Fault Diagnosis of Linear Control Systems Based on the Discrete Wavelet Transform and an ART2 Neural Network

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Abstract: Fault detection and isolation of systems continues to be important problems to be addressed due to the increased complexities of more advanced systems. Early detection and isolation of faults can assist in avoidance of major system breakdowns. Many methods require some model of the plant in order to perform the fault diagnosis. In this paper we present a fault diagnosis method for dynamic systems based on discrete wavelet transform (DWT) and an adaptive resonance theory 2 neural network (ART2 NN). In the proposed method a fault is detected when an error between the system output and the nominal system output cross a predetermined threshold. Once a fault in the system is detected the ART2 NN based fault classifier isolates the fault. The algorithm contains three main steps: fault detection through the threshold test, data preprocessing *via* DWT, and fault isolation using the fault classifier. The simulation results demonstrate the effectiveness of the proposed DWT and ART2 NN based fault diagnosis method.

1. INTRODUCTION

As systems become more complex, the detection, isolation and correction of faults become even more important. The early detection and isolation of faults can help to avoid major system breakdowns.

There have been many methods used for fault detection and isolation (FDI). These methods fall into two major groups [1]: model free methods and model based methods. The model based FDI methods rely on the analytic redundancy concept [2]. However, these methods are dependent on finding a mathematical model for the system that defines the relationship between the system inputs and outputs. However, a mathematical description of this relationship is not easy to obtain in practice, due to the inherent nonlinearities of a system. In order to overcome this problem, it is necessary to find a modeling tool that can approximately represent all of the nonlinear relationships.

The model free methods include limit checking, expert systems [3], and neural network (NN) based *scheme*s. In recent years NN models have been extensively studied in regards to optimum production and control strategies as problem solving tools. Considerable research effort has been devoted to the problem of fault diagnosis [4-6]. The main advantages for the use of NN models for fault diagnosis applications can be found in their inherent ability to approximate nonlinear functions and in their adaptive

learning and parallel processing capabilities. It has been noted that the NN models have a suitable structure that can generally represent unknown nonlinear functions. Therefore, NNs can be used as a powerful tool for handling nonlinear problems. However, these methods find it difficult to isolate new, previously unencountered faults.

In order to overcome this problem, Srinivasan *et al.* [6] proposed an FDI algorithm using the Hopfield and ART1 NN protocols. In this method, the algorithm is divided into three main parts: an estimation of the system parameters, fault detection, and fault isolation using the ART1 NN. However, the ART1 NN is only designed to classify binary patterns. Therefore, the ART2 NN, which uses adaptive resonance theory 2, is more suitable for fault isolation classification because the estimated parameters employ analog patterns.

Lee *et al.* [8] proposed a fault diagnosis method that uses an ART2 NN with uneven vigilance parameters to detect and isolate faults in linear systems. However, a long fault isolation time period is needed due to the complex parameter estimation. The success of the method depends on the accuracy of the estimated parameter. However, it is not easy to precisely estimate the system parameters in noisy environments using this method.

This study presents a new fault diagnosis method for dynamic systems using discrete wavelet transforms (DWT) [9-11] and an ART2 NN employing uneven vigilance parameters. In the proposed method, a fault is detected when an error between the system output and the nominal system output crosses a prede-termined threshold. Once the fault is detected, the

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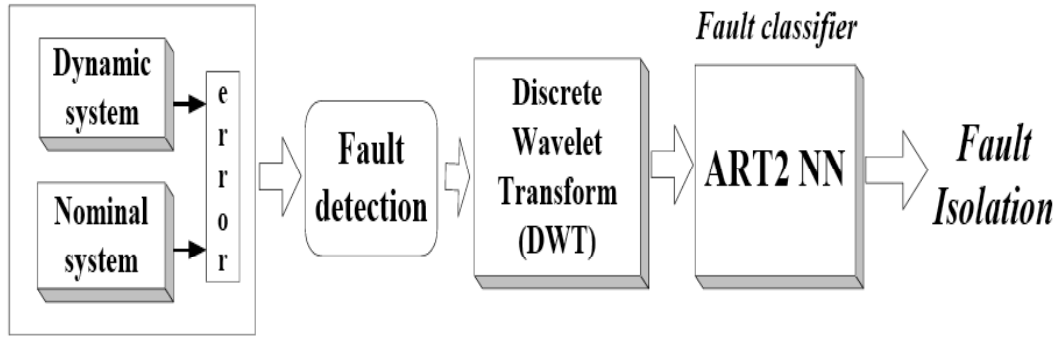
Figure 1: The structure of the proposed fault diagnosis system based on DWT and ART2 NN.

