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Decision tree approach for fault diagnosis of nonlinear

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Abstract: In this paper we proposed a decision tree approach for fault diagnosis of nonlinear systems using tree model CART (classification and regression trees) and MNN (multilayer neural network). In the proposed method, the fault is detected when the errors between the actual system output and the NN nominal system output cross a predetermined threshold. Once a fault in the nonlinear system is detected, CART is used for classifying the fault.

Keywords: CART , fault diagnosis, MNN, nonlinear system

1 INTRODUCTION

There have been many methods for fault diagnosis of the system. These methods fall into two major groups: 1) model free methods, 2) model based methods. The model based fault diagnosis methods are dependent on finding a system mathematical model that defines the relationship between the system inputs and outputs. In practice, however, the mathematical description of the relationship is not easy to obtain due to nonlinearities. To overcome this problem, it is necessary to find the modeling tool of presenting any nonlinear relationship approximately. In recent years, NN(neural network) models have been studied considerably for the fault diagnosis problem [1-3]. Main advantages of the NN model for fault diagnosis applications can be represented by approximating the nonlinear functions and by adaptive learning and parallel processing. Hence this model can be used as a powerful tool for handling nonlinear problems.

This paper presented a decision tree approach for fault diagnosis of nonlinear systems using tree model [4] and MNN [5]. In the proposed method, the fault is detected when the errors between the actual system and the NN nominal system output cross a predetermined threshold. Meanwhile CART is used for classifying the fault. The algorithm contains two main parts: a fault detection part by threshold test and a fault classification part by CART.

2 PROPOSED FAULT DIAGNOSIS METHOD USING NN AND CART

2.1 Fault detection using neural network

Consider a discrete-time nonlinear system,

$$\begin{aligned} y(k+1) = g[\, & y(k),\, y(k-1),\, \cdots, y(k-n+1), \\ & u(k),\, u(k-1),\, \cdots, u(k-m+1)] + \varepsilon(k) \end{aligned} \tag{1}$$

where $u(k)$ and $y(k)$ are the input and the output at time k , respectively, and $\varepsilon(k)$ is the white noise.

In the proposed method, NN nominal system is utilized to detect the fault in nonlinear system. Therefore, MNN`s with BP learning algorithm is adopted in this study [5].

Fault is detected by the following threshold test

$$J_n(k) = \sum_{i=k-L+1}^{k} e_n^2(i) \; > \; \delta_f \tag{2}$$

where $e_n(k) = y(k) - y_n(k)$ is the error between the nominal system output and actual system output. $y_n(k)$ is the NN nominal system output, δ_f is the predetermined threshold for fault detection, L is moving window length.

If the estimated parameters converge to system parameters, then the error between the system output and estimate NN output has a similar property of the system noise. Thus, the error e_n has a normal distribution. Also, the sum of the normalized square errors in the moving window has a χ_L^2 -distribution with L degrees of freedom as follows:

$$\bar{J}_n(k) = \sum_{i=k-L+1}^{k} \frac{e_n^2(i)}{\sigma^2} \; \sim \; \chi_L^2 \tag{3}$$

If the false-alarm probability limit α is

$$\Pr\Big(\sum_{i=k-L+1}^{k} \frac{e_n^2(i)}{\sigma^2} > \delta^\circ \Big) = \alpha \tag{4}$$

and the threshold is obtained as: $\delta_f = \sigma^2 \delta^\circ$

2.2 Fault classification using decision tree algorithm

The decision tree consists of two parts, tree building and tree pruning. In the stage of tree building the initial state of a decision tree, called the root node, is the first internal node, to which all the patterns of the training set are assigned. If the training example consists of all the same class, then there is only a need for the root node. Conversely, if the training examples at the root node consist of two or more classes, a test node is made that will split the training set into two sub-spaces, or secondary nodes. These can either become terminal nodes, in which a classification is reached, or another test node. The process is recursively repeated until each branch results in a terminal node and a completely discriminating tree is obtained.

