f)^2\,\Sigma(g_i - g)^2}}$$

II. BACKROUND

In digital image classification the conventional statistical approaches for image classification use only the gray values. Different advanced techniques in image classification like Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy measures, Genetic Algorithms (GA), and Genetic Algorithms with Neural Networks are being developed for image classification.

Techniques of image classification

Image classification plays an important roll for many Studies in science and different type of environmental applications. There are many classification algorithms have been developed for classification of images. In this section we emphasizes on the analysis and usage of different advanced classification techniques like Artificial Neural Networks, Support Vector Machines, Fuzzy Measures, Genetic algorithms and their combination for digital image classification. Finally the study depicts the comparative analysis of different classification techniques with respect to several parameters.

A. Artificial Neural Network (ANN)

Neural Network can provide suitable solutions for problems, which are generally characterized by non-linear ties, high dimensionality noisy, complex, imprecise, and imperfect or error prone sensor data, and lack of a clearly stated mathematical solution or algorithm. A key benefit of neural networks is that a model of the system can be built from the available data. Image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm.

Textural features, the angular second moment, contrast, correlation and variance are calculated. After extracting the textural features the network is trained by standard back propagation algorithm (BKP).

The back propagation algorithm is implemented in these steps:

1. Initialize weights
2. Feed input vectors and compute the weighting sum and then apply sigmoid function
3. Calculate error term for each output unit
4. Calculate the error term of each of the hidden units
5. adjust the weights

Step 2, 3, 4 and 5 are repeated till the error is within acceptable limits after that it is ready to store for reference values.

B. Support Vector Machines

SVM is a supervised learning process in which data analyze and recognize patterns, used for classification and regression analysis. A good separation is achieved by the hyper plane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. The inductive principle behind SVM is structural risk minimization (SRM). Risk of a learning machine (R) is bounded by the sum of the empirical risk estimated from training samples (Remp) and a confidence interval (ψ): $R \leq R\text{emp} + \psi$ [8]. The strategy of SRM is to keep the empirical risk (Remp) fixed and to minimize the confidence interval (ψ), or to maximize the margin between a separating hyper plane and closest data points [3].

The implementation of SVM required these steps:

A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one "target value" (i.e. the class labels) and several "Attributes" (i.e. the features or observed variables). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

1. Transform data to the format of an SVM package
2. Conduct simple scaling on the data
3. Consider the RBF kernel K(x; y) = $e^{-\gamma\|\mathbf{x}-\mathbf{y}\|^2}$
4. Use cross-validation to and the best parameter C and
5. Use the best parameter C and to train the whole training set
6. Test

The best parameter might be a selected by the size of data set but in practice the one obtained from cross-validation is already suitable for the whole training set. [5]

C. Fuzzy Measures

In Fuzzy measures, different relationships are identified to describe properties of an image. The members of these property set are fuzzy in their contribution. The fuzzy measure gives the possibility to describe different types of stochastic properties in the same form. If the fuzzy property is more related to a region, then a fuzzy measure is used. Fuzzy function is used if a stochastic property is to be described by a particular distribution of gray values. The fusion of these two stochastic properties is represented as a fuzzy measure and fuzzy function defines on an area which is achieved by a fuzzy integral. The result of fuzzy integral is a new fuzzy measure. [4]

The fuzzy measures are implemented in these steps.

1. Extraction of stochastic properties
2. gather Stochastic Information
3. Apply Fuzzy Functions
4. Fusion of Fuzzy Properties by Fuzzy Integrals

The summation of all combinations of fuzzy measures with fuzzy functions makes sure, that all possible properties in all combinations, which should be considered, are used. In such a way an image is obtained, where the (grey) values represent a measure for the membership to the texture. In this way different elementary stochastic properties are combined in many ways for the extraction of relevant information. In order to achieve this different approaches have to be applied for the elimination of the elementary stochastic properties within an image.

D. Genetic Algorithms

The features like texture or the average value of nearby pixels are necessary to get good spectral information. The different kinds of spatial content information could also be added into the pixel feature vector as additional feature dimensions. So there are a large number of choices for additional feature vectors that could make classification Better than just having the raw spectral values as feature vectors.