system output signals are converted into a frequency domain signal by the DWT method. Then the ART2 NN classifier isolates the fault using the DWT coefficients. The algorithm contains three main steps: fault detection through the threshold test, data preprocessing *via* DWT, and fault isolation by the fault classifier. The data preprocessing part, which converts the sampled output signals into the frequency domain by DWT, is especially important in improving the fault diagnosis performance. Simulations have been carried out in order to evaluate the performance of the proposed control system fault diagnosis method.

The remainder of this paper is organized as follows: in the next section, we present the fault diagnosis method using the ART2 NN and DWTs. In Section 3, the simulations are discussed in order to illustrate the proposed fault diagnosis method. The last section provides concluding remarks.

2. FAULT DIAGNOSIS BASED ON DWT AND THE ART2 NN

The algorithm contains three main steps (Figure **1**): fault detection through threshold testing, data pre-processing *via* DWT, and fault isolation by the fault classifier. The data preprocessing method is very important in improving the performance of the fault diagnosis. It converts the sampled output signals to the frequency domain employing the DWT method. The DWT coefficients are then used as inputs to the ART2 NN employing uneven vigilance parameters for the control system fault isolation.

2.1. The Fault Detection by the Threshold Test

Consider a single-input single-output discrete-time linear system:

$$y(k) = a_1 y(k-1) + \cdots + a_n y(k-n)$$
$$+ b_1 u(k-1) + \cdots + b_m u(k-m) + \varepsilon(k) \qquad (1)$$

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

The system parameters consist mostly of more or less intricate relationships of several physical para-meters, e.g. resistances and capacitances. Therefore, system faults can be expressed as a change in the system parameters.

In the proposed method, the nominal system is utilized to detect the system faults. Comparing the actual output of the system with the nominal system output generates errors. A fault is detected when the errors exceed a predetermined threshold value. A fault is detected using the following threshold test:

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

where e_n is the error between the system output and the nominal system output, L is the moving window length, and δ_f s the predetermined threshold for fault detection.

If the estimated parameters converge to the system parameters, then the error between the system output and estimate neural network output has similar properties as system noise [9]. Therefore, error e_n has a normal distribution $N(0, \sigma^2)$. In addition, the sum of the normalized square errors in the moving window has a χ_L^2 -distribution with L degrees of freedom as:

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

if the false-alarm probability limit α is:

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

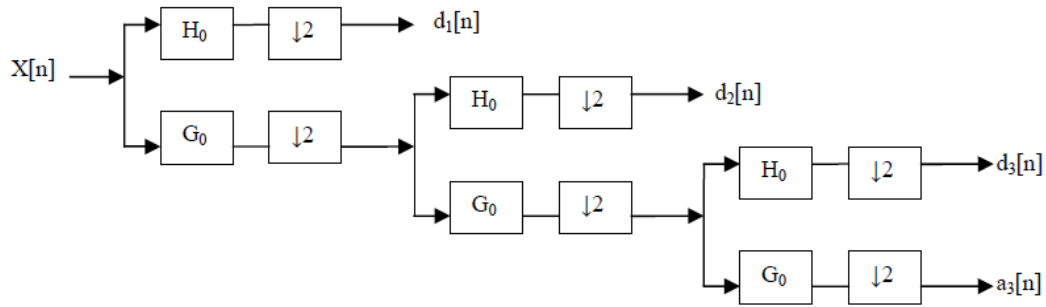and the threshold is obtained by: $\delta_f = \sigma^2 \delta^\circ$

Figure 2: The DWT structure.

Usually, the change in the system parameters caused by a fault is larger than the system noise. Therefore the false-alarm probability is considered in order to select the threshold, calculated using (4). However, when a fault corresponds to small changes in the system parameters, the false-fault detection probability increased. Therefore, a heuristic knowledge of the system is necessary in determining the threshold δ_f .

