Automatic Selection of Input Variables and Initialization Parameters in an Adaptive Neuro Fuzzy Inference System. Application for Modeling Visual Textures in Digital Images

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Abstract. In this paper we present a method for the automatic selection of input variables and some previous parameters, such as number and type of membership functions, in an Adaptive Neuro Fuzzy Inference System (ANFIS) using a Genetic Algorithm with a new fitness function. Both of them constitute a design scheme that we will use for modeling the perception of textures in Digital Images. Some examples are presented, training ANFIS with this scheme for modeling the following visual textures: coarseness, directionality and regularity.

1 Introduction

Texture is an important characteristic for the analysis of many types of images. Evaluating visual textures in images is a difficult task because the term itself is imprecise. The human perception of textures such as granularity, homogeneity, coarseness, directionality, periodicity or regularity is inherently inaccurate, and suggests the use of fuzzy logic for its modeling.

In the last few years, there has been a proliferation of digital images. This vast number of digital visual data sources needs an organizational scheme like a database for its storage and retrieval. There are few image retrieval systems which used content-based retrieval techniques. QBIC [4] and VisualSEEK [5] are examples of these systems. Content-based queries like color and texture are used in this type of systems.

Tamura, Mori and Yamawaki [1] study texture features that correspond to human visual perception. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects. In this paper, we propose to generate three experimental fuzzy systems from an ANFIS that evaluate respectively three of these textural features: coarseness, directionality and regularity in digital images. Figure 1 i-llustrates these textural features. The fuzzy systems could be used for queries in image databases or for classification of a group of digital images by means of their textures using a subset of statistical variables.

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The use of a universal aproximator like ANFIS for modeling a fuzzy system always requires a subset of input variables for training and validation. Moreover, the election of some initial parameters such as the type of membership functions (MFs) or number of MFs is important to obtain positive results. We present a method for automatic selection of input variables and previous parameters in an ANFIS using a Genetic Algorithm (GA) with a new fitness function adapted to this application. The generated fuzzy systems try to simulate the opinion of an expert to evaluate three different types of textures in digital images, using ANFIS and a GA. This GA evaluates the new fitness function proposed, chooses a subset of input variables from a greater set of 12 statistical variables and selects a combination of number and type of membership functions for training ANFIS.

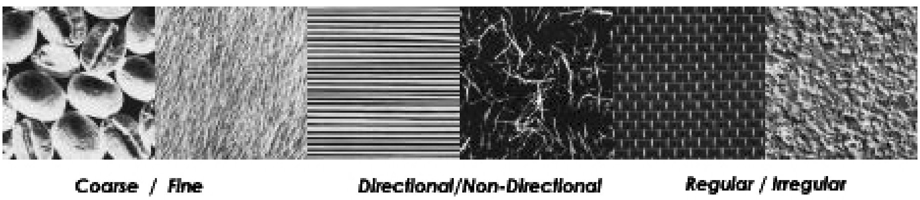

Fig. 1. Examples of textural features

A brief description of ANFIS

ANFIS [3] is a well-known universal aproximator when the number of rules is not restricted. It is composed of two approaches: neural networks and fuzzy logic. In this multi-layered neural network, the first layer carries out a fuzzification process. In the second layer, each node output is the product of the antecedent part of the fuzzy rules. The third layer normalizes the MFs. The fourth layer executes the consequent part of the rules and the fifth layer computes the overall output as the addition of all incoming signals.

The concept of Genetic Algorithm

The GA is a method for solving optimization problems and simulates the process of the biological evolution. The algorithm repeatedly modifies a population of individual solutions. Each individual is often a bit string and is referred as a possible solution for a problem. At each step, the GA selects individuals at random from the cu-rrent group of them (called a population) and uses them to produce the children for the next generation. The GA computes the function to be optimized with each individual, called fitness function, and tries to minimize this. Selection rules, Crossover rules and Mutation rules are used to select the individuals, to exchange genetic material from two parents and to create new genetic material in the population respectively.

The organization of this paper is the following: Section 2 shows a general scheme of the system we have utilized to get the three fuzzy systems and presents the new fitness function used by the GA.

Section 3 presents the format of training and checking vectors used by ANFIS, the collection of images used to generate the vectors and Section 4 shows the simulation results of the fuzzy systems generated by ANFIS.

Finally, Conclusions and Future Works are summarized at the end of this paper.

2 The System Structure, Fitness Function and Principal Algorithm

Figure 2 shows a block diagram representing the structure of our scenario. In this system, we want to minimize the fitness function of the GA to obtain a good fuzzy inference system, because the different output variables selected from ANFIS supply the values of some parameters of this function.

