A Study on Adaptive Neuro Fuzzy Inference System and its Applications

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Abstract - In this paper, we presented an architecture and basic learning process underlying in fuzzy inference system and adaptive neuro fuzzy inference system which is a hybrid network implemented in framework of adaptive network. In real world computing environment, soft computing techniques including neural network, fuzzy logic algorithms have been widely used to derive an actual decision using given input or output data attributes. ANFIS can construct mapping based on both human knowledge and hybrid learning algorithms. This study involves study of ANFIS strategy ANFIS strategy is employed to model nonlinear functions, to control one of the most important parameters of the induction machine and predict a chaotic time series, all yielding more effective, faster response or settling times. Also in this paper, we presented the architecture and basic learning process underlying ANFIS (adaptive-network-based fuzzy inference system) which is a fuzzy inference system implemented in the framework of adaptive networks. Soft computing approaches including artificial neural networks and fuzzy inference have been used widely to model expert behavior. Using given input/output data values, the proposed ANFIS can construct mapping based on both human knowledge (in the form of fuzzy if-then rules) and hybrid learning algorithm. In modeling and simulation, the ANFIS strategy is employed to model nonlinear functions, to control one of the most important parameters of the induction machine and predict a chaotic time series, all yielding more effective, faster response or settling times. Technological innovations in soft computing aim to exploit tolerance for imprecision and have brought automation capabilities to new levels of applications. Process control is an important application of any industry for controlling the complex system parameter and to provide low cost solution. Soft computing techniques can cope with variety of environmental and stability related uncertainties applications. These techniques consist of fuzzy logic (FL), neural network (NN) and genetic algorithms (GA) methodologies to design state-of-art intelligent systems ranging from computer aided diagnosis, computer aided recognition or in intensive care unit [1]. In methodically, the control techniques based on fuzzy modeling or fuzzy identification was first systematically introduced by Takagi and Sugeno, has found diverse applications in fuzzy control for medical diagnosis [3], decision-making and solve problems based on data mining.

Keywords: Study Report, ANFIS, Fuzzy logic, neural network, decision support system, learning algorithm.

1. Introduction

In this paper, we presented the architecture and basic learning process underlying ANFIS (adaptive-network-based fuzzy inference system) which is a fuzzy inference system implemented in the framework of adaptive networks. Soft computing approaches including artificial neural networks and fuzzy inference have been used widely to model expert behavior. Using given input/output data values, the proposed ANFIS can construct mapping based on both human knowledge (in the form of fuzzy if-then rules) and hybrid learning algorithm. In modeling and simulation, the ANFIS strategy is employed to model nonlinear functions, to control one of the most important parameters of the induction machine and predict a chaotic time series, all yielding more effective, faster response or settling times.

Figure 1: Simple Fuzzy Inference System architecture.
However, there are some fundamental aspects of this approach which are in need of better understanding. More specifically, the lack of standard design procedure and optimization process to transform human knowledge or experience into rule base and the data base of the fuzzy inference system [2]. In this paper, we describes a novel class of neuro-fuzzy architecture called Adaptive Neuro-Fuzzy Inference System (ANFIS) with ultimate aim to explain fuzzy inference system via learning and has been widely employed to represent or approximate a nonlinear system. Adaptive systems can be described by constructing a set of fuzzy if-then rules that represent local linear input-output relations of the system. All these methodologies work together and provide flexible information capabilities from one form to another to handle real life ambiguous situations.

It has been proven that Takagi-Sugeno fuzzy systems with affine terms can smoothly approximate any nonlinear functions to any specified accuracy within any compact set, which provides a theoretical foundation for using T-S fuzzy model to represent complex nonlinear system approximately [2]. Control of nonlinear systems based on conventional mathematical tools is a difficult problem because no systematic tools are available to deal with ill-defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes but lacks standard design procedure to employ precise quantitative analyzes. Neural networks work by detecting patterns in data, learning from the relationships and adapting to them. This knowledge is then used to predict the outcome for new combinations of data [2]. In particular, the control technique based on fuzzy modeling or fuzzy identification was first systematically introduced by Takagi and Sugeno [1], has found numerous applications in fuzzy control, for medical diagnosis [3], decision-making and solve problems based on data mining [4]. However, there are some basic aspects of this approach which are in need of better understanding. More specifically, the lack of standard design procedure and optimization process to transform human knowledge or experience into rule base and the data base of the fuzzy inference system. It is hard to interpret tuning of membership function so as to minimize output error index and to choose appropriate network structure. This paper is concerned with novel architecture called Adaptive Neuro-Fuzzy Inference System (ANFIS), has been widely employed to represent or approximate a nonlinear system. Adaptive systems can be described by constructing a set of fuzzy if-then rules that represent local linear input-output relations of the system. In recent years, Takagi-Sugeno (T-S) fuzzy models are playing an important role in dealing with problems concerning a wide class of nonlinear systems. Artificial Neural Network can be used as an alternative means for the knowledge about the engine. ANN is based on binary logic which can store knowledge by learning from recorded data. It has been proven that T-S fuzzy systems with affine terms can smoothly approximate any nonlinear functions to any specified accuracy within any compact set, which provides a theoretical foundation for using T-S fuzzy model to represent complex nonlinear system approximately.