2.2. The Feature Extraction by the Discrete Wavelet Transform Method [9-11]

The signal to be analyzed is multiplied with a wavelet function in the same manner as it would be multiplied with a window function in an STFT (short time fourier transform); the transform is then computed for each segment generated. However, unlike an STFT, in the WT (wavelet transform), the width of the wavelet function changes with each spectral component. The WT at high frequencies obtains a good time resolution and poor frequency resolution, whereas at low frequencies the WT gives a good frequency resolution and a poor time resolution.

The DWT is computed by the successive low-pass and high-pass filtering of the discrete time domain signal, as shown in Figure **2**. In the Figure, the signal is denoted by sequence x[n], where n is an integer. The low pass filter (LPF) is denoted by G_0; the high pass

filter (HPF) is denoted by H_0. At each level, the HPF produces detailed information, d[n], whereas the LPF, associated with the scaling function, produces coarse approximations, a[n].

At each decomposition level, the half band filters produce signals spanning only half of the frequency band. In accordance with Nyquist's rule, if the original signal has the highest frequency of ω, which requires a sampling frequency of 2ω radians, it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians, thereby discarding half the samples with no loss of information. This reduction by two halves in the time resolution for the entire signal is now represented by only half of the number of samples. Therefore, whereas the half band low pass filtering removes half of the frequencies and thus halves the resolution, the reduction by two effectively doubles the scale. With this approach, the time resolution becomes arbitrarily good at high frequencies, whereas the frequency resolution becomes arbitrarily good at low frequencies. The DWT of the original signal is thereby obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition.

Figure **3** shows the reconstruction of the original signal from the wavelet coefficients. Basically, the reconstruction process is the reverse of the decom-position process. The approximation and detail
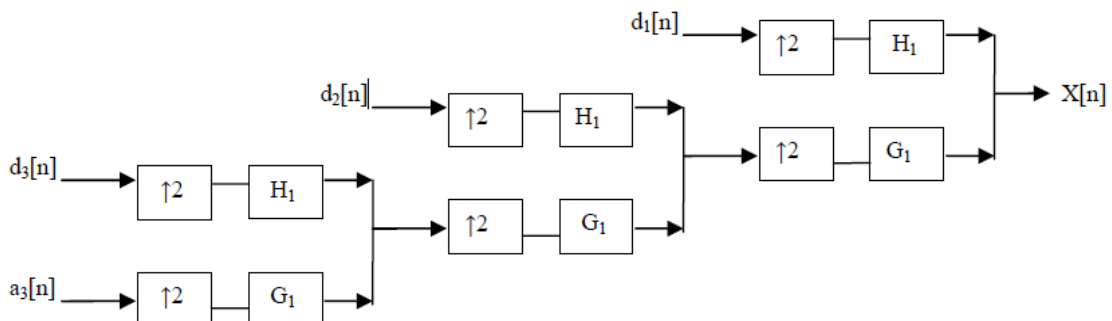
Figure 3: The reconstruction of the original signal.

coefficients at every level are up-sampled by two, passed through the low pass and high pass synthesis filters and then added. This procedure is continued through the same number of levels as in the decomposition process in order to obtain the original signal.

2.3. The Fault Isolation using the ART2 Neural Network

In the proposed method, an ART2 NN employing uneven vigilance parameters is used to isolate the faults. The ART2 NN architecture is shown in Figure **4**. The ART2 NN employing uneven vigilance parameters [8] has the same architecture as a general ART2 NN [7]. However, in the proposed NN an added vigilance test is used to classify the input patterns.
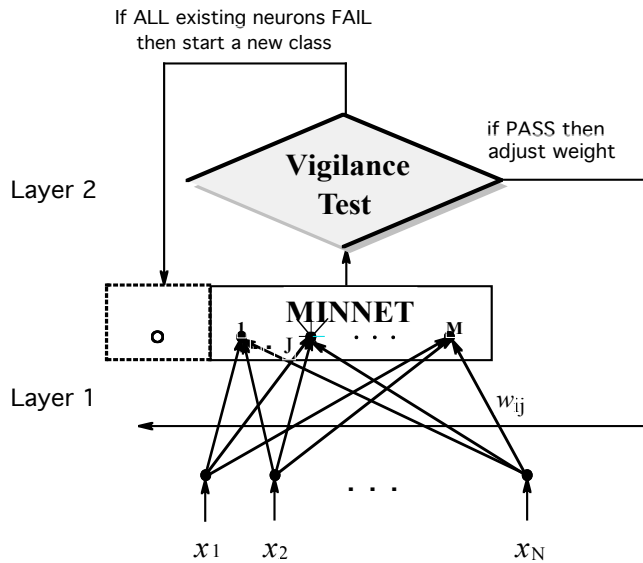

Figure 4: The ART2 NN architecture.

The distance between the input patterns and j-th output node (fault class) is computed using:

$$d_j = \left\| W_j - X \right\|_\infty^E \triangleq \max_i \left| \frac{1}{\varepsilon_i} (w_{ij} - x_i) \right|, \quad j = 1, 2, \cdots, M \qquad (5)$$

where x_i is the input of the input node (DWT coefficient) i, $i=1,2,\ldots, N$, N is the number of input nodes, w_{ij} is the weight from output node j to the input node, and M is the number of the output nodes. $\left\| \bullet \right\|_\infty^E$ is the weighted infinite norm and ε_i is the i-th vigilance parameter for i-th input node. In order to improve the classification accuracy, the vigilance parameter for a parameter with a large magnitude variation needs to be large. On the other hand, the vigilance parameter for a parameter with a small magnitude variation should be small.

If the distance between the input patterns and the J-th output node is at a minimum, then class J becomes the winner node. Verification is done as to whether input pattern X really belongs to the winner class J by performing the following vigilance test:

Vigilance test condition: $\left\| W_J - X \right\|_\infty^E < 1$ (6)

If winner class J passes the vigilance test, the weights of class J are adjusted using:

$$W_J^{new} = \frac{X + W_J^{old} [class_J^{old}]}{[class_J^{old}] + 1} \qquad (7)$$

where $[class_i]$ is the number of the patterns in class i. On the other hand, if class J fails the vigilance test, a new class is created with weight $W_{M+1} = X$.

3. THE SIMULATION RESULTS AND DISCUSSIONS

In this section, the computer simulations carried out to test the performance of the algorithm are discussed. We used MATLAB for these simulation experiments. The transfer function of the position control system (see Figure **5**) is:
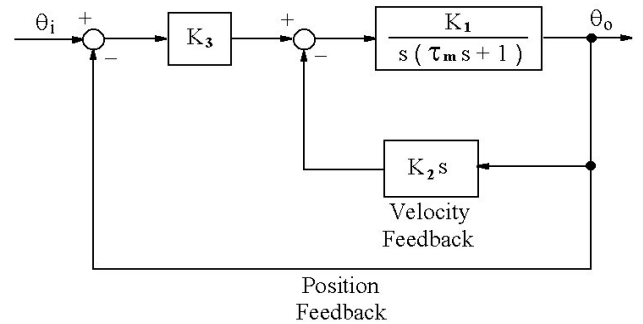
Figure 5: Block diagram of the position control system using DC motor.

$$\frac{\theta_O(s)}{\theta_i(s)} = \frac{K_1 K_3}{\tau_m s^2 + (1 + K_1 K_2)s + K_1 K_3} \qquad (8)$$

$$K_1 = \frac{1}{n}\left(\frac{K_t}{FR_a + K_b K_t} \right), \quad \tau_m = \left(\frac{J_m R_a}{FR_a + K_b K_t} \right)$$

where K_1, K_2, and K_3 are parameters which can be obtained by adjusting each parameter until it overshoots and the steady state error reaches zero. R_a, K_b, K_t, and J_m are the resistance, back emf constant, torque constant, and the inertia of the motor, respectively. The parameter values for the simulations are as follows:

$$R_a = 0.88\Omega, K_b = 1.127\,V/(rad/\sec), K_t = 1.127\,Nm/A$$

Figure 6: The detection and isolation results for Fault #1. (**a**) The system output (solid) and nominal system output (dashed). (**b**) The change of J_L and fault detection (dotted line). (**c**) The DWT coefficients. (**d**) The classification results by the proposed classifier.

