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Analog Fault Detection Comparison between Supply Current and Output Voltage

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Abstract

In view of the difficulties caused by determining threshold for fault detection of analog circuits, a method based on principal component analysis (PCA) was proposed to overcome these difficulties. The basic model of the proposed method and the general rule for analog fault detection were described in detail. Power supply current test has the advantages that only one test point is needed and there is no need to propagate fault effects to the outputs. Fault detection of analog circuits using PCA of power supply current was evaluated by experiment. The signal filtering and amplifying circuit used in the ultrasonic liquid sensor was selected as the research object. And the detection results using power supply current are compared with those using the output voltage under the same stimulus. The results show that the PCA based method can use the information in both time and frequency domain simultaneously, and it can overcome the difficulty in determining threshold by the expert's empirical knowledge. These make it a more suitable candidate for fault detection of analog circuits than pure time-domain or pure frequency-domain methods.

Keywords: *Analog circuits; Fault detection; Principal component analysis (PCA); Power supply current; Output voltage*

1. Introduction

The techniques of fault diagnosis in digital electronic circuits have been mature and cost effective. They have been used widely in the area of computer and other relative areas. However, fault diagnosis of analog circuits still relies on the engineer's experience and intuition. This requires the engineer to have some detailed knowledge of the circuit's operational characteristics and experience in developing test strategies. As a result, analog fault detection and identification is still an iterative and time-consuming process [1-3]. A survey of the research conducted in this area clearly indicates that analog fault diagnosis is complicated due to component tolerances, poor fault models, and nonlinearity issues. Analog fault detection is one of the important parts of analog fault diagnosis, and has become an appealing area of research.

Faults of analog circuits can be classified into two categories: soft faults and hard faults. A stuck-open fault is a kind of hard fault that the component terminals are out of contact with the rest of the circuit and create a high resistance when the fault occurs in the circuit. A stuck-short fault is a short between terminals of the component (effectively shorting out the component from the circuit). Soft faults, on the other hand, are deviations of component parameters which result in performance out of acceptable limits. Compared to hard faults which happen due to excessive deviations, soft faults are by far more difficult to detect because they are caused by the deviations of component parameters [4].

Fault detection of analog circuits has been studied for many years and a lot of methods have been proposed [3-12]. Earlier works often study voltage measurement based methods and they have been used widely in the manufacture and other areas. But fewer and fewer circuit nodes are accessible, with the development of IC technology. Even only

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the output voltage signal is accessible in many cases. So we need to find other testable signals. Fault detection of analog circuits by monitoring power supply current has gained importance recently. Power supply current test has the advantages that only one test point is needed and there is no need to propagate fault effects to the outputs [10].

The magnitude of power supply current under the application of an AC input stimulus is used to detect faults of analog circuits and a CMOS amplifier is used to verify this method in [7]. A method using magnitude and phase spectrum components for fault detection of catastrophic and parametric faults is presented in [8]. The Euclidean distance between faulty circuits and fault-free circuits is used as a measure to detect faults. The Root Mean Square (RMS) value and magnitude spectrum components are combined for analog fault detection in [9]. The magnitude in time domain is combined with the magnitude and phase spectrum components in frequency domain in [10]. The output voltages, power supply current and their cross-correlation are used to detect faults. They find that the fault coverage is further improved by using the cross-correlation method. A method based on wavelet decomposition of dynamic power supply current is presented for fault detection of analog circuits in [11]. The normalized RMS error between the wavelet coefficients of faulty circuits and fault-free circuits is used as a measure to detect faults. However, the threshold should be determined according to the expert's empirical knowledge. It is difficult to determine the thresholds in some cases and the detection results may be different if different thresholds were used.

In this paper, we propose a method based on principal component analysis (PCA) for analog fault detection. It can overcome the difficulty in determining threshold according to the expert's empirical knowledge. Then we evaluate the applicability of PCA for power supply current test of analog circuits, and compare its testability with the traditional output voltage signal. PCA can effectively handle the impact of component tolerances, and it combines the features in time domain and frequency domain to detect faults of analog circuits. So, it can use the information in both time and frequency domain simultaneously. These make it a more suitable candidate for fault detection of analog circuits than pure time-domain or pure frequency-domain methods.

The rest of this paper is organized as follows. Section 2 deals with the method of analog circuits test using PCA. In Section 3, we applied the proposed method to detect faults of the signal filtering and amplifying circuit, which is used in the ultrasonic liquid-level sensor. The power supply current signal and the output voltage signal were used to test the circuits respectively and the results of these two kinds of signals were compared. The PCA-based method was compared with the pure time-domain or pure frequency-domain method, too. Section 4 concludes the paper.

