AN EMPIRICAL APPLICATION OF LINEAR REGRESSION METHOD AND FIR NETWORK FOR FAULT DIAGNOSIS IN NONLINEAR TIME SERIES

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ABSTRACT

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

The described scheme is applied to two fault diagnosis problems using acoustic and vibration data obtained from rotating parts of an automobile and a boring tool, respectively.

Keywords: ***Signal Processing, Filtering, Fault Diagnosis, Linear Regression, Neural Network.***

1.0 INTRODUCTION

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

Very often in practice a relationship is found to exist between two (or more) variables in an unknown system. It is frequently desirable to express this relationship in mathematical form by determining an equation connecting the variable. If the relationship between the variables is linear then a straight line can approximate the given set of data. If it is nonlinear then the approximated curve would be a nonlinear curve e.g. parabola or hyperbola etc.

Signal processing techniques have been studied deeply in both frequency and time domains. It has been reported that the Fast Fourier Transform does not provide good frequency resolution and its windowing process causes spectral leakage in the frequency domain [1]. The parameter modeling techniques such as Yule's auto-regressive technique [2] has been used widely in prediction of the future values. However, there are simple cases, for which this technique is inadequate [3].

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 [4]. The Neural Network (NN), being able to acquire knowledge by a learning process and store in massively parallel/distributed synaptic weights, can solve such complex problems that are intractable. The NNs are successfully used in fields like modeling, time series analysis, pattern recognition, signal processing, and control.

While using NN for system identification, the sample data modify parameters in the neural estimator and bring the neural system's input-output responses closer to the input-output response of the unknown model [5]. System identification is also performed using general parameter (GP) neural networks [6, 7].

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 [8, 9]. A class of TDNN that uses *finite-duration impulse response* (FIR) filters in its input and hidden layers, known as FIR network, are used in time series prediction [10, 11].

In this paper a fault diagnosis scheme [12, 13] for nonlinear time series is described. The fault is detected from regression lines of the raw and filtered time series, where FIR network is used for modeling and filtering the time series. The described scheme is applied to parts/tool breakage detection problems using acoustic and vibration data obtained in normal and abnormal conditions from rotating parts of an automobile and a boring tool, respectively.

The paper is organized as follows: Details of linear regression model are given in Section 2. Section 3 introduces standard neural network and FIR network. Section 4 elaborates the scheme of fault diagnosis using linear regression model and FIR network and its application to parts/tool breakage detection problems. Section 5 concludes the paper after discussing the results and future work.

2.0 LINEAR REGRESSION MODEL

Regression analysis is statistical techniques for modeling and investigating the relationship between variables embedded in an unknown system. In the case of *simple linear regression* a single *regressor* or *predictor* x and a dependent or *response* variable y is considered. For linear relationship the model is:

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

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 [14] is therefore

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

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

3.0 NEURAL NETWORK PPROACH

A typical use of 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. A general view of a neural network is given in Fig. 1.

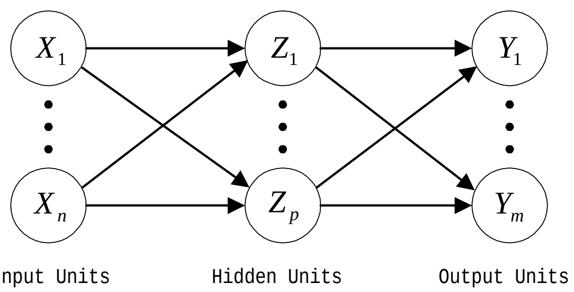

Fig. 1: A Typical Neural Network with One Hidden Layer

3.1 System Identification Using Neural Network

Suppose $d = f(x)$ describes the input-output relation of an unknown time invariant *multiple input-multiple output (MIMO) system.* Let y_i denotes the output of the neural network produced in response to an input vector x_i. The difference between d_i (associated with x_i) and the network output y_i provides the error signal vector e_i, as depicted in Fig. 2. This error signal is in turn used to adjust the free parameters of the network to minimize the squared difference between the outputs of the unknown system and the neural network in a statistical sense, and is computed over the entire training set.

