Neuro-Fuzzy based Image Retrieval System with Improved Shape and Texture Features

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ABSTRACT
A generalized Neuro-Fuzzy based Content Based Image Retrieval (CBIR) system is proposed. The system is trained for colour, texture and shape features using General Fuzzy Min-Max Neural Network (GFMNN). Flexibility and robustness is achieved by accepting any number and types of different input features as well with the concept of class labels assigned for each hyperbox. The existing architecture is simplified and the system is trained in pure clustering mode which helps in reducing the computational complexity. By controlling user parameters the system can categorize images as per the users need. With modified texture and shape features combined with colour features, the proposed CBIR system gives an efficient automated retrieval of similar images.

Keywords
CBIR, GFMNN, Hyperbox, Spatial Grey Level Dependency Matrix (SGLDM), Fourier Descriptors

1. INTRODUCTION
The rapid growth in the number of large-scale archive of image data has brought the need for efficient and robust CBIR systems. Because of large interest in the use of multimedia data in both scientific and commercial fields, there is a need to categorize, store, search and retrieve the relevant data satisfying user requirements. The state of the art in the CBIR systems is to search and retrieve the relevant images in the database that are “close” to the query image using some similarity measure.

Considerable work has been done towards the development of efficient CBIR systems. Two of the prototype systems are IBM Query by Image Content (QBIC) and the MIT Photobook [1]. The major problem observed in these methods are sensitivity to intensity variations, colour distortions and cropping. The Virage developed at Virage Inc. and University of Illinois at Urbana Champaign (UIUC) Multimedia Analysis and Retrieval System (MARS) [2] allows user feedback and can learn to retrieve images. But, both systems often partition a single object to several segments and none of the segments completely represent the object.

Many authors have contributed their work and relative study is in progress for developing an efficient CBIR system. Numbers of feature extraction techniques are suggested to extract low level features of the images based on colour, texture and shape attributes. With this, a feature vector is constructed for the image database and query image is then compared with the database images using some similarity measure. Soft Computing techniques especially the Neural Networks and Fuzzy Logic as well hybrid systems like Neuro-Fuzzy systems are proposed to model the CBIR systems. Such systems are usually trained as an unsupervised learning (clustering mode) to categorize similar images based on the feature vector obtained. To alleviate the semantic gap and perception subjectivity, few authors have suggested Fuzzy Systems for semantic content extraction whereas few papers have explored the concept of Relevance Feedback (RF) in which the user has to decide the relevant images by choosing the sets of positive images in each iteration and the process will continue till user satisfies.

Fundaments of CBIR system with different feature extractions are well explored in [4, 5, 6, 7, 14, 15, 20]. A survey of different feature extraction techniques with experimental comparison is presented by Thomas Deselaers et al. [3]. An experimental comparison of a large number of different image descriptors for content-based image retrieval is presented. A system derived from colour and texture features is described by Sabri Konak [7] whereas shape features are discussed in [8] and [9]. Howarth et al. [5] developed still image retrieval system based on texture features whereas color based image classification is presented in [7]. For colour feature extraction, Greg Pass et al. [20] used colour coverence vector to describe the images and found to be better than the colour histogram approach whereas Pour and Kabir [21] used uni-color and bi-color blocks of color histogram for image retrieval. Srinivasan Selvan et al. [16] introduced a new model for image texture classification using Wavelet Transform. Ruofei Zhang et al. [17] developed a hidden semantic concept discovery methodology for semantics-intensive image retrieval. James French et al. [19] tried to improve the retrieval effectiveness using more than one representation of the images in a collection.

In this paper, a generalized CBIR system is proposed which is trained for improved hybrid features where the system can take any number of different input features. This offers a very good flexibility and robustness. Considering the flexibility and efficiency, we trained our CBIR system using a Fuzzy Neural System called General Fuzzy Min-Max Neural Network (GFMNN) proposed by Bogdan Gabrys et al. [13]. This is capable to extract the underlying structure of the data by means of supervised, unsupervised and partially supervised learning. The reason behind use of GFMNN applies the acquired knowledge to learn a mixture of labeled and unlabeled data. It uses aggregation of hyperbox fuzzy sets to represent a class or cluster [11] [12]. The advantages of such systems are its ability to learn the data in a single pass and no requirement of retraining while adding new data patterns for classification or clustering task. This highly improves the computational efficiency.

CBIR system contains a database of image features. These features are described by means of multi-dimensional feature vector. Whenever query image is submitted its features are extracted from that image. In case of image retrieval these extracted features are compared with database features for similarity measure and matching. Fig. 1 shows such basic system.