2. Analog Circuits Test Using PCA

PCA is one of the most popular methods among the multivariate statistical analysis methods. It constructs model according to large numbers of history data in fault-free condition. PCA summarizes the relevant multi-attributes to a set of irrelevant components named principal components. The principal components are estimated from the eigenvectors of the covariance or correlation matrix of original variables. They are extracted in decreasing order of importance so that the first principal component accounts for as much of the variation as possible and each successive component accounts for a little less. The first few principal components contain most of the variations in the original data set. PCA is capable of treating high dimensional, noisy and correlated data and has been widely used in different areas, such as fault diagnosis, signal processing, and pattern recognition [13-15].

In general, many features of test signals should be observed to estimate the operation condition of circuits-under-test (CUT). The information of these features may be overlapped or redundant in some extent. Two thresholds (high threshold and low threshold) are needed to check one feature. So, if we check n features one by one, $2n$ thresholds are needed. This is single hypothesis test and it is done many times. As we all know, it is difficult to determine thresholds because there may be many features and there is not a general rule to determine these thresholds.

PCA can be used to monitor different variables and the relativities of these variables are taken into considered. In this paper, PCA is used to combine the features of test signal in both time and frequency domain. So, this method can use the information in both time and frequency domain simultaneously. The selected features of test signal are: the mean value, the maximum value, the peak to peak value, the standard deviation in time domain and the magnitude component values of the first four harmonics in frequency domain. These eight features are used to analyze the CUT. At first, the test signals of fault-free circuits are sampled and these eight features are extracted to form the original data. Then the principal component model of fault-free circuit is constructed according to these original data. This model reflects the relations of features in fault-free circuits. If there is a fault in the CUT, these relations will be disturbed. The deviation between features of the CUT and the principal component model can be used to calculate the statistic for fault detection.

The procedures of constructing principal component model [13-15] according to data of fault-free circuits are as follows.

Step 1. Normalize original data. Normalization performs a linear scaling of the input features to avoid large dynamic ranges in one or more dimensions. When input features differ by several orders of magnitude, they can undermine smaller but more important trends in the data. In such cases, normalization can be effectively used to limit the range of feature values. The original data $X \in R^{m \times n}$ are normalized according to (equation 1).

$$x_{ij}^{*} = \frac{x_{ij} - \bar{x}_j}{\sqrt{\operatorname{var}(x_j)}}, i = 1,2,\cdots,m;\ j = 1,2,\cdots,n \tag{1}$$

Where, m is the number of samples, n is the number of features. $\bar{x}_j$ and $\operatorname{var}(x_j)$ are the mean value and variance of the jth feature, respectively. For convenience, the normalized data matrix is also denoted as X in this paper.

Step 2. Compute the correlation matrix C and its eigenvalues and eigenvectors.

$$C = \frac{X^T X}{m-1} = U \Lambda U^T \tag{2}$$

Where, $\Lambda = diag(\lambda_1, \lambda_2, \cdots, \lambda_n)$, $U = [u_1, u_2, \cdots, u_n]$. $\lambda_1, \lambda_2, \cdots, \lambda_n$ are the eigenvalues of C and $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$. $u_1, u_2, \cdots, u_n$ are the corresponding eigenvectors.

Step 3. Select the principal component. Every principal component score vector $\boldsymbol{t}_j$ is the linear combination of X.

$$t_j = Xu_j, j = 1,2,\cdots,n \tag{3}$$

The contribution of variance $\varphi(i)$ can be computed according to (equation 4). Then the cumulative contribution of variance CPV can be expressed as (equation 5).

$$\varphi(i) = \lambda_i \Big/ \sum_{j=1}^{n} \lambda_j \tag{4}$$

$$CPV = \sum_{i=1}^{p} \varphi(i) \tag{5}$$

Where, p is the number of principal components, which can be selected as their corresponding CPV larger than a prescribed threshold by convention. So, data matrix can be reconstructed as (equation 6).

$$X = \hat{X} + \tilde{X} = XPP^{T} + X\bar{P}\bar{P}^{T} = TP^{T} + E \tag{6}$$

Where, $P = [u_1, u_2, \cdots, u_p]$ is the principal component loading matrix, $\bar{P} = [u_{p+1}, u_{p+2}, \cdots, u_n]$ is the residual loading matrix, $T = [t_1, t_2, \cdots, t_p]$ is the principal component score matrix, $E = \tilde{X}$ is the residual matrix. So, data matrix X is decomposed as $\hat{X}$ and $\tilde{X}$, which are the projections on the principal component subspace (PCS) and the projections on the residual subspace (RS), respectively.