We propose a fitness function, which can adapt to different computational scenarios and preferences. The principal variables included in its definition are:

– e_t: *Training Error*. It is the difference between the training data output value and the output of the fuzzy inference system corresponding to the same training data input value.
– e_c: *Checking error*. The difference between the checking data output value and the output of the inference system corresponding to the same checking data input value. In our fitness function, the weight of errors in the equation depends on a coefficient α and we can change the influence of checking error and training error.
– N_R: *Number of rules in FIS*. Rules needed to generate the ANFIS model in an iteration with input variables determined by the GA. A large number of input va-riables suppose a big number of rules and adjustable parameters in the model adjusted by ANFIS, and arises the curse of dimensionality problem. In a determined computational scenario, the characteristics of the computer (memory, CPU speed, multiuser environments…) limit the size of the fuzzy system inferred. In our fitness function, a multiplicative factor γ allows more or less influence in the final value of the fitness function. If $\gamma = 0$, the number of rules has not influenced the function. If all input variables have the same number of MFs (N_{MFs}), then:

$$N_R = {N_{MFs}}^{N_V} \tag{1}$$

– N_v: *Numbers of input variables selected by the GA*. Let us suppose the available number of input variables is *V*. A large number of variables is problematic for the adjustment process of the ANFIS system. In fact, we can have problems with the computational time or with the limits of the available computer. The number of variables N_v selected by the GA in each individual $P=(P_1, P_2 \ldots P_v)$ to form the training and checking vectors in our modeling scenario is:

$$N_V = \sum_{i=1}^{V} P_i \quad , P_i = \{0,1\} \tag{2}$$

We proposed that the number of input variables selected by the GA must be between two limits selected by the user, to assure that the computational time and the use of the available computer are reasonable. If the number of input variables selected by the GA is less or greater than upper and lower limits chosen by the user (Max_{Nv} and Min_{NV}) then it is not necessary to compute a model with this subset of input variables in ANFIS. The coefficient σ is included to increase the value of the fitness function. In this case, the algorithm rejects the individual and the ANFIS is not called in that iteration.

– ***Preferred Variables.*** It is possible that our experience points to a group of input variables that should be in the subset chosen by the GA to obtain a good model. In this case, the fitness function should favor this group of variables. A factor β_i is used to create predominant variables. If none of them exist, then:

$$\sum_{i=1}^{V} P_i \beta_i = 0 \tag{3}$$

A fitness function that includes all the commented parameters in the preceding list is shown in (4).

$$f_{fitness} = \begin{cases} \sigma\left[Max_{NV} - \sum_{i=1}^{V} P_i\right] & \text{if} \quad \sum_{i=1}^{V} P_i > Max_{NV} \\ \sigma\left[Min_{NV} - \sum_{i=1}^{V} P_i\right] & \text{if} \quad \sum_{i=1}^{V} P_i < Min_{NV} \\ \sum_{i=1}^{V} P_i \beta_i + \alpha e_c + (1-\alpha) e_t + \gamma N_R & \text{if} \quad Min_{NV} \le \sum_{i=1}^{V} P_i \le Max_{NV} \end{cases} \tag{4}$$

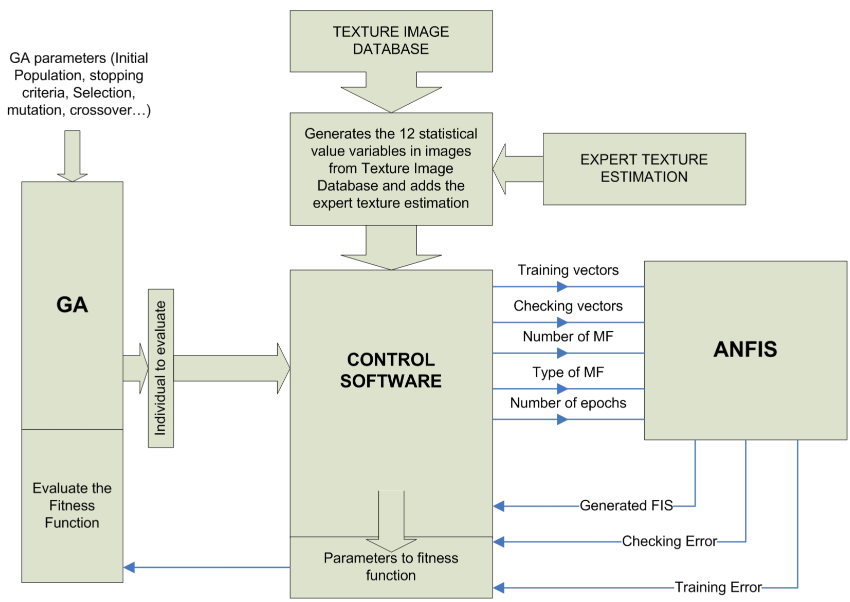

Fig. 2. Block Diagram of the system structure

The principal algorithm is shown below.

Algorithm 1. Obtaining the Fuzzy Inference System (FIS) to model visual textures with a GA and ANFIS (Control software in Figure 1).

