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Object Oriented Classification of Forest Images Using Soft Computing Approach

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Abstract: In this paper the searching capability of build up an object oriented classification system which is capable of classification a given forest scene into its various constituents. To simplify the problem, six categories of forest structures were defined. These categories are trees, bushes, grasses, foliage, sky and background sky .They are sufficient to represent typical forest scenes dealt with in this application. To implement such classification system. We proposed a Genetic Algorithm (GA) to segmentation image and find the best seed for each category. According to this scheme, an image is divided evenly into small block. Then it is processed block by block. For each block, Discrete Cosine Transform (DCT) is applied to determine some of DCT coefficient in compressed domain as the feature vectors. Then take the seed values for each segment and the DCT coefficients to represented the inputs of feed forward neural network. These system successes in classification all objects in image although used different kinds of activation functions (hyperbolic functions), compares among them and find the best of it in obtaining on fast results. As a result the A soft computing method will be higher classification accuracy than that of traditional pixel-based supervised classification and gives convenient environment to use.

Key words: Discrete Cosine Transform, genetic algorithm, neural network, object oriented classification, Soft Computing.

INTRODUCTION

The image classification process consists of three major phases. The first phase is called image segmentation, or object isolation, in which each object is found, and its image is isolated from the rest of the scene. Because of its intuitive properties and simplicity of implementation [1]. The second phase is called feature extraction. This is where the objects are measured. A measurement is the value of some quantifiable property of an object. A feature is a function of one or more measurement, computed so that it quantifies some significant characteristic of the object [2]. The feature extraction process produces a set of features that, taken together, comprise the feature vector. Feature extraction drastically reduces the amount of information that represents all the knowledge upon which the subsequent classification decisions must be based. It is productive to conceptualize an n-dimensional space in which all possible n-element feature vectors reside. Thus, any particular object corresponds to a point in feature space.

The third phase of image analysis is classification. Its output is merely a decision regarding the class to which each object belongs. Each object is recognized as being of one particular type, and the recognition is implemented as a classification process. Each object is assigned to one of several pre-established groups (classes) that represent all the possible types of objects expected to exist in the image. Classification is based solely on the feature vector.

1. Object Oriented Classification

The object oriented classification concept is that important semantic information necessary to interpret an image is not represented in single pixels, but in meaningful image objects and their mutual relations. Image analysis is based on contiguous, homogeneous image regions that are generated by initial image segmentation. Connecting all the regions, the image content is represented as a network of image objects. These image objects act as the building blocks for the subsequent image analysis. In comparison to pixels, image objects carry much more useful information. Thus, they can be characterized by far more properties [3].

1.1. Genetic Algorithm for Image Segmentation

Genetic algorithms (GAs) belong to a class of search techniques that mimic the principles of natural selection to develop solutions of large optimization problems.

GAs operates by maintaining and manipulating a population of potential solutions called chromosomes.

Each chromosome has an associated fitness value which is a qualitative measure of the goodness of the solution encoded in it. This fitness value is used to guide the stochastic selection of chromosomes which are then used to generate new candidate solutions through crossover and mutation. Crossover generates new chromosomes by combining sections of two or more selected parents. Mutation acts by randomly selecting genes which are then altered; thereby preventing suboptimal solutions from persisting and increases diversity in the population. The process of selection, crossover and mutation continues for a fixed number of generations or until a termination condition is satisfied.

Clustering [4] is a popular unsupervised pattern classification technique which partitions the input space into K regions based on some similarity or dissimilarity metric. The number of partitions or clusters may or may not be known a priori. Let the input space S be represented by n points $\{x_1, x_2, \ldots, x_n\}$, and the K clusters be represented by $C_1, C_2, \ldots, C_K$, then

(i) $C_i \neq 0$ for i=1,2, … , K

(ii) $C_i \cap C_j = 0$ for i=1,2, …, K and j=1,2, ..., K , $i \neq j$

(iii) $\bigcup\limits_{i=1}^{K} C_i = S$

1.2. DCT Analysis

The DCT is a widely used frequency analysis method in image processing. It has many advantages over other transform techniques. For example, no complex computation is involved in the DCT; fast DCT implementations are available; and most importantly, energy is packed efficiently into a small number of DCT coefficients.

