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Fault Diagnosis Method for Mobile Ad-Hoc Network by using smart Neural Networks

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Abstract

MANETs are dynamic collection of autonomous nodes that communicate with each other via wireless connections. One of the events that the network should have expected it to be a fault, and the behavior is more important, in this network. So that fault diagnosis can effect on final performance of the network in such a way that it does not fall under the negative impact of the fault. A non-linear neural network is a statistical method for modeling data or the tools to make decisions. Artificial neural network is a method for pattern recognition and classification. Error detection is a problem of categorization or classification. The use of neural networks can be useful in fault diagnosis in MANETs because of fault diagnosis is a classification problem. But one problem with this method is placed in a local optimum. Here a method based on the combination of the back-propagation algorithm, a local search algorithm and learning automata as efficient global search, is proposed. In the proposed method, the algorithm of learning automata adjusting learning rate on neural network according to given formula. For training and testing the neural network of the mobile network parameters that were measured, were used as input and output. The results show that the proposed method in terms of repeatability, reliability and lack of placement in a local optimum is better.

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Keywords: Neural Networks; Learning Automata; MANETs; Fault Diagnosis Systems

1. Introduction

Mobile ad hoc networks (MANETs) are self-organizing wireless networks, which can provide communication service in situations where infrastructure is either not available, not trusted, or should not be relied on in times of emergency[1,2].

Fault identification is one of the important part in many protocols. When the actual behavior is deviated by system or nodes of the system, a diagnosis function started to determine which node performed abnormal behavior that is called diagnosis[3]. Diagnosis is classified based on the occurrence of fault. Several diagnosis methods have been adopted based either on invalidation models, such as the PMC model, or comparison models, broadcast

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comparison model and the generalized comparison model[4]. The comparison model is most promising approaching which a set of task is assigned to nodes and outcomes are compared with their neighbor's outcomes. Various generalized comparison approach have been used.

Three types of diagnosis models have been studied in the context of system-level self-diagnosis: testing, comparison, and probabilistic models. Testing models, such as the classical PMC model[5,6], and its variations such as the BGM model[7] and the HK models[8], assume that each node is assigned a subset of the other units to test and the diagnosis is based on the collection of test outcomes. While, comparison models, such as the Malek's comparison model[9] and the Chwa-Hakimi comparison model[10], assume that a set of jobs is assigned to pairs of distinct units, and the results are compared. The outcomes of these comparisons, i.e., the matching and mismatching results, are used as a basis in order to identify the set of faulty nodes. Fault diagnosis under the testing and comparison models assumes in general a worst case behavior. Finally, probabilistic models[2] do not assume any bound, but instead, only fault sets that have a no negligible probability of occurrence are considered. In this paper, we consider the comparison-based diagnosis approach. The comparison approach has been introduced independently by Malek[9] and by Chwa and Hakimi[10] giving rise to two models. The Malek's model is known as the asymmetric comparison model and that of Chwa and Hakimi is called the symmetric comparison model. In both models it is assumed that two fault-free nodes give matching (0) results while a faulty and a fault-free node give mismatching (1) outcomes. The two models differ in the assumption on tests involving a pair of faulty nodes. In the symmetric model, both test outcomes (0=1) are possible in this case, while in the asymmetric model two faulty nodes always give mismatching outputs (1).

2. The Proposed Model

2.1. Backpropagation Algorithm

Error backpropagation training algorithm, which is an iterative gradient descent algorithm, is a simple way to train multilayer feed forward neural networks.5 The BP algorithm is based on the gradient descent rule:

$$W(\mathrm{n}+1) = \mathrm{W(n)} + \eta G(\mathrm{n}) + \alpha[\mathrm{W(n)} - \mathrm{W(n-1)}] \tag{1}$$

Where W is the weight vector, n is the iteration number, η is the learning rate, α is the momentum factor, and G is the gradient of error function that is given by:

$$G(\mathrm{n}) = -\nabla\, \mathrm{E}_p(\mathrm{n}) \tag{2}$$

E_p is the sum of squared error given by:

$$W(\mathrm{n}+1) = \mathrm{W(n)} + \eta G(\mathrm{n}) + \alpha[\mathrm{W(n)} - \mathrm{W(n-1)}] \tag{3}$$

Where Tp,j and Op,j are desired and actual outputs for pattern p at output node j. A major problem encountered during implementation of the BP learning rule is proper choice and update of the learning rate η to allow convergence, while keeping the number of required iterations at a reasonable number. One of the main reasons for investigating the possibility of the adaptive learning rate rule is the desire to reduce the sensitivity of the learning on the learning rate, without adding more tuning parameters.

2.2. Learning Automata

Learning automata (LA) can be classified into two main families, fixed and variable structure learning automata. Examples of the FSLA are Tsetline, Krinsky, TsetlineG, and Krylov automata. A fixed structure learning automaton is a quintuple (α, Φ, β, F, G) where: