Fault Diagnosis from Nonlinear Time Series Using Time Delay Neural Network

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Fault Diagnosis from Nonlinear Time Series Using Time Delay Neural Network

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A fault diagnosis scheme for nonlinear time series recorded in normal and abnormal conditions is proposed. The fault is first detected from regression lines plotted for the raw time series. Model for the normal time series is estimated using a Finite Impulse Response (FIR) neural network. The trained network is then used for inverse filtering of abnormal time series. The fault is further confirmed/analyzed using the regression lines of the predicted normal and inverse-filtered abnormal conditions time series.

The proposed scheme is tested with a fault diagnosis problem using acoustic data obtained from moving parts of an automobile.

Keywords: Fault diagnosis, linear regression, neural network.

1 INTRODUCTION

In many scientific, economic, and engineering applications there arises the problem of system identification and modeling of nonlinear time series. Once the model is made it can be used either for prediction, fault diagnosis, pattern recognition, or pattern classification.

The information about a dynamic process is often only partial and incomplete. In many real-world problems, data are masked by noise and some dynamic processes are described by chaotic time series in which the data seem to be random without apparent periodicity (1). The Neural Network (NN), being able to acquire knowledge by a learning process and store in massively parallel/distributed synaptic weights, can solve complex problems that are intractable. The NNs are successfully used in fields like modeling, time series analysis, pattern recognition, signal processing, and control.

A kind of neural network, that has short-term memory in the form of *tapped delay lines*, known as time delay neural network (TDNN) has been used in speech processing (2, 3). A class of TDNN, that uses *finite-duration impulse response* (FIR) filters in its synaptic connections between the layers, known as FIR network has been used in time series prediction (4, 5). System identification is also performed using general parameter (GP) neural networks (6, 7).

In this paper a fault diagnosis scheme for nonlinear time series data is proposed. The fault is detected from regression lines of the raw and filtered time series where FIR network is used for modeling and inverse filtering of the time series. The proposed scheme is applied to a fault diagnosis problem using acoustic data obtained in normal and abnormal conditions from moving parts of an automobile.

The paper is organized as follows: Details of linear regression modeling are given in Section 2. Section 3 introduces neural networks and its type FIR network used in this study. Section 4 elaborates the scheme of fault diagnosis using FIR network and its application to acoustic data recorded from mov-

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ing parts of an automobile. Section 5 concludes the paper after discussing the results and future work. Finally, Section 6 summarizes the whole study.

2 LINEAR REGRESSION MODEL

In many problems two or more variables are inherently related, and it is necessary to explore the nature of this relationship. *Regression analysis* is a statistical technique for modeling and investigating the relationship between two or more variables. In the case of *simple linear regression* a single *regressor* or *predictor* x and a *dependent* or *response* variable y is considered. Supposing true relationship between y and x as a straight line and that the observation y at each level of x is a random variable, the observation y can be described by the model

$$y = \beta_0 + \beta_1 x + \epsilon \qquad (1)$$

where intercept β_0 and the slope β_1 are unknown regression coefficients, and ϵ is a random error with mean zero and variance σ^2. The criterion for estimating the regression coefficients is called as *method of least squares*. The fitted or estimated regression line or trend from [8] is therefore

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \qquad (2)$$

where $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 x$, $\hat{\beta}_1 = [\sum_{i=1}^{n} y_i(x_i - \bar{x})^2]/[\sum_{i=1}^{n}(x_i - \bar{x})^2]$, $\hat{y}$ is the estimated linear regression line values, $\bar{y} = \frac{1}{2}\sum_{i=1}^{n} y_i$, and $\bar{x} = \frac{1}{2}\sum_{i=1}^{n} x_i$.

3 NEURAL NETWORKS APPROACH

Neural networks are typically used in pattern recognition, where a collection of features (such as an image) is presented to the network, and the task is to assign the input feature to one or more classes. Another typical use for NN is (nonlinear) regression, where the task is to find a smooth interpolation between points. The time series modeling involves processing of patterns that evolve over time, i.e. the appropriate response at a particular point in time depends not only on the current value of the observable but also on the past.

The main advantage of the neural network is that it enables us to approximate or reconstruct any nonlinear continuous function $F(.)$, therefore such a model is more general and flexible. A general view of a neural network is given in Fig. 1. Many researchers [9, 10] have used NN for time series prediction. In all these cases, temporal information is presented spatially to the network by a time-lagged vector (also called tapped delay line).

3.1 Time Delay Neural Network

The neural network having tapped delay lines placed between the input and hidden layers of a neural network is generally known as a time delay neural network (TDNN). The TDNN maintains a history of its n most recent values, and these values are available to the next layer. A typical connection between input and hidden layers of a TDNN is shown in Fig. 2, where u_i and h_j are the ith and jth neurons of input and hidden layers respectively, and d_n shows the nth times delayed input data. For the latest input in time the delay tag is not shown in Fig. 2. Separate weights are used for each delay line. The TDNNs have been used in speech recognition [2, 3].

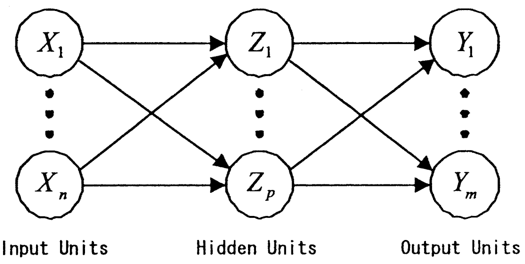

Fig. 1. A typical neural network with one hidden layer.

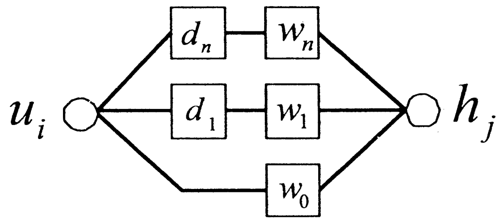

Fig. 2. A typical synaptic connection between input and hidden layers of a TDNN.

3.2 FIR Network

In case of TDNNs the combination of unit delay elements and associated weights may be viewed as a *finite-duration impulse response* (FIR) filter. The networks having such filters are called as FIR networks. In this section training procedure [4] of FIR network is described.

In order to understand clearly, a single neuron extracted from the lth layer of an L-layer static feedforward neural network is represented in the Fig. 3. The output of the neuron, x_j^{l+1}, is taken as a sigmoid function of the weighted sum of its inputs:

$$x_j^{l+1} = f\left(\sum_i w_{i,j}^l x_i^l\right) \qquad (3)$$

where x_i^l and $w_{i,j}^l$ are inputs and weights of the neuron, respectively.

A modification of the basic neuron can be accomplished by replacing each static synaptic weight by a FIR linear filter as shown in Fig. 4. By FIR we mean that for an input excitation of finite duration, the output of the filter will also be of finite duration. The most basic FIR filter can be modeled with a tapped delay line as illustrated in Fig. 5. For this filter, the output $y(k)$ corresponds to a weighted sum of the past delayed values of the input:

$$y(k) = \sum_{n=0}^{T} w(n)x(k-n) \qquad (4)$$

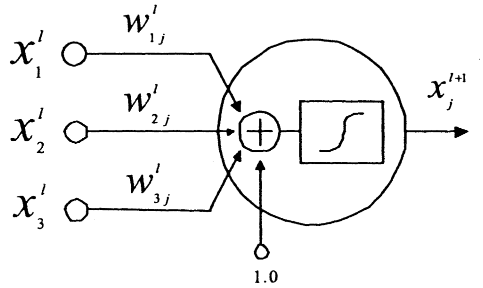

Fig. 3. Static neuron model (feedforward path).