The tree obtained by the tree building step may have a large number of branches which substantially increase the tree's complexity. This could lead to encountering the familiar problem of over-fitting and overspecializing toward the training data. If that happens, the tree may not generalize well for new data sets and thus it is necessary to prune the tree to build smaller tree models. CART uses a tree pruning technique based on the principle of minimal cost complexity pruning which is also known as weakest sub-tree shrinking.

3 SIMULATION RESULTS

The nonlinear system is given as

$$\begin{aligned} y(k) &= \cos(3.14\, p_1)\, y(k-1) - 0.7\, y(k-2) \\ &\quad + u(k-1) + p_2\, u(k-2) + \varepsilon(k) \end{aligned} \tag{5}$$

where, input $u(k) = 0.5\cos(k)$, $\varepsilon(k)$ is white noise with variance $\sigma^2 = 2.56*10^{-4}$, p_1 and p_2 are physical parameters and $p_1 = 0.56$, $p_2 = 0.37$. Here, we choose $\alpha = 0.01$ (1%) and L=30, fault threshold $\delta_f = 0.013$. NNs for fault detection is consists of 4 inputs, one hidden layer with 10 nodes, and one output node. The weights of the NN are adjusted at every time step using a learning rate $\eta = 0.15$, and momentum term $\alpha = 0.1$.

To verify the proposed diagnosis algorithm, one type of fault is the introduced to the system at the 150-th sample number. The following fault is simulated

Fault #1: p_1 is decreased ($p_1 = 0.35$)

The prepared 20 data sets for each system condition (normal, fault #1) were used for training of CART. Fig. 1 shows a classification tree built by CART taking the 15 input data.

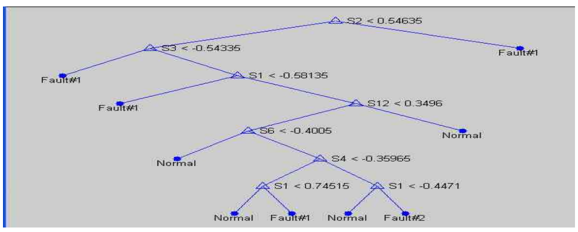
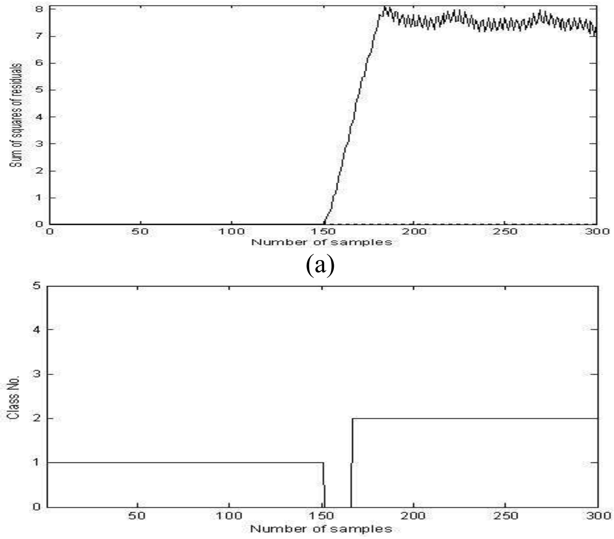


Fig. 1. Trained CART classification tree.

Fig. 2(a) shows the variations of the sum of squares of errors in the moving window, and 2(b) plots fault isolation results by CART. The simulation results show that CART successfully isolates the fault of the nonlinear system.



(a)

(b)

Fig. 2. Results of detection and isolation for fault #1.
(a) Change of J_n and fault detection (dashed line: δ_f)
(b) Classification results by CART

4 CONCLUSION

In this work, we develop a fault diagnosis method using CART and MNN to detect and isolate faults in nonlinear systems. The decision tree is proficient at both maintaining the role of dimensionality reduction and at organizing optimally sized classification trees, and therefore it could be a promising approach to diagnose a fault which is occurred in the systems. Simulations are carried out to evaluate the performance of the proposed NN-based diagnosis method.

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