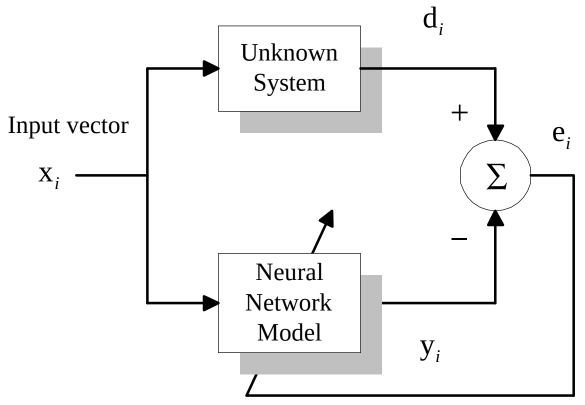

Fig. 2: Block Diagram of System Identification Using Neural Network

3.2 Finite-Duration Impulse Response (FIR) Filter Network

To understand the function of a FIR network, a single neuron extracted from the *l*th layer of an *L*-layer static feedforward neural network adopted from [11] 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. For the simple FIR filter, the output $y(k)$ corresponds to a weighted sum of the past delayed values of the input:

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

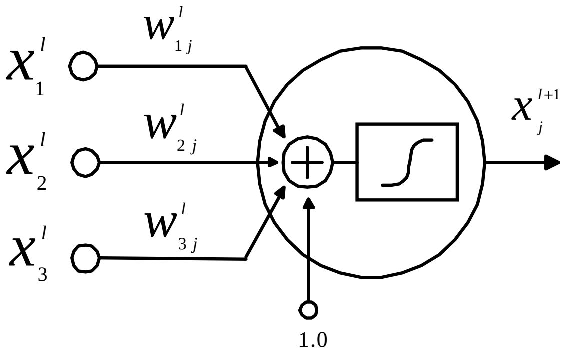

Fig. 3: A Static Neuron Model (Feedforward Path)

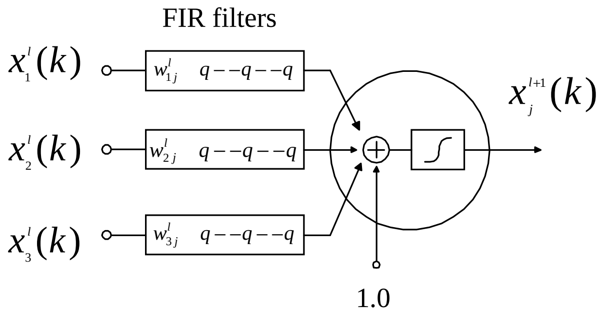

Fig. 4: A FIR Neuron Model (Feedforward Path)

The feedforward response of the FIR network can be written as:

$$x_j^{l+1}(k) = f\left(\sum_i w_{i,j}^l \cdot x_i^l(k)\right) \tag{5}$$

where $x_j^{l+1}(k)$ 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 3 and 5 we may note that the scalars are replaced by vectors. As contrast to standard error backpropagation [15] used in static feedforward neural networks, *temporal back-propagation* is used in FIR networks. The feedback path of selected static and FIR neurons are shown in Figs. 5 and 6, respectively. Complete detail of FIR network is given in [11, 16].

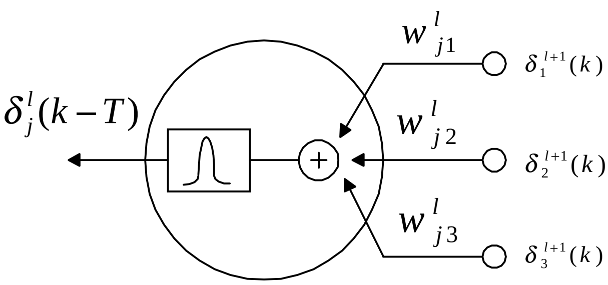

Fig. 5: A Static Neuron Model (Feedback Path)