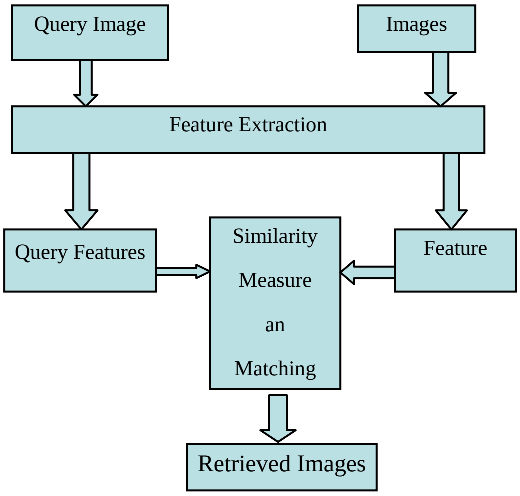

Fig 1: Basic CBIR system

The rest of the paper is organized as follows: feature extraction techniques used for training GFMNN with modifications are described in Section 2. In section 3, brief about GFMNN training, testing and architecture is discussed. Different experimental results with analysis are presented in Section 4. Finally, we conclude the paper in Section 5.

2. FEATURE EXTRACTION

Different texture, color and shape features are considered to describe image features. These extracted features are stored in the form of feature vector in the logical database.

2.1 Texture feature extraction

The techniques used in the statistical approaches for texture feature makes use of the intensity values of each pixel in an image, and apply various statistical formulae to the pixels in order to calculate feature descriptors.

The most popularly used second-order statistical approach for texture features is the Spatial Grey Level Dependency Matrix (SGLDM) method [7]. The method roughly consists of constructing matrices by counting the number of occurrences of pixel pairs of given intensities at a given displacement.

SGLDM has the same size as the number of grey levels in an application. In a case where there exist 32 distinct grey levels, the size of SGLDM will be a 32×32 matrix. Along with the SGLDM matrix, a position operator P is defined which needs to be evaluated. If the pixel intensity is i and the pixel intensity to which the operator points is j, the matrix element C_{ij} of SGLDM will be incremented by one. Hence SGLDM is a function of P which is a function of distance d and angle μ, where the angle could be one specific direction, or a set of directions. It is observed that by considering multiple orientations with different angles while calculating the SGLDM matrix gives better performance than the system considering only one orientation [7]. The algorithm for SGLDM computation considering multiple orientations can be described as –

```
Step 1.    Convert given RGB image to grey scale image
Step 2.    Compute for i, j
    {
     m = img(i, j)
     n = img(i, j+1)            // 0 degree
     SGLDM(m, n) = SGLDM(m, n) + 1
     n = img(i + 1, j + 1)       // 45 degree
     SGLDM(m, n) = SGLDM(m, n) + 1
     n = img(i + 1, j )       // 90 degree
     SGLD(m, n) = SGLDM(m, n) + 1
    }
Step 3.    Compute for i, j
    {
    w = abs(i - j)
IDM = IDM + (SGLDM(i, j) / (1 + (w * w)))
Energy = Energy + sqr(SGLDM (i, j))
Entropy = Entropy - SGLDM(i, j) * log (SGLDM(i, j))
      }
```

For texture patterns the following three statistical functions are obtained from the SGLDM matrix.

$$Energy = \sum_{i,j} p(i,j)^2 \quad (1)$$

$$Entropy = -\sum_{i,j} p(i,j)\log(p(i,j)) \quad (2)$$

$$IDM = \sum_{i,j} \frac{1}{1+(i-j)^2} p(i,j) \quad (3)$$

Where, $p(i,j)$: The value of SGLDM matrix for i^{th} row and j^{th} column.

As an improvement over the existing algorithm

- The SGLDM Matrix is computed for different orientations with different position operators. It is observed that considering multiple orientations while calculating the SGLDM matrix give better performance than the system considering only one orientation.
- Image is divided into minimum number of grids and SGLDM is computed for each grid for better representation of feature vector.
- Only selected statistical functions which cover the homogeneity, non-uniformity and local homogeneity features of the image are computed from constructed SGLDM matrix to reduce the size of feature vector.

2.2 Colour feature extraction

Color is the most extensively used visual content for image retrieval. Its three-dimensional values make its discrimination potentiality superior to the single dimensional gray values of images. The color histogram approach counts the frequency of number of occurrences of each unique color on a sample image. One possible way of storing the color information is to use three different color histograms for each color channel. Another possible method is to have a single color histogram for all of the color channels. In the later approach, the color histogram is simply a compact combination of three histograms.

