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Identification using ANFIS with intelligent hybrid stable learning algorithm approaches and stability analysis of training methods

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ABSTRACT

This paper proposes a novel hybrid learning algorithm with stable learning laws for Adaptive Network based Fuzzy Inference System (ANFIS) as a system identifier and studies the stability of this algorithm. The new hybrid learning algorithm is based on particle swarm optimization (PSO) for training the antecedent part and forgetting factor recursive least square (FFRLS) for training the conclusion part. Two famous training algorithms for ANFIS are the gradient descent (GD) to update antecedent part parameters and using GD or recursive least square (RLS) to update conclusion part parameters. Lyapunov stability theory is used to study the stability of the proposed algorithms. This paper, also studies the stability of PSO as an optimizer in training the identifier. Stable learning algorithms for the antecedent and consequent parts of fuzzy rules are proposed. Some constraints are obtained and simulation results are given to validate the results. It is shown that instability will not occur for the leaning rate and PSO factors in the presence of constraints. The learning rate can be calculated on-line and will provide an adaptive learning rate for the ANFIS structure. This new learning scheme employs adaptive learning rate that is determined by input–output data. Also, stable learning algorithms for two common methods are proposed based on Lyapunov stability theory and some constraints are obtained.

1. Introduction

Fuzzy systems and neural networks are both very popular techniques that have seen increasing interest in recent decades. At a first glance, they seem to be totally different areas with merely marginal connections. However, both methodologies belong to the soft computing area. Soft computing includes approaches to human reasoning and learning that try to make use of the human tolerance for incompleteness, uncertainty, imprecision and fuzziness in decision-making processes.

Many different structures for fuzzy neural networks (FNNs) have been proposed [1]. Among them ANFIS is a neural-network based on fuzzy approach, in which the learning procedures are performed by interleaving the optimization of the antecedent and conclusion parts parameters. Also many types of recurrent fuzzy networks [46–51], have been proposed along with their learning algorithms, such as GD based learning algorithms [52], genetic algorithms (GAs) [53] and evolutionary based [57]. Learning based on GD learning algorithms includes real-time recurrent learning (RTRL) [54], ordered derivative learning [55] and so on [56]. However, most current studies on GA, GD, RLS based are not hybrid. Classic methods such as GD, RLS,... are simple but have some problems during training. We aim to use both evolutionary and classic methods for parameters tuning simultaneously.

In this paper, the procedure of adapting antecedent parameters in ANFIS employs PSO method to adjust the parameters of the membership functions (MFs). The PSO techniques have the advantage of being less computationally expensive for a given size of network topology; a factor which becomes much more important for larger networks and another advantage is their gradient free nature. When we use GD to train antecedent parameters there is high probability we fall in local minima thus using PSO is recommended. This technique is more powerful in search than GD. However, one problem inherent in them is their convergence to local minima and the user set acceleration rates and inertia factor parameters that are sensitive to the learning process [2]. The stability problem of FNN identification is very important in applications. It is well known that normal identification training algorithms (e.g., GD and Least Square Estimation

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(LSE)) are stable under ideal conditions. In the presence of unmodeled dynamics, they might become unstable [3]. The learning procedure of FNNs can be regarded as a type of parameter identification process.

The GD and backpropagation (BP) algorithms are stable, if FNNs models can exactly match nonlinear plants [3].

The stability of GD-BP algorithms for training FNNs using type I an II TSK's rules has been discussed in many studies [1,2–7], but there is no complete work on stability of ANFIS as an FNN using type III TSK's rules.

Some papers [4,5,7] have been written on the stability of FNNs and the popular method is Lyapunov stability. Nevertheless, there have been few studies on the stability analysis using the convergence of learning algorithm. Yu and Li [3] used input to state stability (ISS) techniques for Mamdani and TSK FNNs but the stability of ANFIS as an identifier has not been studied.

Lu and Tsai [58] established the convergence of the RFNN model via Lyapunov stability theory, and studied the stability of the closed-loop control system. They used the GD and FRLS for training consequent and conclusion, respectively but they just analyzed the stability of consequent parameters were trained by GD and did not pay attention to conclusion parameters and the covariance matrix in FRLS as a parameter that changes during the training process.

In this paper, the Lyapunov stability approach is applied to system identification via ANFIS as TSK's type III. The FRLS update rule for the conclusion part of ANFIS is considered and for the antecedent part the population based algorithm in [14,43] is used. The new stable algorithm with time varying and stable constraints for PSO parameters is applied to ANFIS for the first time. This new approach based on combination of RLS and PSO is applied. In addition, the stability analysis of common methods is proposed. These common methods are pure GD and combination of GD and FRLS. The stable learning algorithm with time varying learning rate and covariance matrix with constraints is applied to ANFIS.