$F = 0.0082 \ Nm / (rad / \sec), J_m = 0.0196 \ Kgm^2$

The sampled input-output system can be described by a fourth-order discrete time system as:

$$y(k+1) = a_1 y(k) + a_2 y(k-1) + b_1 u(k) + b_2 u(k-1) + \varepsilon(k) \qquad (9)$$

where a_1, a_2, b_1, $and\,b_2$ are the system parameters, the sampling time is 0.05 s and the output measurement noise is a white noise with a variance of $\sigma^2 = 2.56 * 10^{-4}$. We chose $\alpha = 0.01\,(1\%)$, the moving window length of $L = 30$, and the threshold $\delta_f = 0.013$ (from (3) and (4)). We chose to use 30 input nodes and the vigilance parameters of the ART2 NN with uneven vigilance parameters as $\varepsilon = 5 * 10^4$ [1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1 ,1,1,1,1,1,1,1,1,1,] . The DWT coefficients were also used as inputs to the ART2 NN.

In order to verify the proposed diagnosis algorithm, three different faults were introduced into the system at the 150-th sample number. The following faults were simulated:

Fault #1: Feedback gain K_2=0

Fault #2: Increased resistance ($R_a = 1.76\,\Omega$)

Fault #3: Decreased resistance ($R_a = 0.44\,\Omega$)