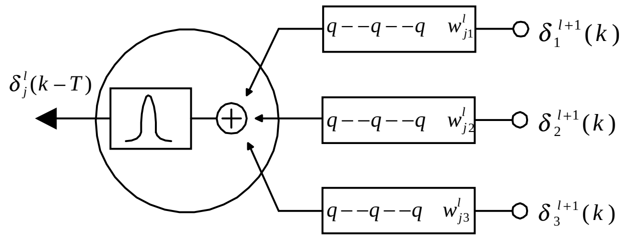

Fig. 6: A FIR Neuron Model (Feedback Path)

4.0 FAULT DIAGNOSIS SCHEME

In the fault diagnosis scheme proposed in [12, 13] the fault is first detected from regression lines of the raw time series, obtained in normal and abnormal conditions, using least square method described in Section 2. Model of the normal condition time series is then estimated using FIR 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 condition time series and inverse-filtered abnormal condition time series.

The above described fault diagnosis scheme is applied to parts/tool breakage detection problems using acoustic data obtained from rotating parts of an automobile and vibration data recorded from a boring tool.

4.1 Rotational Parts Breakage Detection Using Acoustic Data

The described scheme is applied to an automobile's rotating parts breakage detection problem using acoustic data recorded in normal and abnormal conditions through Integrated Sound Level Meter LA-5110, as shown in Fig. 7. Regression lines (Fig. 8) are first plotted for the raw data, using Equation 2, where a significant difference in the amplitude clearly demonstrates the existence of a fault.

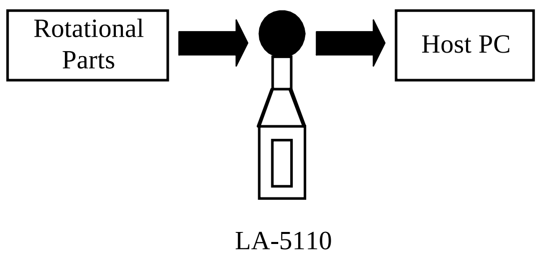

Fig. 7: Rotational Parts Fault Diagnosis Experimental Setup

In this study the FIR network is used to estimate the model for normal condition data. Before model estimation, the two time series are normalized for the range -1 to +1. While using FIR networks, selection of number of layers and taps per layer is quite critical. After performing several simulations the best set of number of layers and taps is selected where the mean squared error (MSE) is low and prediction is good after 10,000 epochs of training. The MSE pattern for the training set of normal condition data is shown in Fig. 9, which clearly indicates that the error goes to zero in around 20 epochs of training. The network with the best set of layer/taps is then trained for up to 30,000 epochs. The selected network structure for acoustic normal condition data with final MSE is given in Table 1.

In total we have 1000 points data. Initial 900 points of normal condition data are used for training and the next 100 data points are used for validation. The input and output of a trained network for normal condition data are shown in Fig. 10, where model estimation capability of a FIR network of an unknown system is quite visible. The predicted data almost follows the training data. The tapped delay lines in FIR network provide short-term dynamic memory for input data that eventually help in better modeling and prediction of data.

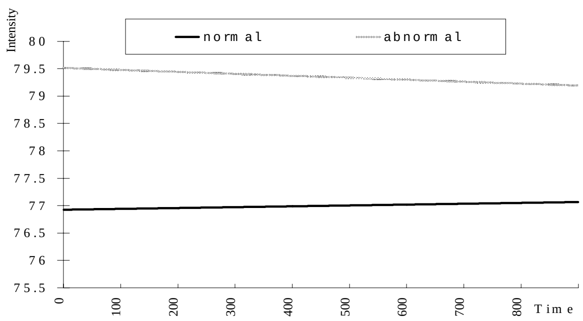

Fig. 8: Regression Lines of the Raw Acoustic Data

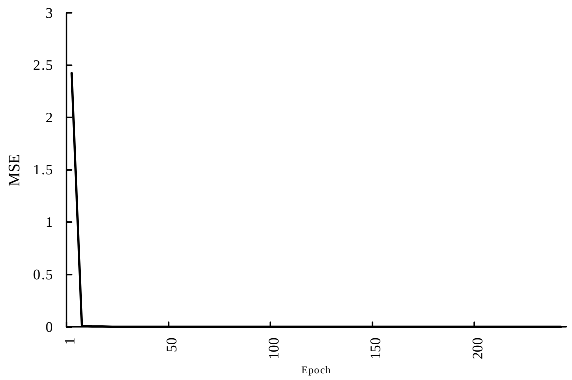

Fig. 9: MSE Pattern for Training Set of Acoustic Normal Condition Data (900 Points)