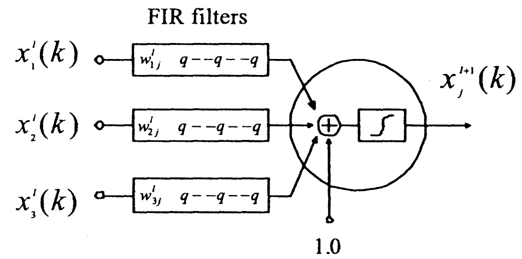

Fig. 4. FIR neuron model (feedforward path).

It may be noted that this corresponds to the *moving average* component of a simple auto-regressive moving average (ARMA) model [10].

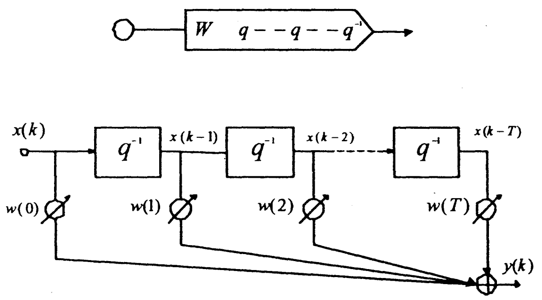

Fig. 5. FIR filter model.

The weight vector for the synaptic filter connecting neuron i to neuron j in layer l is denoted by $w^l_{i,j} = [w^l_{i,j}(0), w^l_{i,j}(1), \ldots, w^l_{i,j}(T^l)]$. Similarly the vector of delayed inputs along the synaptic filter is $x^l_i(k) = [xl_i(k), xl_i(k-1), \ldots, xl_i(k-T^l)]$. Hence the operation of the filter can be expressed as dot product $w^l_{i,j} \cdot x^l_i(k)$. The feedforward response of the FIR network can be written as,

$$x^{l+1}_j(k) = f\left(\sum_i w^l_{i,j} x^l_i(k)\right) \qquad (5)$$

where $x^{l+1}_j(k)$ is the output of a neuron in layer l at time k taken as the sigmoid function of the sum of all filter outputs that feed the neuron. Comparing Equations (1) and (3) it may be observed that the scalars are replaced by vectors. As contrast to standard error backpropagation [11] used in static feedforward neural networks, *temporal backpropagation* is used in FIR networks. The feedback path of selected static and FIR neurons are shown in Figs. 6 and 7, respectively. The final algorithm of temporal backpropagation can be summarized as:

$$w^l_{ij}(k+1) = w^l_{ij}(k) - \eta\sigma^{l+1}_j(k) \cdot x^l_i(k) \qquad (6)$$

$$\sigma_j\ l(k) = \begin{cases} -2e(k)f'(s^L_j(k))) & l = L \\ f'(s^L_j(k)) \cdot \sum_m^{N_{l+1}} \bar{\delta}^{l+1}_m(k) \cdot w^l_j m & 1 \le l \le L-1 \end{cases}$$

where $e_j(k)$ is the error at an output node, $f'()$ is the derivative of the sigmoid function, and $\bar{\delta}^l_m(k) \equiv [\delta^l_m(k)\delta^l_m(k+1)\ldots\delta^l_m(k+T^{l-1})]$ is a vector of propagated gradient terms. It may be noticed that these equations are seen as the vector generalization of the familiar backpropagation algorithm. Complete derivation of the above algorithm is given in [4, 12].

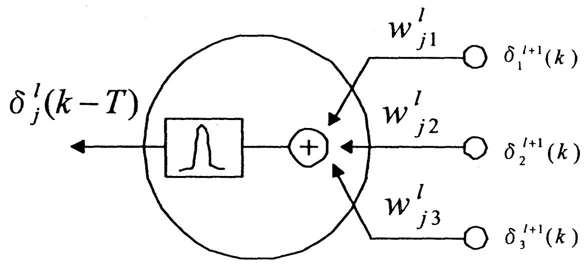

Fig. 6. A static neuron model (feedback path).