The simulation results for Fault #1, Fault #2, and Fault #3 are shown in Figure **6, 7** and **8**, respectively. Figure **6d** and Figure **7d** show the classification results after the three faults classes (i.e., class #1 for normal state, class #2 for Fault #1, class #3 for Fault #2) were generated. Figure **8** shows the results when a new Fault #3 was introduced at the 150-th sample number. Figure **6a** shows the system output and the nominal system output; and Figure **6b** shows the variations of the sum of the squares of the errors in the moving window (the fault occurs at the 150-th sample number). Also, the coefficients of the output signals generated by DWT for f Fault #1 are shown in Figure **6c**. Figure **6d** shows the fault classification results by from the ART2N employing uneven vigilance parameters. The simulation results show that the proposed diagnosis method successfully isolates the faults as class 2. In addition, the results shown in Figures. **7a-d** well illustrate that the fault classifier successfully classifies the fault. Figure **8** shows the detection and isolation
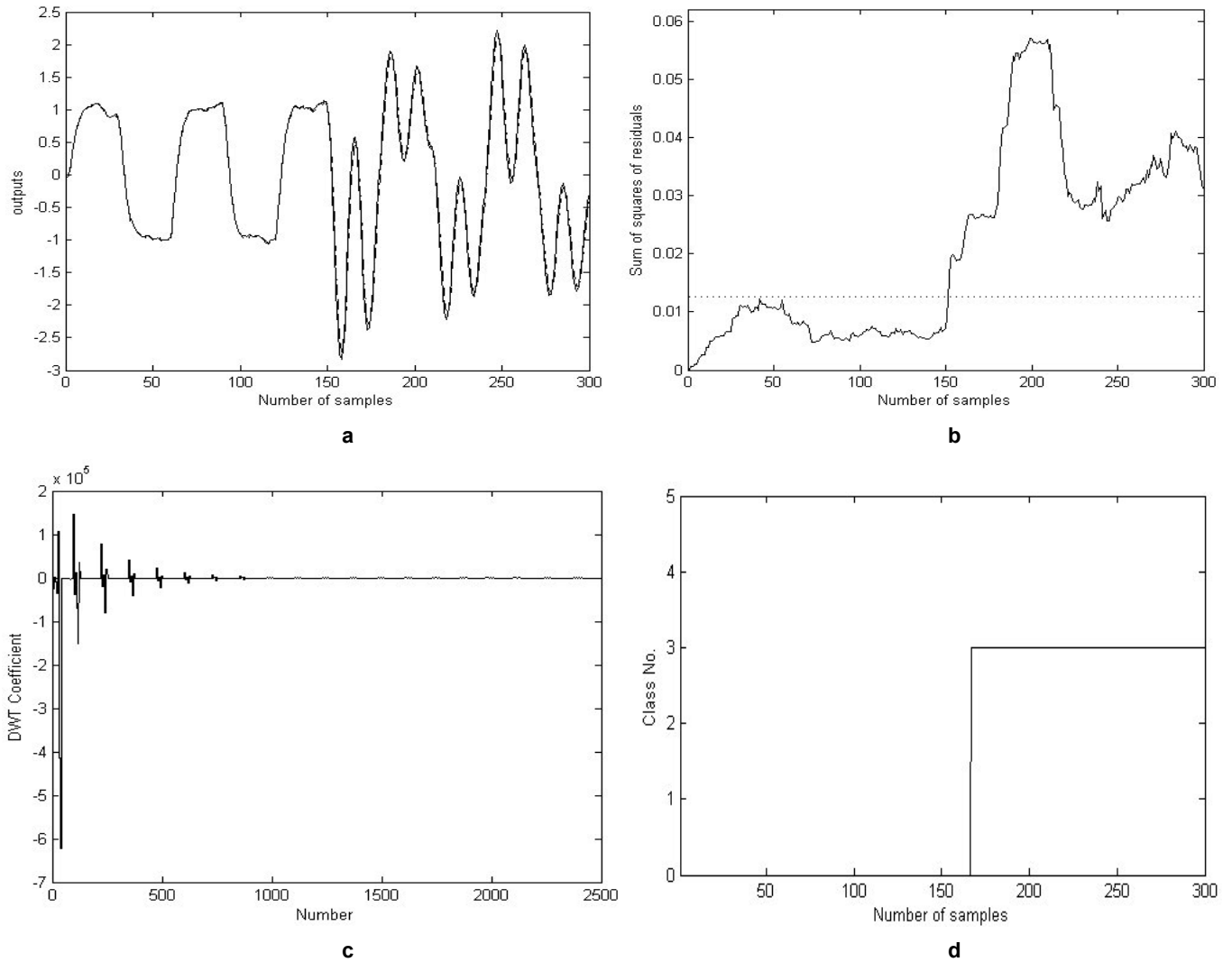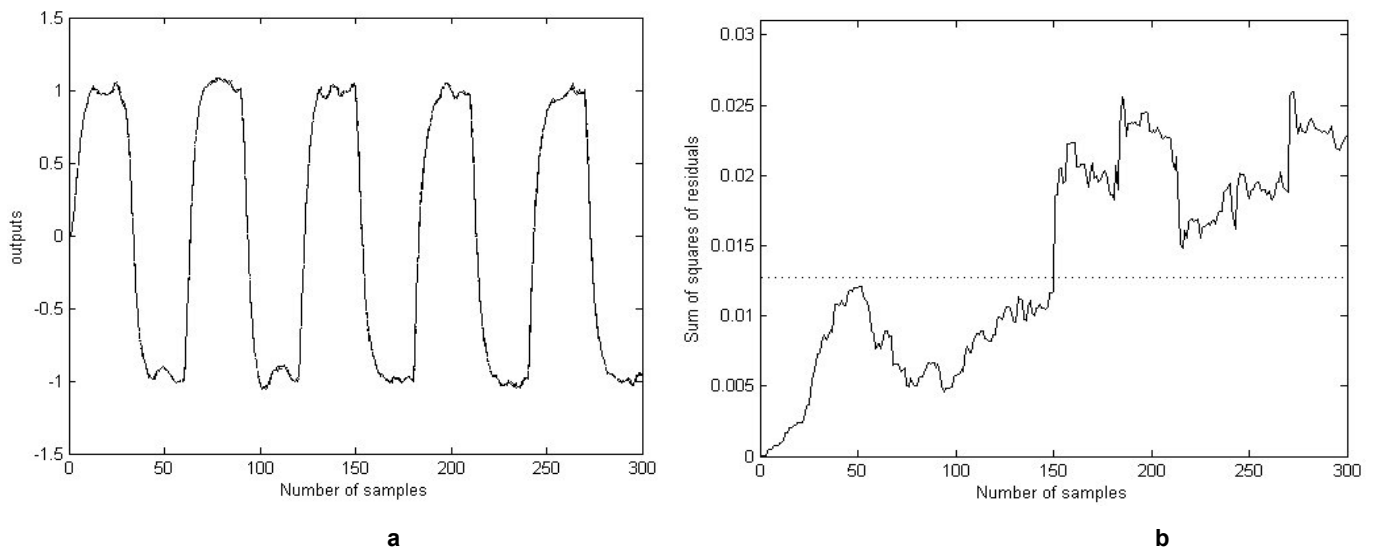
Figure 7: The detection and isolation results for Fault #2. (**a**) The system output (solid) and nominal system output (dashed). (**b**) The change of J_L and fault detection (dotted line). (**c**) The DWT coefficients. (**d**) The classification results by the proposed classifier.
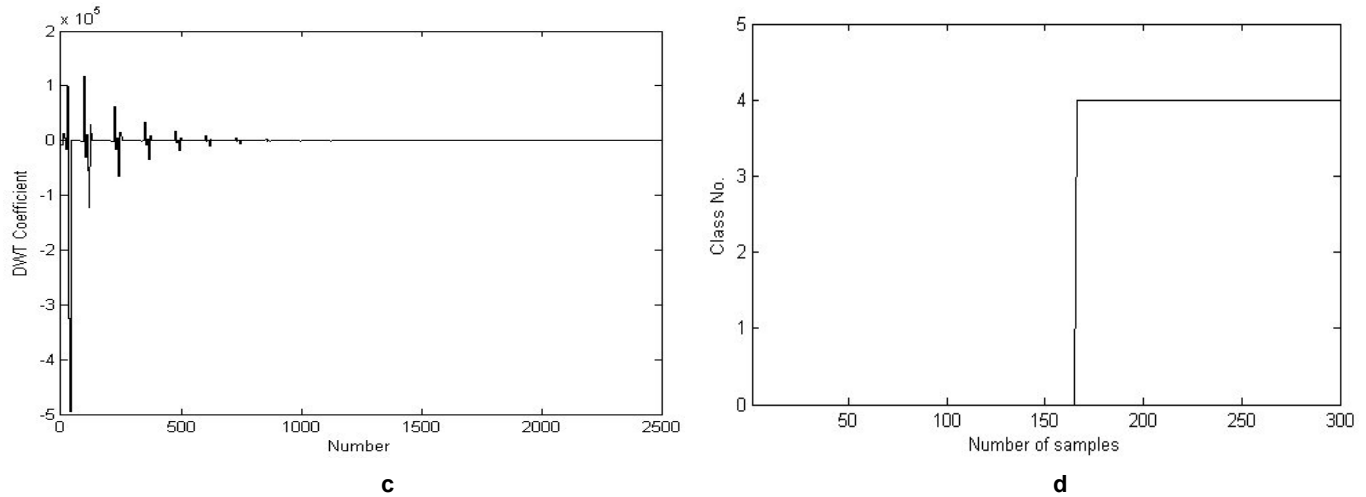
(Figure 8). Continued.

