A LOW INDEXED CONTENT BASED NEURAL NETWORK APPROACH FOR NATURAL OBJECTS RECOGNITION

G.Shyama Chandra Prasad[1] and Dr. A.Govardhan [2] Dr. T.V.Rao [3]

[1]Research Scholar, JNTUH, Hyderabad, AP. India
shyam_gunda2002@yahoo.co.in

[2] Principal, JNTUH College of Engineering, jagitial, Karimnagar, AP, India
govardhan_cse@yahoo.co.in

[3] Principal, Chaithanya Institute of Engineering and Technology, Kakinada, AP, India
tv_venkat@yahoo.com

ABSTRACT

In this paper, an approach to integral color texture invariant information with a neural network approach to object recognition is proposed. A color-texture context for image retrieval system based on the integral information of an image is represented as one compact representation base on color histogram approach. A general and efficient design approach using a neural classifier to cope with small training sets of high dimension, which is a problem frequency encountered in object recognition, is focused in this paper for general images. The proposed system is tested for various colored image samples and the recognition accuracy is evaluated.

KEYWORDS

Color-texture context, recognition system, histogram, neural network.

1. INTRODUCTION

In recent years various advanced techniques were developed in Image Retrieval systems in various areas. Applications like Art, medicine, entertainment, education; manufacturing, etc. make use of vast amount of visual data in the form of images. This generates the need for fast and effective retrieval mechanisms in an efficient manner. Recent Recognition systems based on features like color, shape, texture, spatial layout, object motion, etc., are cited in [1], [2]. Of all the visual features, color is the most dominant and distinguishing one in almost all applications. Hence, segmenting color information's provides prominent regions in the image. Shape features of these regions to obtain shape index used for retrieving based on shape matching were proposed in past. In Current CBIR systems such as IBM's QBIC [3], [4] allow automatic retrieval based on simple characteristics and distribution of color, shape and texture. But they do not consider structural and spatial relationships and fail to capture meaningful contents of the image in general. Also the object identification is semi-automatic. The Chabot project [5] integrates a relational database with retrieval by color analysis. Textual meta-data along with color histograms form the main features used. VisualSEEK [6] allows query by color and spatial layout of color regions. Text based tools for annotating images and searching is provided. A new image representation that uses the concept of localized coherent regions in color and texture space is presented by Chad Carson etal. [7]. Segmentation based on the above features is used and query is based on these features are used for recognition. Some of the popular methods to characterize color information in images are color histograms [8], [9], color moments [10] and color correlograms [11]. Though all these methods provide good characterization of color, they have the problem of high-dimensionality. This leads to more computational time, inefficient indexing and low performance. To overcome these problems, use of SVD [9], dominant color regions approach [12], [13] and color clustering [14] have been proposed. Shape is an important feature for perceptual object recognition and classification of images. Shape description or representation is an important issue both in object recognition and classification. Many techniques such as chain code, polygonal approximations, curvature, Fourier descriptors, radii method and moment descriptors have been proposed and used in various applications [15]. Recently, techniques using shape measure as an important feature have been used for CBIR. Features such as moment invariants and area of region have been used in [3], [16], but do not give perceptual shape similarity. Cortelazzo [17] used chain codes for trademark image shape description and string matching technique. The chain codes are not normalized and string matching is not invariant to shape scale. Jain and Vailaya [18] proposed a shape representation based on the use of a histogram of edge directions. But these are not normalized to scale and computationally expensive in similarity measures. Mehrotra and Gary [19] used coordinates of significant points on the boundary as shape representation. It is not a compact representation and the similarity measure is computationally expensive. Jagadish [20] proposed shape decomposition into a number of rectangles and two pairs of coordinates for each rectangle are used to represent the shape. It is not rotation invariant. A region-based shape representation and indexing scheme that is translation, rotation and scale invariant is proposed by Lu and Sajjanhar [2l]. It conforms to human similarity perception. They have compared it to Fourier descriptor model and found their method to be better. But, the images database consists of only 2D planar shapes and they have considered only binary images. Moreover, shapes with similar eccentricity but different shapes are retrieved as matched images. This paper aims to improve these retrieval method efficiency by the integral approach of color and texture for effectiveness in color image retrieval. A specific color space and texture analysis is selected to increase the performance during segmentation. To increase the retrieval speed during query, similar objects are clustered using a hierarchical clustering algorithm. The new similarity distance algorithm is introduced to minimize error obtained during image recognition. The clustering approach is observed to lower in accuracy when the images are spatially similar. To attain accuracy in such case the information required to classify is to be very large, this result in slower operation. To achieve faster recognition accuracy in this paper a content-based feature approach is merged with advanced learning approach called Neural network for natural object recognition.