The procedures of using the principal component model to detect faults of the CUT are as follows.

Step 1. Sample the signal of CUT. The CUT are stimulated with the same input signal and its test signal is sampled. The features of test signal are computed and they compose a new sample x_{new}. Then the new sample is normalized according to (equation 1).

Step 2. Compute the statistic for detection. x_{new} can be decomposed as $\hat{x}_{new}$ and $\tilde{x}_{new}$, which are the projections on the PCS and the projections on the RS, respectively. Fault detection can then be carried out based on statistical hypothesis tests in these two subspaces [14-15]. The statistic used in the RS is the Q statistic (also referred as squared prediction error, SPE), which is defined as (equation 7).

$$SPE = \left\| x_{new} \bar{P} \right\|^2 = x_{new} \bar{P}\bar{P}^{T} x_{new}^{T} \le \delta_{SPE}^{2} \tag{7}$$

Where, δ_{SPE}^{2} is the control limit for SPE [15]. It can be determined according to (equation 8).

$$\delta_{SPE}^{2} = \theta_1 \left[1 + \frac{C_\alpha h_0 \sqrt{2\theta_2}}{\theta_1} + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^{2}} \right]^{\frac{1}{h_0}} \tag{8}$$

Where, α is the level of significance, C_α is the confidence limits for the (1-α) percentile in a normal distribution, $\theta_i = \sum_{j=p+1}^{n} \lambda_j^{i}$ (i=1, 2, 3), $h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^{2}}$.

If a CUT is fault-free, its SPE statistic will be less than the control limit. If a CUT is faulty, its SPE statistic will exceed the control limit. So, based on the PCA statistical model, the state of a CUT can be judged by its SPE statistic.

3. Experiment Results and Discussion

3.1. Experiment Circuits

In order to investigate the effectiveness of the proposed method, we have applied it to the fault detection of many analog circuits. The signal filtering and amplifying circuit of ultrasonic liquid-level sensor is used as an example in this paper. The nominal values of the components are shown in Figure 1. In our experiment, the number of circuit boards under test is twelve. The principal component model is constructed based on the test data of fault-free circuits. In order to validate the principal component model, we introduce faulty components in the circuit board. The soft faults and their corresponding codes are shown in Table 1, where '↑'and '↓' stand for increase and decrease in the component parameter, respectively. 'Nor' stands for the fault-free state of circuits. The soft faults of Table 1 only include the components which are sensitive to the performance of the circuits, because soft faults cannot happen to the components which are not sensitive to the performance of the circuits. The sensitive components can be determined by sensitive analysis using OrCAD/PSPICE. The sensitive components of this circuit are R1, R2, R4, R5, R6 and C1. Therefore, these six components are taken into considered in the soft faults of the signal filtering and amplifying circuit.

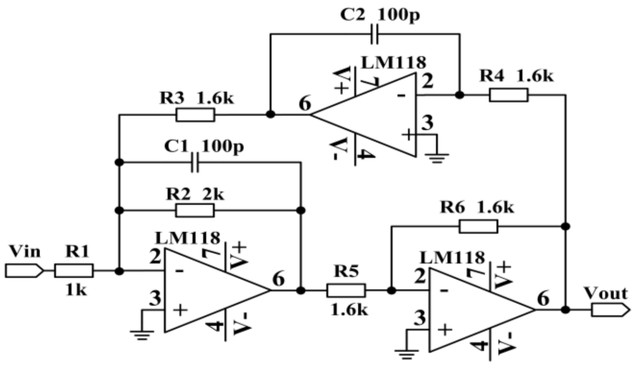


Figure 1. Signal Filtering and Amplifying Circuit used in the Ultrasonic Liquid-Level Sensor

Table 1. Faults and Their Corresponding Codes

Faults	R1↓	R1↑	R2↓	R2↑	R4↓	R4↑	R5↓
Codes	F1	F2	F3	F4	F5	F6	F7
Faults	R5↑	R6↓	R6↑	C1↓	C1↑	Nor	
Codes	F8	F9	F10	F11	F12	F0	