As an improvement over histogram based method, Color Coherence Vector (CCV) is constructed [20] for colour features. It classifies each pixel in given colour bucket as either coherent or incoherent, based on whether or not it is part of large similarly coloured region. It stores the number of coherent versus incoherent pixels with each colour. By separating coherent pixels from incoherent pixels, CCV provides finer distinction than colour histogram.

2.3 Shape feature extraction

Shape is one of the most important features in CBIR. Many shape representations and a retrieval method exists. However, most of those methods unable to represent shape with desired attributes and few are difficult in normalization. Among them, methods based on Fourier descriptors (FD) [8] achieve both well representation and well normalization.

To obtain FDs, shape signatures of the image are obtained and represented in Fourier domain. Shape signatures are constructed from the dominant points of boundary objects which defines the shape attributes. Method of curvature approximation is used to obtain the dominant points of an object.

For FDs, one need to obtain the dominant points along the boundary representing the shape attributes of the object. To get the boundary or an edge of any arbitrary object we perform the following preprocessing steps are performed-

- Histogram
- Binarization and Thresholding
- Edge detection
- Thinning.

Dominant point along the shape boundary are obtained using the method of curvature approximation [8][10]. In curvature approximation, as we traverse along path length t in increasing values of t, a positive curvature corresponds to a concavity on our left, and negative curvature corresponds to a concavity on our right. Therefore idea is to select the points along a curve that corresponds to the positive maximum and negative maximum curvature points. The curvature of smooth curve is

$$k(t) = \frac{x'y'' - y'x''}{(x'^2 + y'^2)^{3/2}} \qquad (4)$$

where, t is path length and k is the curvature of the curve at t. Because of the discrete representation of the curve in a digital image, t is discrete. Thus following commonly used differences are selected

$$x' = x(t+1) - x(t-1)$$
$$x'' = x(t+1) - 2x(t) + x(t-1) \qquad (5)$$

For better accuracy, higher differences are used as follows.

$$x' = x(t+3) - x(t-3)$$
$$x'' = x(t+3) - 2x(t) + x(t-3) \qquad (6)$$

Fig. 3 represents the digital image with thinning and dominant points. The centroid distance function is expressed by the distance of the dominant points from the centroid (x_c, y_c) of the shape as

$$s(t) = ([x(t) - x_c]^2 + [y(t) - y_c]^2)^{1/2}$$

(7)

where, (x_c, y_c) is the centroid of the shape, which is the average of the boundary coordinates

$$x_c = \frac{1}{L}\sum_{t=0}^{L-1} x(t), y_c = \frac{1}{L}\sum_{t=0}^{L-1} y(t).$$

(8)

Assuming the dominant points, $(x(t), y(t)), t = 0,1, \dots, L-1$ extracted in the preprocessing stage, we use centroid distance function given by equation (7) to obtain the Fourier Descriptors. For a given shape signature $s(t), t = 0,1, \dots, L-1$ normalized to N points in the sampling stage, the discrete Fourier transform of $s(t)$ is given by

$$F_k = \frac{1}{N}\sum_{t=0}^{N-1} s(t)\exp\left(\frac{-j2\pi kt}{N}\right), k = 0,1,\dots N-1 \quad (9)$$

The coefficients F_k, $k = 0,1, \dots, N-1$ are usually called the Fourier descriptors (FD) of the shape. The algorithmic steps to obtain FDs are described as –

- Convert a given image into gray scale image.
- Complement the gray scale image and perform binarisation.
- Use direct neighborhood method for edge detection
- Apply thinning algorithm.
- Obtain dominant points which define the shape attributes.
- Apply normalization by zero padding.
- Calculate centroid (x_c, y_c) w.r.t. boundary points (i.e. dominant points).
- Obtain shape signatures $s(t)$.
- Calculate FDs.

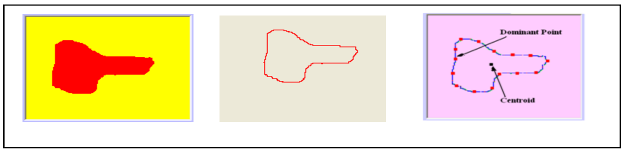

Fig 3: (a) Digital image (b) Thinning (c) Dominant points and Centroid

As an improvement over the existing method

- Preprocessing is applied to obtain the boundary of an image to determine the dominant points.
- Curvature approximation with higher differences is used to obtain the dominant points which defines the shape attributes of an object. Thus selecting these dominant points are important to obtain FDs.
- Best choice of signature values $s(t)$ are selected among the set of dominant points. We keep these values exactly equal to N to get the best

representations of these signatures in transformed domain. i.e. Fourier domain here.