2. LOW INDEX TEXTURAL COLOR FEATURE EXTRACTION

Texture is described as a mostly regular spatial replication of a NN pattern, or as an irregular, or random distribution of pixel values. According to the chosen model of deterministic or stochastic, the texture attributes derive from the computation of characteristic visual cues such as periodicity, orientation, principal axes and symmetry axes or from the probability density functions of the pixel values, or spectral energies or any other statistical based models. The most commonly used spatial measure for texture discrimination is the co-occurrence matrix, which describes spatial relationships between gray levels in a texture. Some texture features, such as energy, entropy, contrast, homogeneity, tendency to clustering can be computed starting from the co-occurrence matrix, as proposed by Haralick. Similar textural measures, such as contrast, coarseness and directionality, were used for texture discrimination in the QBIC system. Another idea is to compute the power spectrum of the texture image, by a Fourier transform. Energies within different sub-masks concentrical, diadically -spaced disks, or circular sectors form a vector based on which textures are discriminated. For the extraction of features the image is partitioned into 4 by 4 blocks, a size that provides a compromise between texture granularity, segmentation coarseness, and computation time. As part of pre-processing, each 4x4 block is replaced by a single block containing the average value ever the 4 by 4 block. This way, we still have a good texture granularity while reducing the number of total pixels per image, therefore decreasing the computation time.

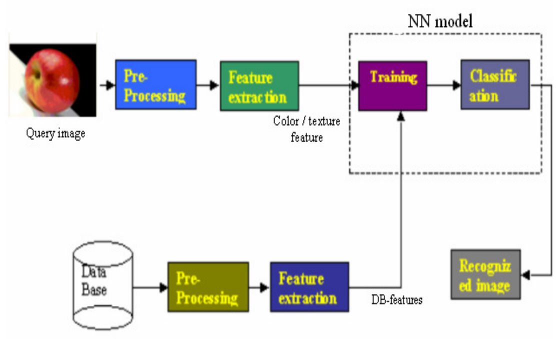


Figure 1: Block diagram of Image Retrieval System

To segment an image into objects, six features are extracted from each block. Three features are color features, and the other three are texture features. The HSV color space is selected during color feature extraction due to its ability for easy transformation from RGB to HSV and vice versa. Since HSV color space is natural and approximately perceptually uniform, the quantization of HSV can produce a collection of colors that is also compact and complete. These features are denoted as {F1, F2, and F3}. To obtain the texture features, Daubechies wavelet transform to the L component of the image is applied. It represents the energy in high frequency bands of the Daubechies wavelet transform. After a one-level wavelet transform, a 4 by 4 block is decomposed into four frequency bands, each band containing a 2 by 2 matrix of coefficients. Suppose the coefficients in the HL band are $\{c_{k+i}, c_{k,l+i}, c_{k+1,l+i}\}$.Then, the feature of the block in the HL band is computed as:

$$f = \left(\frac{1}{4} \sum_{i=0}^{1} \sum_{j=0}^{1} c_{k+i,l+j}^{2} \right)^{\frac{1}{2}} \qquad (1)$$

The other two features are computed similarly in the LH and HH bands. These three features of the block are denoted as {F4, F5, and F6}. In this paper, we did not consider shape features during similarity distance computation. Li and Wang (2000) considered shape features into retrieval distance computation only for textured images, while non-textured images considered the shape features. A textured image defined as an image of a surface, a pattern of similarity shaped objects, or an essential element of an object. To do this, Li and Wang presented a manual pre classified images in the database into texture and non-texture images. The distance computation is different between textured images and non-textured images. In this paper, to avoid manual pre-classification, the computation of the similarity distance for texture and non-texture images is performed automatically using the same distance formula.