The normalized abnormal condition time series data are then fed into the FIR network trained for normal condition data. This process may be called as inverse filtering. We adopted this process in order to differentiate clearly between normal and abnormal conditions time series. The regression lines (Fig. 11) for the predicted normal condition data and the inverse filtered abnormal condition data, are then plotted using Equations 2. A significant difference in these two lines confirms the existence of the fault that was first detected from the observation of the linear regression lines of the two original time series (Fig. 8).

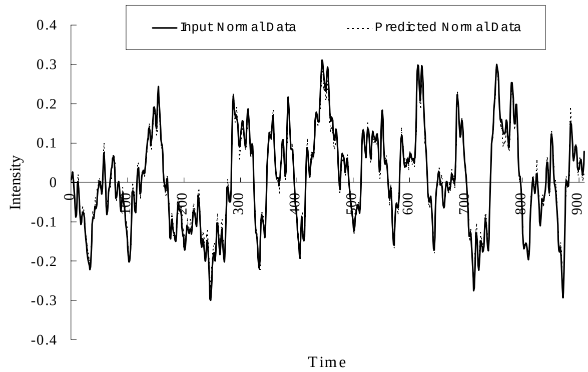

Fig. 10: Input and Output of the Network Trained with Normal Condition Acoustic Data

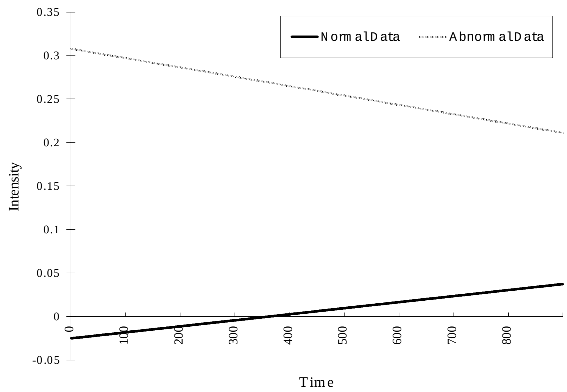

Fig. 11: Regression Lines of the Predicted Normal Condition and Inverse-Filtered Abnormal Condition Acoustic Data

4.2 Boring Tool Breakage Detection Using Vibration Data

The described scheme is applied a boring tool breakage detection problem. An accelerometer (PV-65) is used to acquire the vibration data in normal and abnormal conditions. The data acquisition scheme is shown in Fig. 12. Regression lines are first plotted for the raw data using Equation 2, as shown in Fig. 13. Significant differences in the amplitudes and shapes of these lines clearly exhibit the existence of a fault.

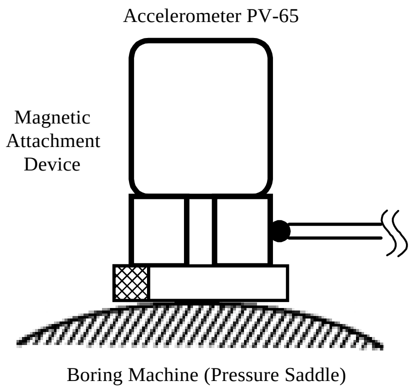

Fig. 12: Boring Machine Fault Diagnosis Experimental Setup

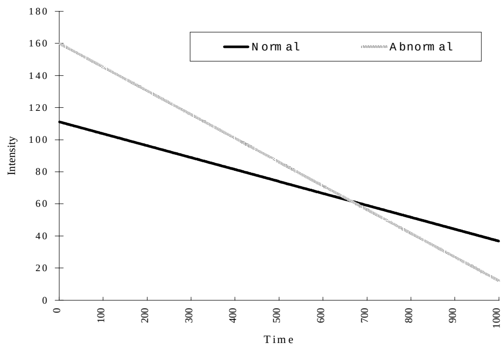

Fig. 13: Regression Lines of the Raw Vibration Data

The FIR network is then used to estimate the model for normal condition data. Before model estimation both the normal and abnormal conditions time series data are normalized for the range -1 to +1. Out of total 1000 data points, initial 900 points of the normal condition data are used for training and the remaining 100 data points are used for validation as in the case of acoustic data. The MSE pattern for the training set of normal condition data is shown in Fig. 14, where it can be observed that error signal goes to zero in around 10 epochs of training.