3. GFMNN TRAINING

While training, various extracted features of images are normalized and given as input to the GFMNN. Initially it is trained for different images and the different clusters of images are formed. The clusters are labeled and stored in the database with their respective image paths.

In GFMNN [13], the decision whether the input pattern belongs to a particular class or cluster depends mainly on the membership value describing the degree to which an input pattern fits within the hyperbox [11][12][13]. A hyperbox defines a region in the n-dimensional pattern space which is defined by its min and max points.

The GFMNN learning algorithm has following steps -

- Initialization: Initialize the j^{th} hyperbox as per the dimension of input pattern X_h .
- Hyperbox Expansion: When the h^{th} input pattern X_h is presented, the hyperbox B_j with the highest degree of membership and allowing expansion (if needed) is found. If neither of the existing hyperboxes include or can expand to include the input X_h , then a new hyperbox B_k is created , initialized and adjusted.
- Hyperbox Overlap Test: assuming that hyperbox was expanded in the previous step, we test it for overlapping with all other hyperboxes.
- Hyperbox Contraction*:* With overlap observed in i^{th} dimensions, the two hyperboxes need to be adjusted in the same dimension.

When the GFMNN is used for pure clustering mode the existing architecture can be simplified as shown in Fig. 4. It has input layer with n nodes as n features and output layer as m hyperbox nodes as m clusters formed after successful training.

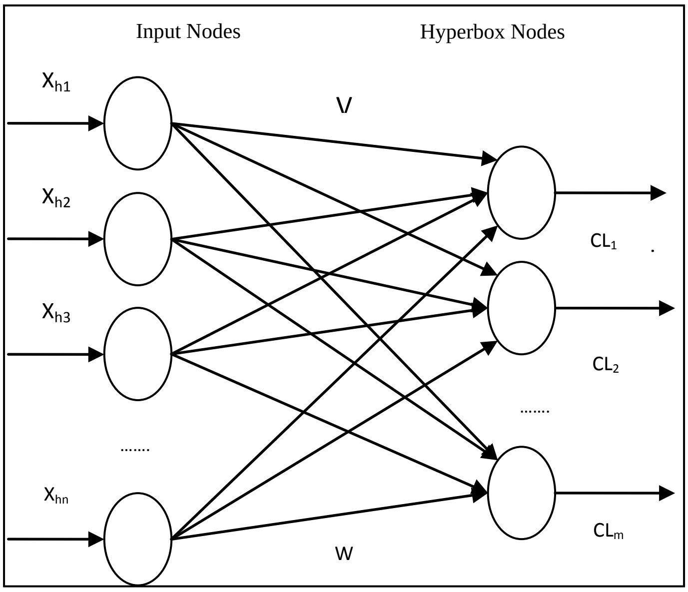

Fig 4: The two-layer neural network for GFMNN clustering algorithm

For retrieving, when image is specified as an input query, the texture, colour and shape features are extracted and stored in database along with the image paths. These extracted features are given to the trained GFMNN Neural Network which fires the respective cluster neuron (Hyperbox node) and all the images which belong to that cluster are retrieved from the database.

4. EXPERIMENTAL RESULTS

The performance of the system is analyzed using COREL data set consisting of 1000 images of 10 different classes. We considered total 500 images of 5 different classes namely Bus, Dinosaur, Flower, Elephant and Horse to test our system for its effectiveness. Different experimental results performed are discussed in this section.

To improve the performance of the system, it is desirable to speed up the query processing. For this, we divide the textured images into few fixed sized grids and calculate the IDM, Energy, Entropy value for each grid and stored in texture database. After determining number of grids, we tested whether these many grids are sufficient or not. Accordingly we divided the textured images into 9 grids.

After training and testing the Neural Network for different images, we observed that for higher value of user defined parameter ‘θ’ which regulates the maximum size of hyperbox, less number of hyperboxes are created which may leads to misclassification of input pattern. For small value of ‘θ’, more number of hyperboxes are created, which may leads to data over fitting. To find the best value of this parameter the network is trained for several different θs and verified by checking the number of misclassifications. The retrieval efficiency depends on the number of hyperbox count which is a function of θ. Following results depicts the flexibility and efficiency of the system.