For the DCT, we convert an RGB image in to gray level image by using HVI model then work on this image. For each n×n data block a two-dimensional DCT can be written in terms of pixel values f(i,j) for i,j =0,1,…,N-1 and the frequency-domain transform coefficients F(u,v):

$$F(u,v) = \frac{1}{\sqrt{2n}} C(u)C(v) \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} f(i,j)$$
$$.\cos\left[\frac{(2i+1)u\pi}{2N}\right].\cos\left[\frac{(2j+1)v\pi}{2N}\right] \quad (1)$$

For u,v=0,1,…N-1, Where

$$c(x) = \begin{cases} \dfrac{1}{\sqrt{2}} & for \quad x = 0 \\ 1 & otherwise \end{cases} \quad (2)$$

The inverse DCT transform is given by

$$f(i,j) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} c(u).v(v).F(u,v).\cos\left[\frac{(2i+1)u\pi}{2N}\right].\cos\left[\frac{(2j+1)v\pi}{2N}\right] \quad (3)$$

For i,j=0,1,…N-1

To better understand the idea of DCT analysis, a forward DCT was first computed on the forest image data. One typical region was chosen from the image for each of the six categories under study, i.e., tree, foliage, bush, grass, background sky and sky. Then the DCT coefficients were generated for the selected cluster with the block size 8×8.[5].

1.3. Artificial Neural Network

Neural networks are computer algorithms inspired by the way information is processed in the nervous system. An important difference between neural networks and other AI techniques is their ability to learn. The network "learns" by adjusting the interconnection (called weights) between layers. When the network is adequately trained, it is able to generalize relevant output for a set of input data. A valuable property of neural networks is that of generalization, whereby a trained neural network is able to provide a correct matching in the form of output data for a set of previously unseen input data. Learning typically occurs by example through training, where the training algorithm iteratively adjusts the connection weights (synapses) [6].

2. The Proposed Method

The objective of this paper is to present a method to design object oriented classification system by using hybrid techniques represented by soft computing approach to classify forest images into the objects which consisting them depending on the best seed for each cluster and the DCT coefficients (i.e., their features), this search concerns itself with classifying six kinds of objects (Tree, Foliage, Bush, Grass, Sky, Background sky) to the forest scenes under study. Figure 1 explains the block diagram of system. The different steps of this method are now discussed in detail.
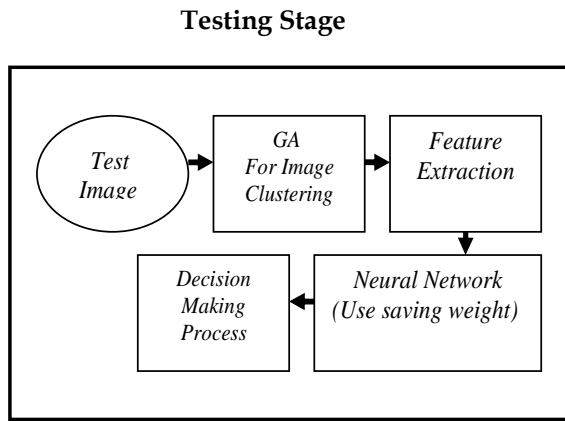
Training Stage

Testing Stage
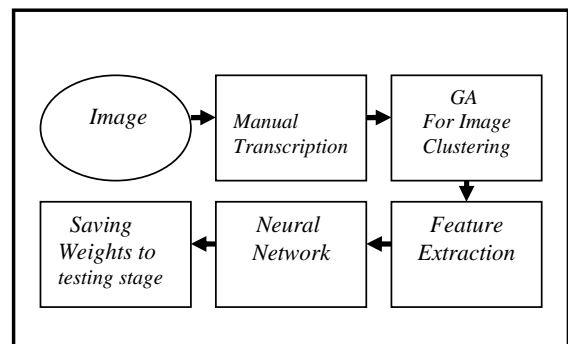
Figure (1): A block diagram of overall system

2.1. Manual Transcription

According to the system design, one needs transcribed training data to build statistical model. For this purpose, the digital images were clustered into different regions, which were labeled with appropriate category names.

For now, six categories have been defined for the image transcription. These categories are necessary for describing a forestry scene. The definitions of these categories are given in Table 1.

Table (1): The six categories used in manual transcription of the forest images.

Category	Description
Tree	a woody perennial plant having a single, usually elongated, main stem, generally with few or no branches on its lower part
Foliage	a cluster of leaves, flowers, and branches
Bush	a low densely branches shrub or a close thicket of shrubs suggesting a single plant
Grass	Grass or land covered with growing grass, or other green-colored ground cover
Sky	a region typically containing sky and few obstructions such as trees, strictly limited to the top of the image
Background sky	a region with sky in the background and other objects in the foreground, but sit clearly identified as sky

2.2. GA for Image Clustering

The genetic clustering algorithm explained in the following procedure

Procedure genetic clustering
Input: image data set is array of pixels for each color.
Output: set of cluster centers where each center contains five numbers (representing the coordinates of the centers and based component of color)

Set Kmin, Kmax to min and max cluster number expected respectively**;**

Set MaxGen to max epoch allowed;

Set $Gen \leftarrow 1$

DO **for** each chromosome in the population

Randomly choose K, $Kmin \leq K \leq Kmax$;