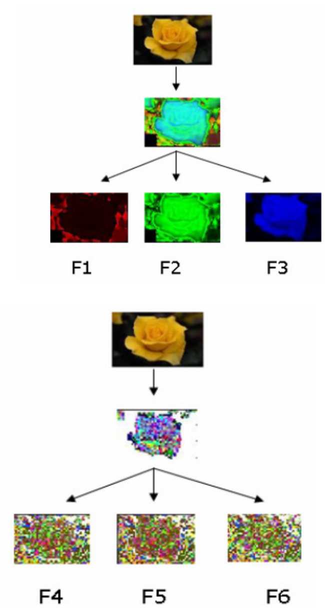


Figure 2: Color and texture feature of a given query image

3. NEURAL NETWORK

Neural networks are important for their ability to adapt. Neural nets represent entirely different models from those related to other symbolic systems. The difference occurs in the way the nets store and retrieve information .The information in a neural net is found to be distributed throughout the network and not localized. The nets are capable of making memory associations. They can handle a large amount of data, fast and efficiently. They are also fault tolerant, i.e. even if few neurons fail; it will not disable the entire system. The architecture of neural network is a multiplayer feed forward network in which 'n' number of input neurons and 'm' number of output neurons with the hidden layer existing between input and output layer .The interconnection between the input layer and the hidden layer forms hypothetical connection and between hidden layer and output layer forms the waited connections. The training algorithm is used for updating of weights in all interconnections.

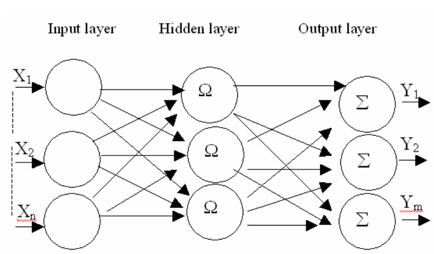


Figure 3: A neural network model considered for implementation

A neural network model is shown in Figure.3, the network is considered as a mapping:

$$\Re^T \longrightarrow \Re^S$$

Let $P \in \Re^T$ be the input vector and $C_i \in \Re^T$ $(1 \leq i \leq u)$ be the prototype of the input vector. The output of each neural unit is as follows:

$$R_i(P)=Ri(\|P- C_i\|) \qquad i=1\ldots\ldots u \qquad (2)$$

Where(||-||) indicates the Euclidean norm on the input space. Usually, the Gaussian function is preferred among all possible functions due to the fact that it is factorizable. Hence

$$R_i(P)=\exp[-(\|P- C_i\|)^2 s \ \sigma_i^2] \qquad (3)$$

Where σ_i^2 is the width of the ith neural unit. The jth output y_i (P)of an neural network is

$$y_i (P)=\sum^u_{i=1} R_i(P) X \ w(j,i) \qquad (4)$$

where R_o =1, w(j,i) is the weight or strength of the ith receptive field to the jth output and w(j,0) is the bias of the jth output. In order to reduce the network complexity, the bias is not considered in the following analysis. We can see from (3) and (4) that the outputs of a neural classifier are characterized by a linear discriminant function. They generate linear decision boundaries (hyper planes) in the output space. Consequently, the performance of a neural classifier strongly depends on the separability of classes in the k-dimensional space generated by the nonlinear transformation carried out by the neural units.