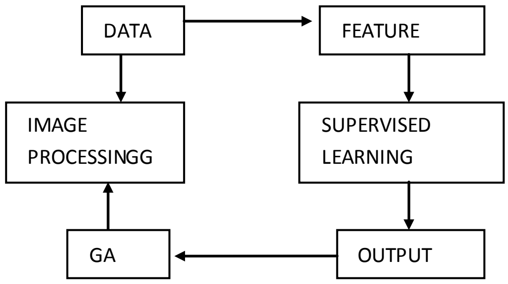

Fig: shows the process of genetic algorithm process

The genetic programming system based on a linear chromosome that manipulates image processing programs that take the raw pixel data planes and transform them into a set of feature planes. This set of feature planes is in effect just a multi-spectral image of the same width and height as the input image, but perhaps having a different number of planes, and derived from the original image via a certain sequence of image processing operations. The system then applies a conventional supervised classification algorithm to the feature planes to produce a final output image plane, which specifies for each pixel in the image, whether that feature is there or not. Figure illustrates this hybrid scheme. In this structure finally raw data planes are transformed into a set of feature planes by an image processing program that is evolved by genetic algorithm. [6]

E. Comparison of Image Classification Techniques

The image classification techniques like artificial neural networks, support vector machines, fuzzy logic, genetic algorithms and their combination are analyzed and compared with respect to several parameters. Artificial neural networks have the advantages mainly of more tolerance to noise inputs and representation of Boolean function apart from others. But too many attributes may result in over fitting. In support vector machines over fitting is unlikely to occur. The computational complexity and complexity of decision rule are reduced in SVM. Fuzzy measures have the benefit of identification of various stochastic relationships to describe the properties of the image. But prior knowledge is very important to get good results.

Genetic algorithms are primarily used in optimization and always have a good solution. But the computation of scoring function is nontrivial. The artificial neural networks and support vector machines follows non-parametric approach whereas fuzzy measures use stochastic properties for image classification. The selection of non-linear boundary is efficient when the data have only few input variables in ANN and vice versa in SVM. In fuzzy logic it depends on prior knowledge whereas in genetic algorithms it depends on the direction of decision. The training speed in the neural networks depends on network structure, momentum rate, learning rate and converging criteria. In SVM it depends on training data size and class reparability. Fuzzy logic incorporates the training speed depending on the isolation of the relevant information by iterative application of the fuzzy integral. The training speed could be improved by refining irrelevant and noisy genes in genetic algorithms. Along with these the parameters accuracy and general performance are tabulated in Table. [4]

Parameter	**Artificial neural network**	**Support vector machine**	**Fuzzy logic**	**Genetic algorithm**
Type of approach	Non parametric	Non parametric with binary classifier	Stochastic	Large time series data
Non linear decision boundaries	Efficient when the data have only few input variables	Efficient when the data have more input variables	Depends on prior knowledge for decision boundaries	Depends on the direction of decisions
Training speed	Network structure, momentum rate ,learning rate, converging criteria	Training data size, kernel parameter	Iterative application of the fuzzy integral.	Referring irrelevant and noise genes.
Accuracy	Depends on number of input classes.	Depends on selection of optimal hyper plane.	Selection of cutting threshold	Selection of genes.
General performance	Network structure	Kernel parameter	Fused fuzzy integral.	Feature selection.

Image retrieval using the relevance feedback

Relevance feedback retrieval systems prompt the user for feedback on retrieval results and then use this feedback on subsequent retrievals with the goal of increasing retrieval Performance [10]. A user presents an image query to the system where upon the system retrieves a fixed number of images using a default Similarity metric [11]. The user then rates each returned result with respect to how useful the result is for his or her retrieval task at hand. Ratings may be simply "relevant" or "not Relevant" or may have finer gradations of relevancy such as "somewhat relevant," "not Sure and "somewhat irrelevant." The relevance feedback algorithm uses this feedback Information to select another set of images to retrieve for the user; whether the new and previous sets are disjoint depends on the particular system. The system's goal is to effectively infer which images in the database are of interest to the user based on this feedback. The user could then rate these images in the second set in a similar way and the process may iterate indefinitely in this closed-loop fashion [8,] [1].