In least square method, forgetting can be viewed as giving less weight to older data and more weight to recent data. The main difference in the classical least square method is how the covariance matrix is updated. In the classical RLS the covariance vanishes to zero with time, losing its capability to keep track of changes in the parameter. The RLS with forgetting has been widely used in estimation and tracking of time varying parameters in various fields of engineering. However when excitation of the system is poor this scheme can lead to the covariance "wind-up" problem. During poor excitations old information is continuously forgotten while there is very little new dynamic information coming in. This might lead to the exponential growth of the covariance matrix and as a result the estimator becomes extremely sensitive and therefore susceptible to numerical and computational errors [59]. This problem has been investigated by many researchers in the field and several solutions, mostly ad hoc, have been proposed to avoid covariance "wind-up". The idea of most of these schemes is to limit the growth of covariance matrix for example by introducing an upper bound. A popular scheme is proposed by Fortescue et al. [59] in which a time-varying forgetting factor is used. During low excitations, the forgetting factor is closer to unity to enhance the performance of the estimator.

In another approach, Sripada and Fisher [60] proposed an on/off method along with a time-varying forgetting factor for improving performance. The concept of resetting the covariance matrix during low excitations has also been investigated in [61]. Both papers provide good discussions about behavior of the system during low excitations. Kulhavy and Zarrop discuss the concept of RLS with forgetting factor from a more general perspective in [62]. One other popular refinement to the RLS with forgetting scheme is the concept of "directional forgetting" for reducing the possibility of the estimator windup when the incoming information is non-uniformly distributed over all parameters. The idea is that if a recursive forgetting method is being used, the information related to non-excited directions will gradually be lost. This results in unlimited growth of some of the elements of the covariance matrix and can lead to large estimation errors. Implementation of the concept of directional forgetting is again ad hoc and is reflected in updating the covariance matrix, $P(k)$. That is, if the incoming information is not uniformly distributed in the parameter space the proposed schemes perform a selective amplification of the covariance matrix. Hagglund [63] and Kulhavy [64] have developed one of the early versions of this algorithm. Bittani et al. discuss the convergence of RLS with directional forgetting in [65]. Cao and Schwartz [66] explain some of the limitations of the earlier directional forgetting scheme and propose an improved directional forgetting approach. Vahidi et al. [67] introduced RLS with multiple forgetting factors accounts for different rates of change for different parameters.

The rest of the article is organized as follows: in Section 2 ANFIS structure and learning algorithms are reviewed. In Section 3 the stability analysis of the pure GD and GD + FRLS learning algorithms for ANFIS is discussed and stability constraints for both the learning algorithms are found. In Section 4 the PSO method is discussed. In Section 5 ANFIS stability analysis are discussed and stability constraints for novel hybrid training algorithm are found. Simulation and application of this method to nonlinear identification and another new method are presented in Section 6. Section 7 presents conclusions.

2. The concept of ANFIS

2.1. ANFIS structure

In this section, type III ANFIS topology and the learning method that used for this neuro-fuzzy network are presented. Both neural network and fuzzy logic [9] are model-free estimators and share the common ability to deal with uncertainties and noise. Both of them encode the information in parallel and distribute architectures in a numerical framework. Hence, it is possible to convert fuzzy logic architecture to a neural network and vice versa. This makes it possible to combine the advantages of neural network and fuzzy logic. A network obtained in this way could use excellent training algorithms that neural networks have at their disposal, to obtain the parameters that would not have been possible in fuzzy logic architecture. Moreover, the network obtained in this way would not remain a black box, because this network would have fuzzy logic capabilities to interpret in terms of linguistic variables [10].

The ANFIS combines two approaches: neural networks and fuzzy systems. If both these two intelligent approaches are combined, good reasoning will be achieved in quality and quantity. In other words, both fuzzy reasoning and network calculation will be available simultaneously.

The ANFIS is composed of two parts. The first is the antecedent part and the second is the conclusion part, which are connected to each other by fuzzy rules base in network form. The ANFIS structure shown in Fig. 1 is a five layer network. It can be described as a multi-layered neural network as shown in Fig. 1. The first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the MFs, the fourth layer executes the conclusion part of the fuzzy rules, and the last layer computes the output of the fuzzy system by summing up the outputs of layer four. The feedforward equations of the ANFIS structure with two inputs and