4. SIMULATION RESULTS

For the evaluation of the suggested approach a image data set of 1000 images of natural color images are considered, few class images are as shown below,

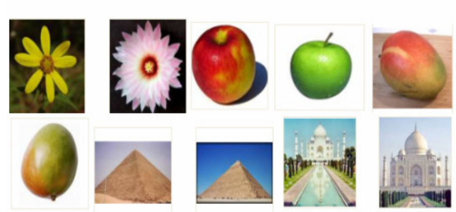


Figure 4 considered class images in data base

These images are trained with color texture features. The data from feature extraction is fed to Hierarchical Cluster modelling to perform pixel clustering with a NN algorithm as mentioned in previous section. Once features of all images in the database are extracted, the HC model performs the second clustering to group similar objects. To compute the overall similarity distance computation each object is matched to every other object in the database and calculates their distances. During the experiment we analyze different values of similarity measure. We noticed that when similarity measure value is ≤ 0.5, the number of clusters were very low, mostly one or two clusters. When the similarity value is ≥ 0.9 the number of clusters were very high typically greater than 15. From each image, during the pixel clustering, we set the similarity measure to be 0.6, 0.7 and 0.8. The number of cluster based on these measures is recorded and the average number of cluster for each similarity measure is computed. The recognition observations obtained were made for the samples outside the data base images and the recognitions accuracy were evaluated, the obtained recognition are as presented below,

For the considered query image,

a) At similarity measure of 0.6;

Figure 5 Query image

The retrieved classified images are,

Figure 6 obtained classified Images

b) At similarity measure of 0.7;

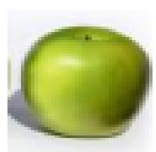


Figure 7 Query image

The retrieved classified images are,

Figure 8 obtained classified Images

c) At similarity measure of 0.8;

Figure 9 Query image

The retrieved classified images are,

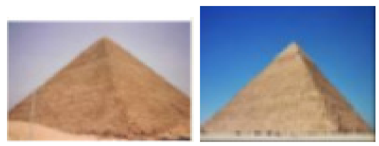


Figure 10obtained classified Images

The similarity distance plot for the query image in the data base is as shown below,

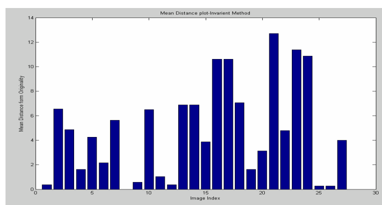
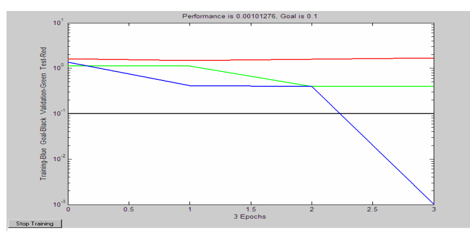


Figure 11 Obtained similarity plot for the given query image at SM=0.8

Training, validation, testing rate for the query image



The obtained Classification Performance is as presented below,

Images	No. of units	β	η	Epochs	MSE	NO M
Q_1	40	0.5 -0.6	1.0-1.2	20-200	25.58	4/5
Q_1	40	0.55-0.65	1.0-1.2	20-200	27.35	4/5
Q_1	40	0.55-0.7	0.78 -1.1	20-120	32.54	3/5
Q_1	40	0.7-0.85	0.99-1.4	20 -150	33.04	5/5

5. CONCLUSION

An image recognition system is developed with lower feature index with neural network. The performance of the developed algorithm has been observed to perform better estimation with faster computation. The system performs better when the contrast between the main object and the background is visible in the image and performs worse when the image is complex and the objects have smooth edges. During the implementation, it is also seen that by considering object uniqueness during similarity distance computation improve the accuracy during retrieval. Compared with the existing system, proposed system has the advantage of an improvement in image segmentation accuracy, especially for simple images and an improvement during similarity distance computation by using the parameter of object uniqueness into consideration

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