

An Improved Principal Component Analysis in the Fault Detection of Multi-sensor System of Mobile Robot

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Abstract—To cope with the fault detection in dynamic conditions of inertial components in the mobile robots, an improved principal component analysis (PCA) method was proposed. This work took a five gyroscopes redundancy allocation model to realize the measurement of the attitude. It is hard to distinguish the fault message from dynamic message in dynamic system that results in false alarm and missing inspection, so we firstly used the parity vector to preprocess the measurement data from the sensors. A fault was detected when the preprocessed data was dealt with PCA method. The effectiveness of the improved PCA method introduced in this paper was verified by comparing fault detection capabilities of conventional PCA method under the dynamic conditions of the step fault. The results of the simulation and experimental verification of the method was expected to contribute to the fault detection and improve the accuracy and reliability of the multi-sensors system in dynamic conditions.

Keywords—Measurement Data Processing, Mobile Robot, Sensor Redundancy, PCA, Parity Vector, Fault Detection.

1 Introduction

The mobile robot plays a more and more important role in industries and our daily life. The reliability of the mobile robots is regarded as one of the critical issues that needs to be addressed for the widely acceptance in different environments [1-3]. To achieve this, both the system reliability and faults detection need to be considered during the design and manufacture processes.

To maximize reliability of system, the redundancy allocation problem has been well developed [4]. In mobile robot attitude control system, the inertial sensors are the core components which can influence the accuracy and reliability of the system [5]. Hardware redundancy for inertial sensors has been studied since 1970s and has been widely used in mobile robots these years to enhance the fault-tolerant capability [6]. When the sensors configuration matrix is determined, faults can be detected through the corresponding integrity detection algorithm, e.g. parity vector and principal component analysis.

In fault detection, the parity vector method has been developed well and is applied in real-time system by deriving the parity vector through the relationship between the

state variables and output of the system [7]. This approach can also be used in the designated sensor's fault detection whose main idea is to design a performance criterion sensitive to specified sensor's fault and insensitive to other sensor's fault and noise [8]. Thus, the parity vector shows effective in separating the fault data from dynamic data in dynamic system.

Principal component analysis has found extensively application in fault detection based on the correlation between the process variables. PCA is able to decompose the original data space into two orthogonal subspaces called principal component subspace (PCS) and residual subspace (RS) by its dimensionality reduction capability so as to construct a new set of data. The change information of process variables can be mainly described in PCS when there is strong correlation between variables [9-10].

A major limitation of the traditional PCA method is that the model built from the data is time-invariant [11]. In other words, it is a static model which performs poorly in dynamic system since the normal changes may result in false alarm that would compromise the reliability of the system. To overcome this, various methods have been proposed by authors and research institutions. Li & Henry put forward two recursive PCA algorithms to reduce the false alarms in process monitoring [12]. On this basis, a recursive kernel PCA (RKPCA) algorithm has been studied due to its good response to dynamic nonlinear monitoring by capturing the time-varying and nonlinear relationship between the process variables [13]. But we still lack a method that combine the virtue of parity vector and PCA.

In this paper, we constructed a redundant system consisting of five inertial sensors to enhance the system reliability. The data collected from the sensors were pre-processed using parity vector to isolate the dynamic measurement one. Then the PCA model was constructed based on the standardized parity vector. Finally we calculated the squared prediction error SPE and Hotelling T2 statistic and compared them with the preset threshold value. After the simulation in MATLAB, the method was tested on an experimental platform to evaluate the consistency. In order to obtain the real-time state of the robot, the data collected by sensors were transmitted to the monitor center by a wireless module.

2 The design of five gyroscopes redundant system

This paper constructed a cone geometry configuration system with five inertial sensors (gyroscopes) for the measurement of mobile robot's attitude. The configuration of five sensors is based on the idea of fault tolerant system, if there are only 3 sensors of the system, the system can easily loss its function once one sensor broke down. Besides, for 4 sensors system although lower detection failure rate is achieved with, the fault sensor can't be isolated. Considering the process and cost, the system consisting of 5 sensors is able to realize the attitude measurement as well as fault detection and isolation with minimum number.

The geometry configuration of five sensors case is shown in Figure 1. The input axes of sensors are placed perpendicular to the five side faces of the hexahedron. The alpha angle between p axis and input axis is 54.7356° [14]. When a fault is included

in the redundant inertial system, the measurement equation can be described as follows:

$$m = Hx + \varepsilon + f \quad (1)$$

where m is a $n \times 1$ measurement vector of the n sensors, H is a $n \times 3$ measurement matrix of the state space to the sensor space, x is a 3×1 state vector of p, q, r , ε is a $n \times 1$ measurement noise vector with a normal distribution (white noise), and f is a $n \times 1$ fault vector.