4 FAULT DIAGNOSIS SCHEME

A fault diagnosis scheme [13] using nonlinear time series is proposed in which the fault is first detected using regression lines of the raw time series recorded in normal and abnormal conditions. Both of the time series are then normalized for the range -1 to +1. The normalized normal condition data are used to train a FIR network. The trained network is

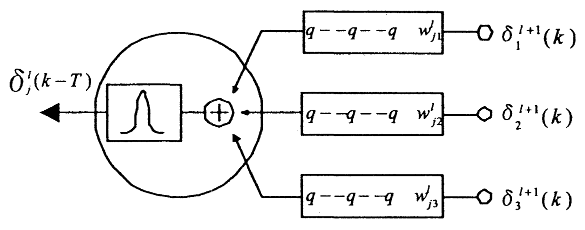

Fig. 7. A FIR neuron model (feedback path).

then used for inverse filtering the abnormal condition data. The regression lines plotted for predicted normal condition data and inverse-filtered abnormal condition data are used to further diagnose the fault.

The proposed scheme is tested with a fault diagnosis problem using acoustic data recorded from moving parts of an automobile.

4.1 Fault Diagnosis Scheme applied to Acoustic Data

The proposed scheme is applied to a fault diagnosis problem using normal and abnormal conditions acoustic data recorded from moving parts of an automobile. Regression lines of the raw data plotted using the least square method described in section 2 are shown in Fig. 8. The difference in the amplitude and behavior of these lines clearly indicate the existence of a fault.

Before model estimation, the two time series are passed through a moving average filter, of window size 3, to remove the noise without loosing the peaks. Initial 100 values of raw and filtered normal and abnormal conditions data are shown in Figs. 9 and 10, respectively. Both of the filtered time series are then normalized for -1 to +1, as shown in Figs. 11 and 12, respectively.

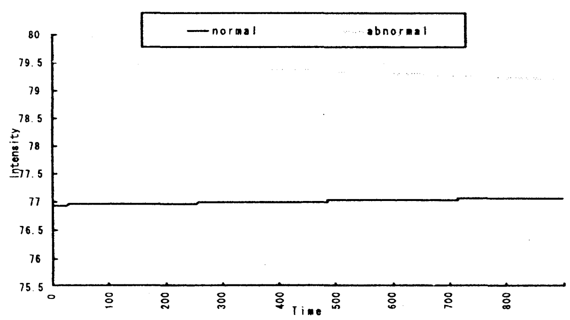

Fig. 8. Regression lines of the raw time series.

In this study the FIR network is used to estimate the model for normal condition data reason being its short-term dynamic memories available in the form of FIR filters. While using FIR networks selection of number of layers and taps per layer is quite critical. After performing several simulations the best network structure is selected when the mean squared error (MSE) is low and prediction is good after 10,000 epochs of training.

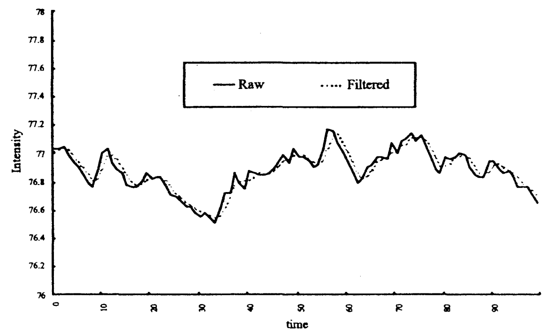

Fig. 9. Initial 100 values of raw and filtered normal condition data.

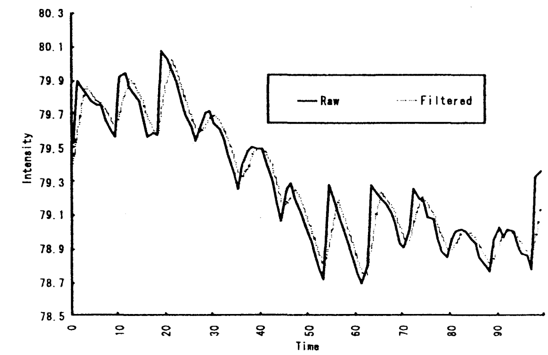

Fig. 10. Initial 100 values of raw and filtered abnormal condition data.