2. Literature survey

There are various application areas in which ANN and FL have been successfully implemented whether individually or complementing each other’s strengths. A combined neuro-fuzzy approach has seen enormous preferences recently from researchers working in different domains. A comprehensive study of existing work in assorted areas using soft computing methodologies specifically focusing on neural networks and fuzzy logic. A computational technique to deal with non-linear and complex problem was discussed by J.R Jang (1993). This study involves fuzzy inference system implemented in the construction of adaptive networks. The proposed ANFIS can generate an input-output mapping based on human knowledge and predetermined input-output data pairs using the hybrid algorithm. The simulation studies for system architecture is utilized to model nonlinear functions, identify nonlinear components online in a control system and predicts a chaotic time series, all yields remarkable results. Further, author compared system with artificial neural networks and preliminary tested. A comprehensive survey of neuro-fuzzy rule generation algorithms for real-time applications is examined by S. Mitra et al. (2000). The proposed algorithms use fuzzy sets and an aid in giving information in a more human comprehensible or natural form and can handle uncertainties at various levels. An extensive investigation shows the qualitative better results can be obtained using rule extraction and rule refinement. Models are the group on the basis of their level of neuro-fuzzy synthesis. The proposed methodology has an additional benefit in other soft other soft computing tools like genetic algorithms and rough sets. Based on fuzzy inference system, real-life application to medical diagnosis is provided. Usefulness of adaptive neuro-fuzzy system for predicting surface roughness in turning operation is examined by S. S. Roy (2005). Various input parameter
namely cutting speed, feed rate and depth of cut have been used for encoding the problem. Two different membership functions triangular and bell shaped were adopted during the training phase. This approach compares ANFIS values with experimental data for both triangular and bell shaped membership functions. The developed model based on first-order Takagi-Sugeno and Kang for turning operation showed a higher prediction accuracy using bell membership function. A novel approach solving problems for the air conditioning system by means of Mamdani and Sugeno-type fuzzy inference models was discussed by Arshdeep et al. (2012). This approach outlines the basic difference between the Mamdani-type FIS and Sugeno-type FIS. This study suggests choosing an enhanced membership function of the two FIS for the air conditioning system. Based on inference system implementation author concluded from this paper that for air conditioning system Mamdani-type FIS and Sugeno-type FIS performs similarly but by using Sugeno-type FIS model it allows the air conditioning system to operate at its full capacity. Medical diagnosis applications of ANFIS were introduced by Tamer (2012). The proposed approach uses Sugeno-type adaptive-network-based fuzzy inference system (ANFIS) to prognosticate the existence of mycobacterium tuberculosis. Dataset collected from 503 different patient records which are obtained from a private health clinic. The patient record has 30 different attributes which cover demographical and medical test data. ANFIS model was generated by using 250 records. The proposed model classifies the instances with the exactness of 97%, whereas rough set algorithm does the same classification with an accuracy of 92%. This learning has a contribution on forecasting patients before the medical tests. The inaccuracy of mathematical modeling of the plants usually degrades the performance of the controller, especially for nonlinear and complex control problems. Use of ANFIS controller for controlling non-linear system was explained by A.V Gite (2013). The simulation study suggests that ANFIS is the best controller as compared to conventional PID controller. The proposed technique can be used in the temperature water controller. A medical expert system for diagnosing of tuberculosis was proposed by Navneet et al. (2015). The proposed Medical Expert Solution (MES) system was to assist medical doctors to diagnose symptoms related to a given tropical disease, suggest the likely ailment, and advances possible treatment based on the MES diagnosis. Abu-Rub et al. (2013) presented an application of ANFIS for maximum power delivery to the load based on maximum power point tracking. The proposed ANFIS based MPPT offers an enormously fast dynamic response with high accuracy. Authors projected technique is tested for isolated load conditions. Simulation and experimental approaches are used to validate the proposed scheme. C. Loganathan et al. (2014) had successfully considered a system that uses a fuzzy system to characterize knowledge in an interpretable manner and have the learning ability derived from a Runge-Kutta learning method (RKLM) to adjust its membership functions and parameters in order to augment the system performance. The dilemma to discovery appropriate membership functions and fuzzy rules are often a tiring process of trial and error. It requires users to recognize the data before training, which is usually difficult to achieve when the database is relatively large. To overcome these problems, the author explained a hybrid of back propagation neural network and RKLM can combine the advantages of two systems.