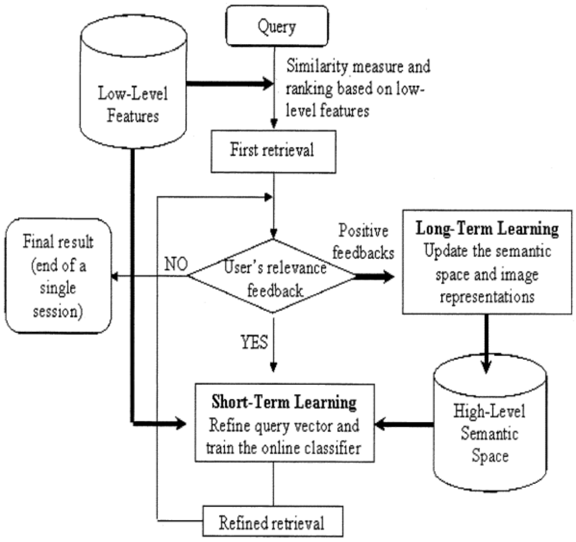

Fig -2 Query processing in image retrieval.

III. PREVIOUS WORK

Over segmenting the images using an automatic algorithm and letting the user group the smaller region into objects, can be adopted as an alternative partitioning method. The previous method use the low level features, descriptor that does not lies in the border class and low level texture [7]. Some system uses the SVM as the learning tool , the results of the previous are given in the figure in terms of iteration used and how much learning done based on the graph shown in figure.3.

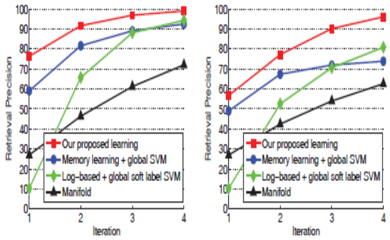

Fig 3. Retrieval result per itration.

IV. PROPOSED MODEL

We proposed a new approach for Content based image retrieval system feedback based image classifier in efficient manner. We have prepared a database consisting a number of images. Here user required to input the test image or query image and selected object images. Now Features like texture is then extracted from test (query) image and object images. Similarities distances are measured and calculating linear Coefficient of Correlation between tests (query) and object images. On the basis of coefficient of correlation Training set is formed into two categories (relevant and irrelevant). Then using those labeling the neural network based classifier is trained. [7]. these feedback rounds go on iteratively and each time a refinement of the images shown to the user is done. Finally those images which are judged by the classifier as positive are taken. The classifier results are produced in a decision tree algorithm to extract rules from it. Now the query image is plotted in the positive set. Those images which are nearest to the query image based on these rules set similarity ranking are taken and shown to the user.

We are going to follow these steps for our proposed technique.

Step1: Preprocessing

1. Converting the image into the workable format(.bmp,jpg)
2. Change into gray scale image

Step2: Feature extraction

1. Texture feature are extracted into the algorithm
2. Make the feature vector by making the average value of each pixel byte.

Step3: Similarity computation

1. Compute the similarity on the basis of the distance above and below the threshold value

Step4: Mark the relevant and irrelevant images

Step5: Classify the image set

Step6: Train the SVM / neural network

V. CONCLUSION

Here the above approach develop a tool that enhances the effectiveness of image retrieval from the image databases including the images that have similarity on boundary, texture and the high level feature similarity.By using the neural network we can change the threshold value to compare the similarity of pixel . We can change the hidden layers of the neural network to check high level of similarity between the query and database images. The percentage of match of the image is decreased by increasing the hidden layers of the neural network. We have taken the database of 5 images that are small bitmap image and query the image the given table shows the result. Some of the parameter we have fixed till , as maximum error ,no of input unit for the layers ,no of hidden unit ,no of output unit shown in table 1.

No of layers per unit	**Iteration**	**Errors**	**Percentage match**
1	**3**	**.857**	**57%**
2	**537**	**.847**	**40%**
3	**150**	**1.1**	**37%**
4	**350**	**.94**	**32%**
5	**124**	**.97**	**23%**

Table 1

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