Input
t : type of texture property to model (coarseness, directionality, regularity
Max_{NV}
Min_{NV}
$P=(P1,P2,\ldots Pv)$; current individual to evaluate
Mex_t: Set of expert values from texture properties
β_i
γ
N_{ep}: Number of training epochs

Initialization
Valid_individual = false
Best_value_fitness_function = σ : (a large value)
$t_c = 0$: Computational time

Begin: While stopping criteria of GA == false
Load P from actual population
Extract N_v
If $N_v > Max_{NV}$ or $N_v < Min_{NV}$
  Valid_individual = false
  Goto *Begin*
Else
  Valid_individual = true
  Generate *training_vectors* and *checking_vectors* from $P_i=1$ and Mex_t
  Extract *type_of_MF* and *Number_of_MFs* from P
  Calculate N_R
  Generate *initial_FIS*
  Adjusted_FIS = ANFIS (*initial_FIS, type_of_MF, number_of_MFs,*N_{ep}*,training_v, checking_v*)
  Evaluate Y (by the GA)
  If Y < *best_value_fitness_function*
  best_value_fitness_function = Y
  best_FIS = *Adjusted_FIS*
if population is complete
  Generate new population (by the GA)

3 Texture Image Database and ANFIS Input Variables

The texture database used to train and check the system generated by ANFIS consists of 110 different textures images of 640x640 pixels. These images are from the Brodatz album [6]. All of them are gray scale texture images of two types: structural textures, formed by texture primitives that are repeated systematically within the texture and statistical textures where no repetitive texture can be identified.

We use a set of texture's descriptors to form the training and validation vectors to be applied to ANFIS. These descriptors are based on statistical approaches. Six of them are based on statistical properties of the intensity histogram: mean, standard deviation, smoothness, third moment, uniformity and entropy (positions 1 to 6 in our algorithm).

Spectral measures of texture are based on the Fourier spectrum and are useful for distinguishing between periodic and non periodic textures. We express the spectrum in polar coordinates to produce a function *S(r,θ)*, where S is the spectrum function and r and θ are the variables in the coordinate system. $S_\theta(r)$, for a fixed value of θ, shows the behavior of the spectrum along a radial direction from the origin. $S_r(\theta)$, for description is obtained in this way: shows the behavior along a circle centered on the origin. A global description is obtained in this way:

$$S(r)=\sum_{\theta=0}^{\pi} S_\theta(r) \quad (5) \qquad S(\theta)=\sum_{r=1}^{R_0} S_r(\theta) \quad (6)$$

Where R_0 is the radius of a circle centered at the origin of an image.

Using the mean and variance of both functions and computing the difference between the maximum and the statistical mean of them, we obtain six more input variables (positions 7 to 12 in our algorithm). Finally, we execute a normalization of all input variables. An explanation of all these descriptors can be seen in [6].

The 220 images are evaluated by an expert that assigns three numerical values in the range [0,1] of real numbers to his visual perception of the following characteristics of the image: coarseness, directionality and regularity.

We use 110 training vectors and 110 checking vectors for training and validation of the fuzzy system inferred by ANFIS for each texture property. The value estimated by the expert is the last position in each vector (the output for ANFIS). The number of training epochs is fixed to 200 on the simulations.

4 Simulation Results

The software used has been developed in Matlab®, and involves the Fuzzy Logic, Genetic Algorithm and Image Processing Toolboxes. The GA chooses the number of MFs (2 or 3) and the type of MFs to be used (Gaussian, combination of two Gaussians, bell and product of 2 sigmoids functions). The size of each population is fixed to 25 individuals (max. 50 generations). The coefficient σ is equal to 100 and γ=0 in all the simulations.

We have carried out two simulations by each type of texture, obtaining six Fuzzy Inference Systems representing the criteria of an expert. Table 1 shows the principal characteristics of each simulation and a summary of the simulation results.

Table 1. Simulation results

				Variables selected by the GA			*Restrictions (NV)*	
Texture	**α**	**βi**	**Fitness**	**Type of MFs**	**NMFs**	**Inputs selected**	**Max**	**Min**
Coarse (1)	0.7	$\beta_{3,4}$=0.2	1.3833	gauss	3	3, 4, 11	3	3
Coarse (2)	0.7	0	0.1221	psig	2	8, 9, 12	4	2
Directionality (1)	0.7	0	0.1639	gbell	2 (fixed)	6, 8, 10, 11	5	2
Directionality (2)	0.7	0	0.1530	gauss	3	2, 7, 11, 12	4	2
Regularity (1)	0.7	0	0.1741	gauss2	3	1, 2, 6, 7	4	3
Regularity (2)	0.5	β_5=0.1	0.1833	gauss	2 (fixed)	1, 2, 5, 6, 7	5	2

5 Conclusions and Future Works

A complete structure to generate various FISs to model the human opinion of some characteristics of visual textures is presented in this paper. These FISs can be used for evaluating the texture characteristics in a set of images or for carrying out queries in image databases. In this case, the different images are the inputs and the FIS evaluates its grade of texture. The fitness function proposed, when use with the structure shown in figure 2, is a generalized equation, and its use can be extended to other applications. We have obtained good models of Mackey-Glass chaotic series with the same algorithm presented in this paper, where the GA chooses the subset of input variables for ANFIS from a complete set of 20 input variables (from *u(t-19)* to *u(t)*).

Future research may include a more complete set of input variables (Co-ocurrence matrices, Markov fields, Local Binary Patterns (LBP) or Gabor decomposition), and applications which automatically assign a different number of MFs at each input; determine specialized mutation or crossover functions, or substitute the GA by other approaches. Combining techniques of image segmentation is desirable if the images contain different types of textures.

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