3. Fuzzy logic

Fuzzy set theory, which was initially introduced by LoftiZadeh in 1965, is a powerful tool to deal with the imprecision characteristics in decision-making problems involving uncertainty and vagueness of real world applications [5]. Fuzzy inference is a process of mapping from a given input to an output dataset using the theory of fuzzy sets. Knowledge is encoded as using a set of explicit linguistic rules, which can be easily understood by people without technical expertise. Fuzzy systems implement nonlinear systems using linguistic variables in a straightforward when adequate knowledge about the system is available. The fuzzy logic module was used as a decision-making tool to resolve any uncertainty in the decision made by the neural networks. Fuzzy Set Theory (FST), a dominant tool used to handle imprecision and uncertainty can be used to deal with the concept of partial true and partial false values aiming attractability, stoutness and low cost solutions for real world challenges. Unlike Boolean logic or classical logic, which assumes that every fact is either entirely true or false, fuzzy logic extends Boolean logic to handle vague and imprecise expressions. Fuzzy set theory offers the ability to express the ambiguity of human thinking and translate expert knowledge into computable numerical data. It can
deal with linguistic terms which explain its implementation in solving problems in medicine and supplementary areas of application. A fuzzy system consists of a set of fuzzy IF-THEN rules that describe the input-output mapping relationship of the networks. Hybrid systems utilize methodologies of soft computing (fuzzy logic, neural computing, genetic computing etc.) provide a perspective method to build fuzzy inference system when information about object system incomplete. Main components of fuzzy logic are fuzzification, which translates crisp (real-valued) inputs into fuzzy values; rule base reasoning, an inference engine that applies a fuzzy reasoning mechanism to obtain a fuzzy output using rules; and defuzzification, which translates this latter output into a crisp value, as shown in “figure 1”. The purpose of fuzzification is to map system input values from 0 to 1 via defined input membership functions. In rule-based reasoning, the fuzzy input values membership values are mapped to classify fuzzy output through a table containing if-then rules. Rules are expressed as a logic implication p → q where p is called the antecedent of the rule and q is called the consequence of the rule .Defuzzification is a process which produces single system output (crisp) values by using a defuzzification formula and fuzzy output membership outputs. The fuzzy inference system is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. It has found successful applications in a wide variety of fields, such as automatic control, data classification, decision analysis, expert systems, and pattern recognition.

In real world computing environment, the information is not complete, precise and certain, making very intricate to derive a definite conclusion. Clinical decision support can be defined as active knowledge systems that form a significant part in field of clinical knowledge management technologies to generate case-specific advice. This system makes use of knowledge management in such a way to achieve clinical advice for patient care based on multiple items of patient data. Various Clinical Decision Support Systems have been constructed with the help of Artificial intelligence. Usages of these systems are now widely available in various hospitals and health clinics. They are proved to be very valuable for patient as well as for medical experts in making the prompt decisions about the ailment. Clinical decision support system is broadly classified into two main categories; (i) Knowledge-based clinical decision support system (ii) Non-knowledge based clinical decision support system as shown in Figure 3.

Figure 3: Clinical Decision Support System using Different Methodological Branches.