The selected set of layers/taps for the normal condition data modeling is given in Table 1. The MSE after 10,000 epochs of training at different set of taps are shown in Fig. 13 where hidden node taps are set to 3. The FIR network with the best set of layer/taps is then trained for up to 30,000 epochs. Initial 900 points of normal condition data are used for training and the next 100 data are used for validation. The input and predicted output of a trained network for normal condition data are shown in Fig. 14. It can be noticed from this figure that the predicted data follow the training data but for the validation data set the error becomes high but it follows the pattern. Good learning for the training data set is of prime importance in the proposed scheme. The trained network is then used to predict the normal condition data. The trained network is also used to inverse-filter the abnormal condition data. The inverse-filtered abnormal condition data are shown in Fig. 15. The regression lines are plotted for predicted normal and inverse-filtered abnormal conditions data as shown in Fig. 16. A significant difference in the two lines confirms the existence of the fault that is first detected from the observation of the regression lines for the raw time series (see Fig.

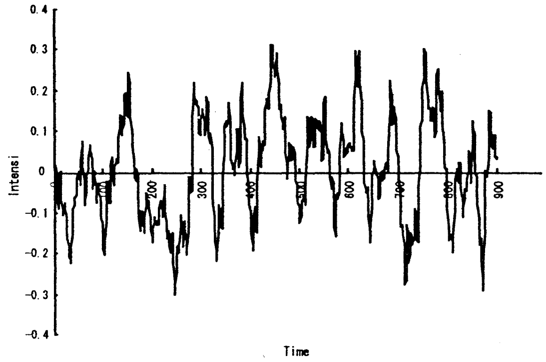

Fig. 11. . The normalized normal condition data.

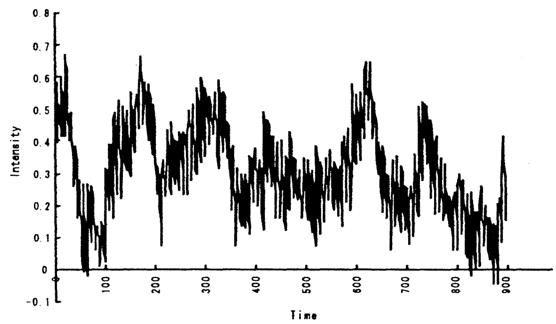

Fig. 12. The normalized abnormal condition data.

8). The fault is more clearly visible in Fig. 16, so it can be said that the sensitivity of the fault detection using regression lines increases by the use of FIR network.

Table 1. FIR Network structure for acoustic normal condition data

Network Parameters	Value
Layers	2
Input Node	1
Input Taps	10/node
Hidden Nodes	30
Hidden Taps	3/node
Output Node	1
Epochs	30,000
MSE	0.000113998

5 CONCLUSION

A fault diagnosis scheme is proposed where the fault is first detected from the regression lines of the raw time series. The fault is then confirmed and analyzed from the regression lines of the predicted normal and inverse-filtered abnormal conditions time series. The process of inverse filtering the abnormal condition data, through the FIR network

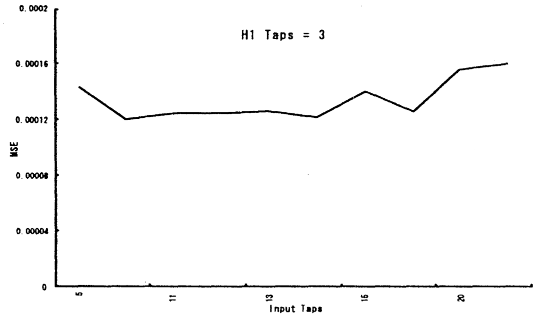

Fig. 13. MSE after 10,000 epochs training of normal condition data.