Table 1. Training of GFMM Neural Network for Colour

Sr. No.	θ	Number of HyperBox Count
1.	0.09	13
2.	0.11	12
3.	0.15	11
4.	0.17	10
5.	0.22	09
6.	0.24	08
7.	0.25	07
8.	0.27	6
9.	0.35	5
10.	0.40	4

Table 2. Training of GFMM Neural Network for Texture

Sr. No.	θ	Number of HyperBox Count
1.	0.05	49
2.	0.07	46
3.	0.09	38

4.	0.11	32
5.	0.13	30
6.	0.15	17
7.	0.17	22
8.	0.19	21
9.	0.23	13
10.	0.25	12

Table 3. Training of GFMM Neural Network for Color and Texture

Sr. No.	θ	Number of HyperBox Count
1.	0.05	30
2.	0.07	26
3.	0.09	21
4.	0.11	18
5.	0.13	15
6.	0.15	16
7.	0.17	13
8.	0.19	10
9.	0.23	11
10.	0.25	10

Table 4. Training of GFMM Neural Network for Shape

Sr. No.	θ	No. of HyperBox count
1.	0.07	66
2.	0.09	52
3.	0.11	52
4.	0.13	46
5.	0.15	40
6.	0.17	39
7.	0.19	39
8.	0.21	31
9.	0.23	28
10.	0.25	33

The retrieval efficiency in terms of Precision (P) and Recall (R) is obtained as-

$$\text{Precision (P)} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}$$

$$\text{Recall (R)} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in database}}$$

(10)

Table 5 and Fig. 5 show the precision and recall of image retrieval for different features for COREL dataset. Better results are obtained by combining heterogeneous features for colour, texture and shape at the price of increased complexity due to more number of features.

Table 5. Retrieval Result for Different Features

Cluster Name	Retrieval Results					
	Colour		Texture		Combined with Shape	
	P	R	P	R	P	R
Bus	0.70	0.60	0.72	0.66	0.88	0.84
Dinosaur	0.64	0.58	0.76	0.72	0.87	0.84
Flowers	0.72	0.70	0.74	0.71	0.76	0.85
Elephant	0.68	0.58	0.70	0.64	0.85	0.82
Horse	0.72	0.60	0.73	0.68	0.84	0.83
Average	0.69	0.61	0.73	0.68	0.84	0.83

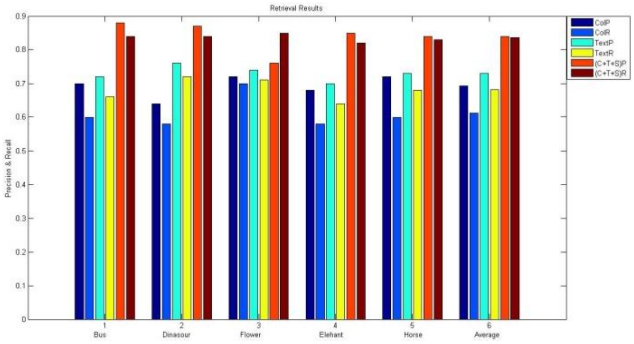

Fig 5: Retrieval Results

Table 6 shows the comparison of average precision obtained by proposed system for colour features with few existing methods [21] obtained for the sets of images present in COREL database. The images are classified into 10 different categories. In proposed system, the precision and recall is obtained based on the number of images retrieved which is a count of number of images being referenced by the hyperboxes created with the same class labels during training process.

Table 6. Average Retrieval Efficiency

Method	Retrieval Efficiency
SCH	0.449 (100*)
Uni and Bi-color Blocks	0.605 (100)
Proposed	0.66 (100)

Where, *: The number of retrieved images.

The retrieval efficiency in terms of average precision is further improved to about 80% for hybrid features with the proposed system.

5. CONCLUSION

A CBIR system that evaluates the similarity of each image in its database to a query image in terms of textural, colour and shape characteristics using Fuzzy Neural Network is proposed.

The statistical approach have adopted to extract texture features from both the query images and the images in the database. It is observed that by considering multiple orientations while calculating the SGLDM matrix gives better performance than the system considering only one orientation. The Inverse Difference Moment, energy, entropy have been selected as an optimal subset of the set of second order statistical features that can be extracted from Spatial Grey Level Dependency Matrices.

In the proposed approach, the centroid distance function is expressed by the distance of the dominant points from the centroid of the shape. These dominant points represent the well defined shape attributes which are obtained using curvature approximation method. Shape retrieval using FDs derived from the centroid distance signature is significantly better than that using FDs derived from other signatures. The property that centroid distance captures both local and global features of shape makes it desirable as shape representation.

The various extracted features of image are given to the GFMNN Neural Network. Initially it is trained for different images and different clusters of images in the form of hyperboxes are generated. These clusters are labeled and stored in database with their respective image paths. Retrieval Results of combined training using the concept of class labels are considerably improved with best choice of hyperbox expansion coefficient θ.With the vast number of images available on-line, quality CBIR systems are critical. The performance and results obtained for the proposed system are better as compared to other CBIR systems in terms of flexibility, robustness and retrieval efficiency.

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