Randomly choose K_i seed from the data set;

Distribute these seeds in the chromosome;

Set unfilled position to don't car symbol ($);
End for

Repeat

Do **for** each chromosome in the population

Extract the K_i centers stored in it;

Perform clustering by assigning each point

to the cluster corresponding to the cluster

center;

Compute DB index (DBI);

Compute fitness as 1/DBI

End for

Keep the best individual

Select subpopulation of parents;

Perform recombination between parents with

probability Pr;

Perform mutation on child with probability Pm;

Randomly choose one position of chromosome;

If this position is $ **Then**

Randomly choose a point from image data set

and make it as a center

Else

Make this position $

End if

$Gen \leftarrow Gen + 1$

Until (Gen > MaxGen)

Return the best seed for each cluster

End

The following example explains the population initialization

Example (1):-Let K_{min} =2 and K_{max} =8. Let the random number K_i be equal to 3 for chromosome i. Then this chromosome will encode the centers of 3 clusters. Let the 3 cluster centers (3 randomly chosen points from the data set) be
(X_1,Y_1,R_1,G_1,B_1), (X_2,Y_2,R_2,G_2,B_2),(X_3,Y_3,R_3,G_3,B_3)
On random distribution of these centers in the chromosome, it may look like
\$ \$ (X_3,Y_3,R_3,G_3,B_3) \$ \$ (X_1,Y_1,R_1,G_1,B_1) \$ (X_2,Y_2,R_2,G_2,B_2)

2.2.1 Fitness Function [7]

The fitness of a chromosome is computed using the Davies–Bouldin index. This index is a function of the ratio of the sum of within-cluster scatter to between-cluster separation. The scatter within C_i , the ith cluster, is computed as

$$S_{i,q} = \left(\frac{1}{|C_i|} \sum_{x \in C_i} \left\{ \|x - z_i\|_2^q \right\} \right)^{1/q} \qquad (4)$$

Where, z_i is the centroid of C_i , and is defined as

$$z_i = \frac{\sum_{x \in c_i} x}{n_i} \qquad (5)$$

and n_i is the cardinality of C_i (i.e., the number of points in cluster C_i). The distance between cluster C_i and C_j is defined as (3.3)

$$d_{ij,t} = \left\{ \sum_{s=1}^{p} |z_{is} - z_{js}|^t \right\}^{1/t} = \|z_i - z_j\|_t \qquad (6)$$

Specifically, Si,q used in this article, is the average Euclidean distance of the vectors in class i to the centroid of class i. While dij,t is the Minkowski distance of order t between the centroids that characterize clusters i and j(i.e., in this work ,we use t=4). Subsequently we compute

$$R_{i,qt} = \max_{j, j \neq i} \left\{ \frac{S_{i,q} + S_{j,q}}{d_{ij,t}} \right\} \qquad (7)$$

The Davies–Bouldin (DB) index is then defined as

$$DB = \frac{1}{k} \sum_{i=1}^{k} R_{i,qt} \qquad (8)$$

The objective is to minimize the DB index for achieving proper clustering.

The fitness function for chromosome j is defined as 1/DBj, where DBj is the Davies–Bouldin index computed for this chromosome. Where the maximization of the fitness function will ensure minimization of the DB index.

2.2.2 Genetic Operations

The following genetic operations are performed on the population of chromosomes for number of generations.

Selection: conventional proportional selection is applied on the population of chromosomes. Here, a chromosome receives a number of copies that is proportional to its fitness in the population.

Recombination: during recombination each cluster center is considered to be an indivisible gene, single point recombination, applied stochastically. The following example (2) is explains the recombination process.

Example (2): Suppose recombination occurs between the following two chromosomes:

P1= \$ (X1, Y1, R1, G1, B1) \$\$ (X2, Y2, R2, G2, B2) \$ (X3, Y3, R3, G3, B3) (X4, Y4, R4, G4, B4) \$\$

P2= (X5, Y5, R5, G5, B5) \$\$\$ (X6, Y6, R6, G6, B6) \$(X7,Y7,R7,G7,B7)(X8,Y8,R8,G8,B8)\$(X9,Y9,Rr9, G9,B9)

Let the recombination position be 5 as shown above. Then the offspring are

Offspring1= \$ (X1, Y1, R1, G1, B1) \$\$(X2, Y2,R2,G2,B2) \$ (X7,Y7,R7,G7,B7)(X8, Y8, R8, G8,B8) \$ (X9,Y9,R9,G9,B9)

Offspring2= (X5, Y5, Rr5, G5, B5) \$\$\$ (X6, Y6, R6, G6, B6) \$ (X3, Y3, Rr3, G3, B3) (X4, Y4, R4, G4, B4) \$\$.