c

d

Figure 8: The detection and isolation results for Fault #3. (**a**) The system output (solid) and nominal system output (dashed). (**b**) The change of J_L and fault detection (dotted line). (**c**) The DWT coefficients. (**d**) The classification results by the proposed classifier.

results for the new Fault #3. From the results, we can see that the proposed FDI system successfully diagnoses the faults which occurred in the control system.

4. CONCLUSIONS

This paper introduced a fault diagnosis method using DWT and the ART2 NN employing uneven vigilance parameters. The method contains three main steps: fault detection through threshold testing, data preprocessing based on DWT, and fault isolation using the ART2 NN-based fault classifier. A fault is detected when the errors between the system output and the nominal system output cross a predetermined threshold δ_f. As soon as a fault is detected, the sampled output signals are converted into the frequency domain using DWT. The ART2 NN fault classifier then classifies the fault that occurred in the control system using the DWT coefficients.

The DWT based data preprocessing is very important in the improvement of the performance of the fault diagnosis. The DWT method, which is effective in removing the system noise from the system output signal, extracts the frequency spectrum characteristics of the fault signal. Since the ART2 NN is an unsupervised NN, it can adaptively learn and classify the input patterns without a priori knowledge of the classes. Therefore, the ART2 NN-based fault classifier does not need to possess the knowledge of all the

possible faults in order to isolate the faults occurring in the system. The computer simulation results verify that the proposed diagnosis method using DWT and ART2 NN can be successfully applied to the FDI problem in a position control system.

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