The network with the best set of layers/taps, selected after rigorous simulation, is trained for up to 30,000 epochs. The selected FIR structure for modeling the normal condition vibration data is given in Table 1, where we can notice that only 15 taps in the input layer were enough to model the vibration data as compare to 30 taps in the case of acoustic data. The input and the predicted output of a trained network for normal condition data are shown in Fig. 15 where the model estimation capability of FIR network is again clearly visible.

Table 1: FIR Network Structures for Acoustic and Vibration (Normal Condition) Data

Network Structure	Acoustic Data	Vibration Data
Layers	2	2
Input Node	1	1
Input Taps	10/node	18/node
Hidden Nodes	30	15
Hidden Taps	3/node	3/node
Output Node	1	1
Epochs	30,000	30,000
MSE	0.000113998	0.00401513

The normalized abnormal condition time series data are then inverse filtered through the FIR network. The regression lines for the time series, i.e. predicted normal condition data and filtered abnormal condition data, are shown in Fig. 16. Again a significant difference in the two lines confirms the existence of the fault that was first detected from the observation of the regression lines of the two original time data (Fig. 13).

Fig. 14: MSE Pattern for Training Set of Normal Condition Vibration Data (900 points)

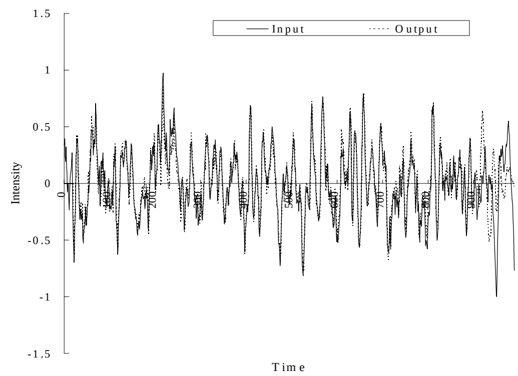

Fig. 15: Input and Output of the Network Trained with Normal Condition Vibration Data

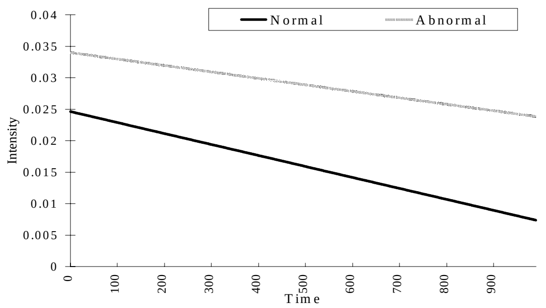

Fig. 16: Regression Lines of the Predicted Normal Condition and Inverse-Filtered Abnormal Condition Vibration Data

5.0 CONCLUSION

The described fault diagnosis scheme is applied to two real-world problems using acoustic and vibration data recorded from rotating parts of an automobile and a boring tool. Initial fault detection using regression lines of the raw data are confirmed from the regression lines of the predicted normal and filtered abnormal conditions' data. The process of filtering the abnormal condition data, through the FIR network trained for normal condition data, provides more detailed information about the fault. Hence it can be said that the described fault diagnosis scheme is suitable for the given two fault diagnosis problems. The FIR network is found suitable for model estimation of unknown systems, which may be helpful for other applications such as pattern recognition, etc.

To achieve better approximation of the unknown system some preprocessing or filtering technique e.g. moving average or median filter may be helpful.

The selected FIR network structure is good only for the used application. To estimate model for other data fresh simulation would be needed.

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BIOGRAPHY

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