Mutation: each valid position (i.e., which is not \$) in a chromosome is mutated.

2.3. Feature Extraction

After we got the number of cluster expected in image data set we can extracted some of the DCT coefficients in compressed domain as feature vectors. Each sub block (cluster) contains one DC coefficients and other AC coefficients. In this paper we extract the feature set of 16 vector components in which first one is DC coefficient of each sub-block which represents the average energy or intensity of the block and other 15 AC coefficients which represent some different pattern of image variation and directional information of the texture. Then use these 16 values with the value of best seed for each cluster as feature vectors of neural network.

2.4. Neural Network

After we got the feature vectors that represented each sub block we can train the Back propagation (BP) neural network. BP is one of the most famous training algorithms for multilayer perceptrons. BP is a gradient descent technique to minimize the error E for a particular training pattern. For adjusting the weight Wij from i-th input unit to the jth output, in the batched mode variant the descent is based on the gradient $\nabla E \left(\frac{\delta E}{\delta w_{ij}} \right)$ for the total training set:

$$\Delta w_{ij}(n) = -\varepsilon * \frac{\delta E}{\delta w_{ij}} + \alpha * \Delta w_{ij}(n-1) \qquad (9)$$

The gradient gives the direction of error E. The parameters ε and α are the learning rate and momentum respectively. In this paper we deal with different kinds of activation functions called hyper police function such as

$$f(net) = \frac{\exp(net) - \exp(-net)}{2} \qquad (10)$$

$$f(net) = \frac{\exp(net) + \exp(-net)}{2} \qquad (11)$$

$$f(net) = \frac{\exp(net) - \exp(-net)}{\exp(net) + \exp(-net)} \qquad (12)$$

$$f(net) = \frac{\exp(net) + \exp(-net)}{\exp(net) - \exp(-net)} \qquad (13)$$

$$f(net) = \frac{2}{\exp(net) + \exp(-net)} \qquad (14)$$

$$f(net) = \frac{2}{\exp(net) - \exp(-net)} \qquad (15)$$

Where net represented the input vector multiply by weights.

In this work we used different types of activation functions in neural network to classification the same features vectors and compares between the results of it to find the fast method in classification by fixed all other parameters of ANN.

3. Experiment Setup and Result

Figure (2): Image of Forest Scenes

In our research, we attempted to classify 6 different types of objects using soft computing approach. We used DCT coefficients to represent the different textures. In most real life situations the number of clusters in a data set is not known a priori. The real challenge in this situation is to be able to automatically evolve a proper value of K as well as providing the appropriate clustering. Figure 2 explains the test area of system.

How these system works? To answer about this query first we need to know the role of each tool in this system.

Genetic clustering algorithm applied to find the actual number of clusters existing in that image data set. Before this, we need to determine some of parameters relate to GA such as (population size= 50 individuals, minimum number of clusters=more than one, the probability of crossover=90%, the probability of mutation = 10%, number of generation =100). And by experiment we find number of clusters in this image =48 distributed between the different objects in image with DB=0.12501 and fitness of best solution=0.87499.

After that we used DCT analysis to find textural features of each object in image.

As a result the ANN is trained on 123 input vectors. The corresponding output classes vectors. The number of input nodes = 21. And the number of output nodes =6. The convergence rate between the actual and desired output is achieved by: 22 hidden nodes, 0.25 learning coefficient, 0.0009 momentum coefficient and 2800 epochs. The allowable error equal 0.000001.

By compare the results of different types of activation functions, we find the equations (12), (13) given fast results than other equations with number of epochs=200.

Finally we can say the best results of this system obtains when the maximization of the fitness function will ensure minimization of the DB index and using some of the DCT coefficients (16 coefficients) as explained in section (1.2) pulse using equations number 12 & 13 as activation function of back propagation neural network.

4. Conclusions

In this paper, we attempted to classify 6 different kinds of forest scenes using genetic clustering algorithm and neural network. For texture feature we consider the DCT coefficient, which does not require additional complex computation for feature extraction. As the high frequency coefficient is less sensitive to human visual system, we constructed a feature matrix consisting of the few coefficients of each block.

The randomly estimation of the number of the clusters that are found in the image may lead to error in classification process. Therefore, the proposed methodology can solve this problem by determining it

automatically**.**

The proposed prediction models based on soft computing on the other hand are easy to implement and produces desirable mapping function by training on the given data set. Choosing suitable parameters for the soft computing models is more or less a trial and error approach. Optimal results will depend on the selection of parameters. Selection of optimal parameters may be formulated as an evolutionary search to make soft computing model fully adaptable and optimal according to the requirement.

As a result of our developed classification software in test area, it is expected that proposed method is high accuracy than traditional method. It will serve convenient surroundings to non-specialist users.

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