3.2. Fault Detection Using Power Supply Current

The power supplies for this signal filtering and amplifying circuit are a 12V DC and a -12V DC. The currents passing through the 12V DC and the -12V DC are measured separately under the application of an input stimulus. So, we can acquire two power supply current signals from one circuit board. One signal is the current passing through the 12V DC, named $I_{DD}+$ in this paper. The other signal is the current passing through the -12V DC, named $I_{DD}-$ in this paper. A 4 V(p-p), 1 MHz sinusoidal wave source is applied as an input signal. The $I_{DD}+$ and $I_{DD}-$ of every circuit board are sampled at 250 MHz. Figure 2 shows the waveforms of power supply current when the circuit is fault-free. The features used to analyze the power supply current signal are the same as those described in Section 2. These features are combined by PCA to detect faults of the CUT. As an example, Figure 3 shows the waveforms of power supply current when resistor R1↓. The detection results of these experimental circuit boards are shown in Table 2. 'T' stands for the detection results using features in pure time-domain. 'F' stands for the detection results using features in pure frequency-domain. 'TF' stands for the detection results using features in both time and frequency domain simultaneously. The detection results of a kind of fault are measured by the fault detection rate *FDR*, which is defined as (equation 9).

$$FDR = \frac{right}{all} \times 100 \ \% \tag{9}$$

Where, *right* is the number of faults which are detected rightly among the samples for a kind of fault. *all* is the number of samples for this kind of fault.

Table 2. Fault Detection Rate using I_{DD}+ and I_{DD}- [%]

Fault Codes	*FDR* using I_{DD}+			*FDR* using I_{DD}-		
	T	F	TF	T	F	TF
F0	100	100	100	100	100	100
F1	100	100	100	100	100	100
F2	100	0	100	100	100	100
F3	66.67	100	100	100	100	100
F4	50	100	100	100	100	100
F5	91.67	75	100	100	100	100
F6	100	83.33	100	100	100	100
F7	100	100	100	100	100	100
F8	100	100	100	100	100	100
F9	83.33	50	100	100	100	100
F10	100	100	100	100	100	100
F11	25	100	100	100	100	100
F12	100	91.67	100	100	100	100

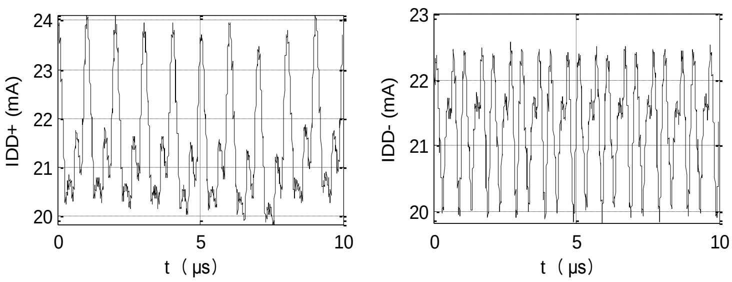


Figure 2. Waveforms of Power Supply Current when the Circuit is Fault-free

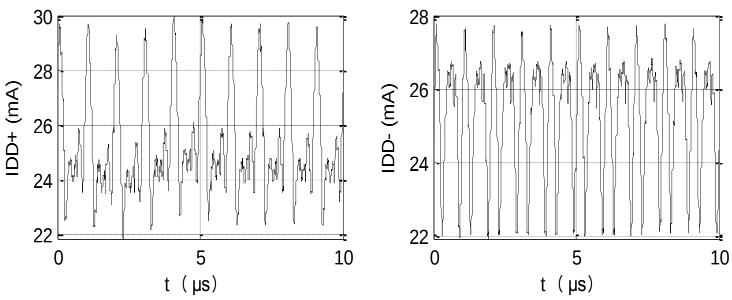
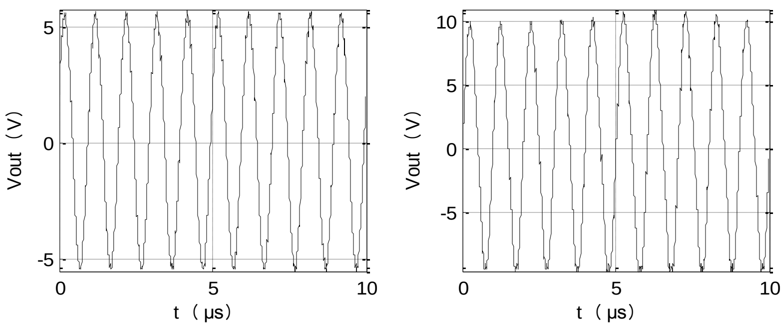


Figure 3. Waveforms of Power Supply Current when Resistor R1↓

3.3. Fault Detection Using Output Voltages

To compare the detection results using power supply current, the output voltage (V_{out}) of the signal filtering and amplifying circuit is also measured under the application of the same stimulus. The sample frequency is 250MHz, too. Firstly, we construct the principal component model using the measured data of fault-free circuits. Then this principal component model is used to detect faults of the CUT. The V_{out} signal of CUT is sampled and its features are computed. These features are compared with the principal component model to calculate the statistic for fault detection. Table 3 shows the detection results using the V_{out} signal.