The knowledge-based decision support system framework mainly includes usage of If-then type rules, which are also referred as production rules to conclude the output of reasoning mechanism. The input data is usually associated with these rules. For example, if fever intensity is high then generate warning severe. The knowledge-based system generally divided into three main parts: knowledge base, database rules and inference engine mechanism to compute effectively. Knowledge based system comprises of the database model and fuzzy logic model. The inference engine uses set of rules to
combine patient information and to provide output. Fuzzy systems are useful in two general contexts: (i) situations involving highly complex systems whose behaviour are not well understood, and (ii) in situations where approximate, but fast solution is required [14, 3]. Such inference procedure derives conclusions from a set of fuzzy if-then rules and known facts. Fuzzy reasoning is also known as approximate reasoning. Fuzzy reasoning is made by using basic rules of inference such as two valued logic modus ponens in which the truth value of one proposition can be inferred from the truth value of other proposition given that one proposition implicates other. Fuzzy systems implement nonlinear systems making use of linguistic variables in a straightforward method when adequate knowledge about the system is available. The fuzzy logic module was used as a decision-making tool to resolve any uncertainty in the decision made by the neural networks. Fuzzy Set Theory (FST), a dominant tool used to handle imprecision and uncertainty can be used to deal with the concept of partial true and partial false values aiming attractability, stoutness and low cost solutions for real world challenges. The system that focuses on the procedure having no knowledge base data is termed as machine learning algorithm or non-knowledge based clinical decision support system. It is further classified into two main categories as neural networks (NN), genetic algorithm (GA).

3.2. Neural Network

In order to attain relationship between the symptoms and diagnosis, neural networks make use of nodes and weighted connections. This fulfills the need not to write rules for input. However, the system fails to explain the reason for using the data in a particular way. Simulation studies shows that the self-organizing process of training the neural network in which it isn’t given any priory information about the categories it is required to identify, is capable of extracting appropriate information from input data in order to produce clusters that correspond to class. Furthermore it requires only a small proportion of available data to train the network. Usage of neural networks is very important especially in complex multi-variable systems in order to avoid costly medical treatment. Neural Networks have been widely useful for modeling complex databases of medical information and to solve non-linear statistical modeling problems. Training of neural network-based systems can be done by using numerical data and fuzzy rules can be extracted from neural networks. These networks are trained in order to optimize performance of network in estimating output for particular input space. Back propagation training algorithm, a popular approach used with medical databases adjusts weight of an ANN to minimize a cost function. The ANN maintains correct classification rates and allows a large reduction in complexity of the systems. The use of the weight-elimination cost function is well enough to overcome the network memorization problems.

4. Adaptive Neuro Fuzzy Inference System

Jang in 1993 proposed architecture and learning algorithms which is combination of fuzzy logic with neural networks for drawing inference [4]. It is a model that is proficient in constructing input-output mapping accurately based on both human knowledge using data in the form of fuzzy if-then rules and predetermined input output data pairs. The adaptive-network-based fuzzy inference system maps input data using input membership functions (MFs) with its associated parameters, and then through output MFs to conclude outputs. The initial membership functions and rules for the fuzzy inference system can be calculated by employing human expert knowledge about the target system to be modelled. ANFIS can then refine the fuzzy if-then rules and membership functions to illustrate the input-output behaviour of a complex system [13]. Multi-
layer adaptive network-based fuzzy inference architecture consists of totally five layers to implement different node functions to learn and tune parameters in a FIS using a hybrid learning mode. The hybrid learning algorithm allows identifying parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the back-propagation gradient descent method for training FIS membership function parameters to follow a given training data set. Figure 2 shows entire system architecture consists of five layers, namely fuzzy layer, product layer, normalized layer, defuzzy layer and output layer. Hybrid neuro system is a powerful framework for handling practical classification problems and is able to create class boundaries that reduce its misclassification rates. During the forward pass, with fixed premise parameters, the least squared error estimation approach is employed to update the consequent parameters and to pass the errors to the backward pass.

**Figure 4. Basic ANFIS Structure for Two Input Sugeno Fuzzy Model.**

The first-order Sugeno fuzzy model allows use of consequent part of fuzzy inference system having linear values and the parameter can be predicted by using a simple least-squares error method. For simplicity, it is assumed that FIS under consideration has two inputs, x and y, and one output, z. A typical rule set having two fuzzy if-then rules Takagi and Sugeno fuzzy rules can be expressed as using Equation 1.

