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Integrated built-in-test false and missed alarms reduction based on forward infinite impulse response & recurrent finite impulse response dynamic neural networks

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A B S T R A C T

Built-in tests (BITs) are widely used in mechanical systems to perform state identification, whereas the BIT false and missed alarms cause trouble to the operators or beneficiaries to make correct judgments. Artificial neural networks (ANN) are previously used for false and missed alarms identification, which has the features such as self-organizing and self-study. However, these ANN models generally do not incorporate the temporal effect of the bottom-level threshold comparison outputs and the historical temporal features are not fully considered. To improve the situation, this paper proposes a new integrated BIT design methodology by incorporating a novel type of dynamic neural networks (DNN) model. The new DNN model is termed as Forward IIR & Recurrent FIR DNN (FIRF-DNN), where its component neurons, network structures, and input/output relationships are discussed. The condition monitoring false and missed alarms reduction implementation scheme based on FIRF-DNN model is also illustrated, which is composed of three stages including model training, false and missed alarms detection, and false and missed alarms suppression. Finally, the proposed methodology is demonstrated in the application study and the experimental results are analyzed.

1. Introduction

State identification is a critical issue in mechanical systems for automatic manufacturing, fault diagnosis, and prompt maintenance [1]. Built-in test (BIT) is an assortment of on-board hardware or software elements, serving as an online means to detect and identify the current system state [2,3]. A BIT design is supposed to guarantee a high quality of testing with high targeted state coverage and low incorrect indications. However, the false and missed alarm problem has long been troublesome for the BIT operators and beneficiaries [4–6]. A false alarm refers to the BIT alarm that is given when the targeted state does not really occur [7]. A missed alarm refers to the BIT missing detections when a targeted state has already occurred [8]. Both alarms can be regarded as transient states [9]. Intense false and missed alarms would reduce diagnosis accuracy and system availability, and the cost of making incorrect decisions would be very high [10,11].

The method of direct comparison of the monitoring signal value with the pre-determined threshold is universally used in BIT designs. However, the false and missed alarms of BITs in mechanical systems occurs frequently due to the fluctuations of monitoring signals. Some typical conventional BITs emerged to ameliorate the situation, including delayed tests, repeated

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Acronym

BIT	built-in tests
ANN	artificial neural networks
DNN	dynamic neural networks
RNN	recurrent neural networks
KNN	k-nearest neighbor
IIR	infinite impulse response
FIR	finite impulse response
FIRF-DNN	forward IIR & recurrent FIR dynamic neural networks
SVM	support vector machine
FAR	false alarm rate
FATP	false alarm time proximity
MAR	missed alarm rate
MATP	missed alarm time proximity

Notation

n_1	input data dimension
n_2	hidden neuron numbers
n_3	output data dimension
N	maximum delays of IIR filters (i.e. IIR slide window length minus 1)
M	maximum delays of FIR filters (i.e. IIR slide window length)
$\mathbf{x}^{(1)}[t] = [x_j^{(1)}[t]]_{n_1\times 1}$	input vector at time t of input layer
$\mathbf{w}^{(2)} = [w_{k,j}^{(2)}]_{n_2\times(n_1+n_2+1)}$	weight matrix of hidden layer
$\mathbf{w}^{(3)} = [w_{l,k}^{(3)}]_{n_3\times(n_2+1)}$	weight matrix of output layer
$\mathbf{a} = [a_{T,j}]_{(N+1)\times n_1}$	parameter matrix of IIR module
$\mathbf{b} = [b_{S,k}]_{M\times n_2}$	parameter matrix of FIR module
$\mathbf{u}^{(out)}[t] = [u_j^{(out)}[t]]_{n_2\times 1}$	output vector of IIR filters at time t
$\mathbf{u}^{(IIR)}[t] = [u_j^{(IIR)}[t]]_{(n_2+1)\times 1}$	output vector of IIR module at time t
$\mathbf{v}^{(out)}[t] = [v_k^{(out)}[t]]_{n_2\times 1}$	output vector of the FIR filters at time t
$\mathbf{v}^{(FIR)}[t] = [v_k^{(FIR)}[t]]_{n_2\times 1}$	output vector of the FIR module at time t
$\mathbf{p}^{(2)}[t] = [p_k^{(2)}[t]]_{n_2\times 1}$	vector after multiplying $\mathbf{u}^{(IIR)}[t]$ and $\mathbf{w}^{(2)}$ in hidden layer
$\mathbf{q}^{(2)}[t] = [q_k^{(2)}[t]]_{n_2\times 1}$	output vector of hidden layer at time t in hidden layer
$\mathbf{y}[t] = [y_l^{(3)}[t]]_{n_3\times 1}$	output vector at time t of output layer
$f(\cdot)$	activation function
$g(\cdot)$	derivative of activation function
$\tilde{\mathbf{y}}[t] = [\tilde{y}_l[t]]_{n_3\times 1}$	desired output vector at time t
$E[t]$	error evaluation function at time t

tests, voting tests, etc. [12,13]. These methods, rather than merely exploiting the current information, emphasize the integration of the bottom-level threshold comparison results in the recent period.

Other conventional false and missed alarms reduction strategies include propagation analysis [14,15], adaptive threshold [16], correlation analysis [17], etc. They merely adopt some intuitive and simple logics, and process the raw BIT output in a rather easy way. Nevertheless, such methods can be widely applicable and may work well in some situations where the phenomenon of false and missed alarms is not severe.

Apart from the conventional false and missed alarms reduction methods, artificial intelligence is also widely incorporated in the BIT designs. Previous works have focused on k-nearest neighbor (KNN) algorithm [18], artificial neural networks (ANN) [19–21], empirical mode decomposition (EMD) [22], Bayesian networks [23], information fusion techniques [24], etc. A BIT designed with the artificial intelligence is called "smart BIT" [25,26].

ANN is one type of fundamental models used in state identification of mechanical products and systems [27–29], and one of its major goal is to recognize false and missed alarms [19–21]. It is said that the BITs using ANN show an improved state identification accuracy. However, these ANN models generally do not incorporate the temporal cumulative effect because a single input sample is either irrelative to time or relative to a moment instead of a period of time. The false and missed alarm probabilities are assumed static and constant during the whole lifetime, and the time-varying feature is not well considered.