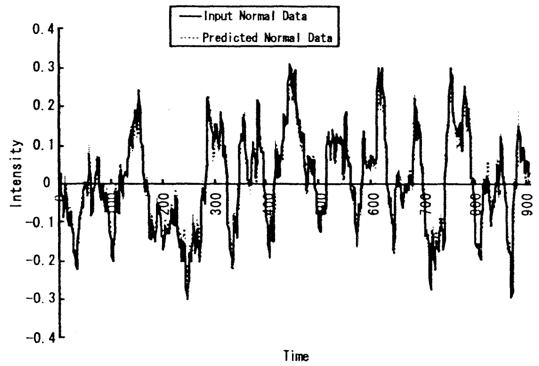

Fig. 14. Input and predicted output of the network trained with normalized normal condition data.

trained for normal condition data, is adopted in order to make sure that the two available time series are different from each other. It provides more detailed information about fault.

The selected set of layers and taps for the FIR network is good for only this application. To estimate model for any other time series new simulations would be needed. Window size 3 for the moving average pre-filter is selected randomly. A bigger window size would result in better filtering hence better modeling.

6 SUMMARY

In this paper a fault diagnosis scheme for nonlinear data set recorded in normal and abnormal conditions is proposed. The fault is first detected from regression lines, plotted using least square method, for the raw time series. Model for the normal time series is then estimated using a FIR network. The trained network is used for predicting the normal condition data and inverse filtering the abnormal condition data. The fault is further confirmed/analyzed using the linear regression lines of the predicted normal and inverse-filtered abnormal conditions time series.

The proposed scheme is successfully applied to a fault diagnosis problem using acoustic time series

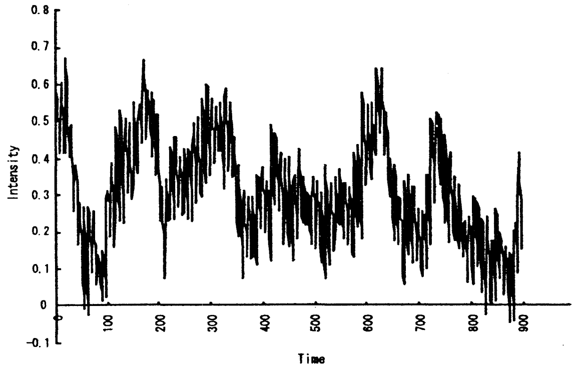

Fig. 15. Inverse-filtered abnormal condition data.

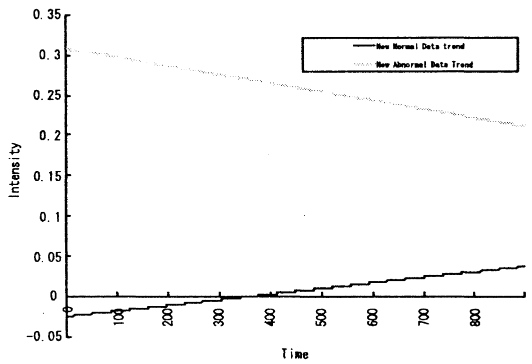

Fig. 16. Linear regression lines of the predicted normal and inverse-filtered abnormal conditions data.

obtained from moving parts of an automobile.

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非線形時系列データを使用した遅延時間ニューラルネットワークによる故障診断

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概要

記録された正常･異常の非線形時系列データに対する故障診断技術に関しての提案である。故障はまず、生データから線形回帰傾向によって検知した。時系列のモデルはFinite Impulse Response (FIR)ニューラルネットワークで構成されている。学習されたネットワークは、その後異常時系列データの逆フィルタとして使用している。故障は更に、予測した正常時系列データと逆フィルタをかけた異常時系列データを使用し､線形回帰傾向を用いて分析した。その応用として、実際に自動車トランスミッションギアの傷の検出を行った研究について記してある。

キーワード：故障診断、線形回帰傾向、ニューラルネットワーク

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