Rule 1: If x is A1 and y is B1 then 
\[ z_1 = p_1x + q_1y + r_1 \]  
Rule 2: If x is A2 and y is B2 then 
\[ z_2 = p_2x + q_2y + r_2 \]  
where A1, A2 and B1, B2 are the membership functions for the inputs x and y, respectively; p1, q1, r1 and p2, q2, r2 are linear parameters having values in the then-part of fuzzy if-then rules, and are called consequent parameters. The architecture of ANFIS consists of five layers, and an introduction of the model layers is presented below.

**Layers 1:** Each input node i in this layer is an adaptive node which generates membership grade of linguistic variable. It is a fuzzy layer, in which v and d are input of system. O1,i is the output of the ith node of layer 1. Each adaptive node is a square node with square function defined by using Equation (2):

\[ O1,i = \mu v,i(v) \]  
where O1,i and O1,j denote output function and \( \mu v,i \) and \( \mu d,j \) denote membership function. Both bell-shaped and gaussian membership function can be used for fuzzy sets due to their nonlinear, smooth and continuous derivatives. Parameters in this layer are referred to as ‘premise parameter’.

**Layer 2:** Every node in this layer is fixed. This layer receives input values vi from first layer and acts as a membership function to represent fuzzy sets of respective input variables to check weights of each membership function. Each node in this layer estimates the firing strength (wi) of a rule. The output in this layer can be represented using Equation 3:

\[ O2,i = wi = \mu v,i(v) \mu d,j(d), \quad i = 1, 2 \]  
In general, any T-norm operator that performs fuzzy AND can be used as a node function in this layer.

**Layer 3:** Every node in this layer is a circle node labelled with N, indicating normalization to the firing strength from previous layer. The ith node performs pre-condition matching of fuzzy rules, i.e. it calculates the ratio of the ith rule’s firing strength to the sum of all rules firing strengths. The output of this layer can be expressed as \( wi \) using Equation 4.

\[ O3,i = wi = wiw1+w2, \quad i = 1, 2 \]  
For convenience, output of this layer is known as normalized firing strengths.

**Layer 4:** In this layer, the nodes are adaptive nodes. The resultant output is simply a product of normalized firing rule strength and first order polynomial. Weighted output of rule represented by node function and computed as using equation 5:

\[ O4,i = wi fi = wt(piv + qid + ri) \]  
where O4,i represents layer 4 output. In this layer, pi, qi and ri are linear parameter or consequent parameter and fi is a linear function of input variables.

**Layer 5:** This layer aggregates the qualified consequents to produce a crisp output. The single node in this layer is fixed which transforms fuzzy classification results into crisp values. It computes the weighted average of all
incoming signals to calculate output signals calculated using equation 6.

\[ O_5,i = \sum w_{i1}i + w_{i2}, i = 1, 2 \ldots \ldots \ldots \ldots \ldots (6) \]

Thus, it is observed that when the values of premise parameter are fixed, the overall output of the adaptive network can be expressed as linear combination of a consequent parameter. Hybrid neuro fuzzy systems can be used in diagnosis of pulmonary lung diseases, cortical malformations, hepatitis and diabetes, rheumatic and pancreatic diseases. A fuzzy rule based expert system can be designed to detect stage of tuberculosis and accordingly these fuzzy rules are updated using rule mining techniques. Based on this technique that generates classes of tuberculosis suits the needs of pulmonary physicians and reduce the time consumed in generating diagnosis of ailment.

5. Conclusion

We have described the clinical decision support system along with architecture of adaptive network based fuzzy inference systems (ANFIS). Based on hybrid learning algorithm, the proposed architecture can improve the quality of generated relevant fuzzy if-then rules obtained from human experts to illustrate the input-output behavior of a complex system. Fuzzy logic provides a means for drawing the subjective decision making process in an algorithm suitable for computer implementation. We have described the architecture of adaptive network based fuzzy inference systems (ANFIS) with type-1 and type-2 reasoning mechanisms. By employing hybrid learning algorithm, the proposed architecture can improve the quality of generated relevant fuzzy if-then rules obtained from human experts to describe the input-output behavior of a complex system. These characteristics are especially useful for modeling systems for which there is no analytical description available, but behaviors can be described by the human expert. However, when human expert is not available, nor is a linguistic description, the design process of the model can still set up intuitively reasonable initial membership functions and start the learning process to generate a set of fuzzy if-then rules to approximate a desired output. The adaptive network structure can have a number of variants of the model, which greatly relieves the burden of the human designer.

6. References