(a) V_{out} when the circuit is falut-free (b) V_{out} when resistor R1↓

Figure 4. Waveforms of Output Voltages

Table 3. Fault Detection Rate using V_{out} [%]

Fault Codes	T	F	TF	Fault Codes	T	F	TF
F0	100	91.67	100	F7	100	100	100
F1	100	100	100	F8	100	100	100
F2	100	100	100	F9	100	100	100
F3	100	100	100	F10	100	100	100
F4	100	100	100	F11	100	100	100
F5	100	100	100	F12	100	100	100
F6	100	100	100				

3.4. Discussion

The detection results using the I_{DD}+ signal are shown in Table 2. It can be observed that some faults cannot be detected correctly using the I_{DD}+ signal. F3, F4, F5, F9 and F11 cannot be detected correctly using the features in time domain. F2, F5, F6, F9 and F12 cannot be detected correctly using the features in frequency domain. The *FDR* of F2 equals to 0. This means that this fault type cannot be detected. If we use PCA to combine the features of I_{DD}+ in both time and frequency domain, all the faults can be detected rightly. The *FDR* of every fault type equals to 100%. So, the method based on PCA can be used to detect faults of analog circuits. The features in both time and frequency domain can be combined by the proposed method. It can detect faults of analog circuits by information fusion.

The threshold is computed according to Eq. (8) when the proposed method is used. But the thresholds should be determined by expert's empirical knowledge when other methods are used [7-11]. It is difficult to determine the thresholds in some cases and different thresholds may give different results. So, the proposed method can overcome the difficulty to determine threshold by the expert's empirical knowledge.

As we can see from Table 3, almost every kind of faults can be detected rightly using the V_{out} signal. But the *FDR* of F0 is 91.67% when the 'F' method is used. So, some fault-free circuits may be thought as faulty circuits by this method. If we use the 'T' method or the 'TF' method, all the faults can be detected rightly.

If the I_{DD}- signal is measured, all the faults can be detected rightly when using every one of the 'T', 'F' and 'TF'. The detection results using the I_{DD}- signal are shown in Table 2. The *FDR* of every fault type equals to 100%. So, we can use power supply current to test the signal filtering and amplifying circuit, which is used in the ultrasonic liquid-level sensor. And I_{DD}- is more effective than I_{DD}+ or V_{out}.

If the detection result is not so satisfactory when using one signal, we can try to use these three signals together to test the circuits-under-test. But the test process will be more complex and this will need more test cost.

4. Conclusions

Analog fault detection is complicated due to component tolerances, poor fault models, and nonlinearity issues. Appropriate analysis is required to extract specific knowledge about the CUT. A method based on PCA is presented for fault detection of analog circuits in this paper. At first, the principal component model of fault-free circuit is constructed. Then the circuits-under-test are compared with the principal component model to calculate the statistic for fault detection. The features in both time and frequency domain are combined by this method to detect faults of analog circuits with tolerances. As an example, the PCA based method was applied to detect faults of the signal filtering and amplifying circuit, which is used in the ultrasonic liquid-level sensor. The results were compared with those using the features in pure time-domain or in pure frequency-domain. The proposed method can use the information in both time and frequency domain simultaneously and overcome the difficulty in determining threshold by the expert's empirical knowledge. These make it a good candidate for fault detection of analog circuits.

Power supply current test has the advantages that only one test point is needed and there is no need to propagate fault effects to the outputs. A sinusoidal wave source is applied as an input stimulus and the dynamic power supply current of the signal filtering and amplifying circuit is sampled and analyzed. The features of power supply current are combined by PCA to detect faults of circuits-under-test. The results show that power supply current contains information about the circuit's faults, and can be used for fault detection of analog circuits by analyzing this signal. The detection results are compared with those using the traditional output voltage signal. We can see that the I_{DD}- signal is more effective than I_{DD}+ signal and V_{out} signal. If the detection result is not satisfactory when using one signal, we can use these three signals together to test the circuits-under-test. But the test process will be more complex and this will need more test cost.

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