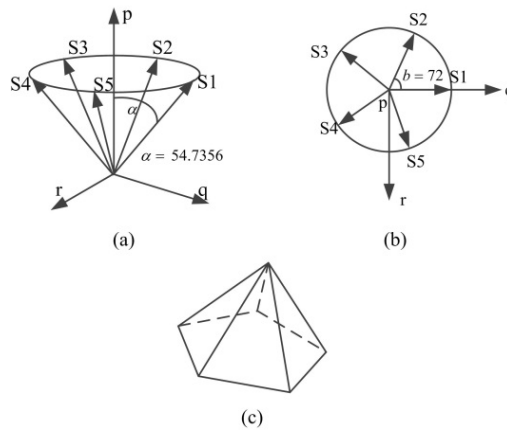


Fig. 1. Five inertial sensors redundant configuration scheme

Based on Figure 1 the measurement matrix H of redundant configuration with five gyros can be obtained as follows:

$$H = \begin{bmatrix} \cos \alpha & \sin \alpha & 0 \\ \cos \alpha & \sin \alpha \cos b & -\sin \alpha \sin b \\ \cos \alpha & -\sin \alpha \cos(b/2) & -\sin \alpha \sin(b/2) \\ \cos \alpha & -\sin \alpha \cos(b/2) & \sin \alpha \sin(b/2) \\ \cos \alpha & \sin \alpha \cos b & \sin \alpha \sin b \end{bmatrix} \quad (2)$$

The columns of the matrix represent the five gyros' coordinate in the p axis, q axis and r axis respectively.

In order to evaluate the measurement precision affected by the configuration of the sensors, the concept of geometric dilution of precision (GDOP), which is often used in evaluating the positional accuracy in GPS, is introduced [15-16]. Similar to the GDOP application in GPS, the measurement accuracy depends on the error covariance. The formula of GDOP can be expressed as:

$$GDOP = \sqrt{\text{TRACE}[(H^T H)^{-1}]} \quad (3)$$

Here, $(H^T H)^{-1}$ is the covariance matrix. According to [14], the optimal configuration for the measurement performance in redundant inertial sensor systems is defined as the configuration which minimizes the GDOP. The necessary and sufficient condition for the configuration to be optimal is $(H^T H) = \frac{n}{3} I$. The computing result of $(H^T H)$ is as follows:

$$(H^T H) = \begin{bmatrix} 1.6667 & 0 & 0 \\ 0 & 1.6667 & 0 \\ 0 & 0 & 1.6667 \end{bmatrix} \quad (4)$$

The computing result of $(H^T H)$ meets the condition of $(H^T H) = \frac{n}{3} I$, where $n = 5$. It shows that the attitude measurement and control system consisting of five sensors with the configuration introduced provides the optimal measurement performance.

3 Improved PCA

3.1 PCA modeling based on parity vector

When the fault occurs in the dynamic environment, it is difficult to distinguish the dynamic data and the fault data of sensors by using the traditional PCA method. To solve this problem, the paper put forward an improved PCA method based on a parity vector which has a linear relationship in redundant measurement. It is only a function of measurement noise in fault-free occasion, while in the presence of faults, it is a function of noise and fault. In virtue of this feature, faults can be detected [7].

A decoupling matrix V satisfies the condition:

$$\begin{cases} VH = 0 \\ VV^T = I_{n-3} \\ V^T V = I_n - H(H^T H)^{-1} H^T \end{cases} \quad (5)$$

The parity vector is constructed as follows:

$$p = Vm = V(Hx + \varepsilon + f) \quad (6)$$

where m is the measurements of the sensors, ε is the measurement noise and error

of the sensors and f is the fault of sensors. According to (5), the parity vector for failure-free and failure occasions respectively hold:

$$p = V\varepsilon \quad (7)$$

and:

$$p = V\varepsilon + Vf \quad (8)$$

Therefore, the parity vector can be applied in online data pretreatment when the sensors are exposed to a dynamic environment. The dynamic data is isolated through the decoupling matrix V so that we don't mistake dynamic data for fault data. The decoupling matrix V can be obtained based on the potter algorithm [17]:

$$V = \begin{bmatrix} 0.6324 & -0.5117 & 0.1955 & 0.1955 & -0.5117 \\ 0 & 0.3717 & -0.6015 & 0.6015 & -0.3717 \end{bmatrix} \quad (9)$$

After the data preprocessing by using parity vector, the PCA model was built based on (7) in normal operation. In other word, it's effective to build PCA model by parity vector of measurement noise due to the characteristic that noise frees to the movement of system.

For convenience, we process the parity vector of measurement noise into $X \in R^{n \times k}$ which is a normalized matrix with n samples and k variables. The correlation coefficient matrix R is calculated based on a standardized data matrix X , the matrix R is defined as follows:

$$R = \frac{1}{n-1} X^T X \quad (10)$$

And then we compute eigenvalues λ_i of matrix R and orthonormal eigenvectors p_i . Among them, $i = 1, 2, \dots, k$, $\lambda_1 > \lambda_2 > \dots > \lambda_k > 0$. The measured data matrix is decomposed as:

$$X = TP^T + \tilde{T}\tilde{P}^T = \hat{X} + E \quad (11)$$

where $P = [p_1, p_2, \dots, p_l] \in R^{k \times l}$ and $\tilde{P} = [p_{l+1}, p_{l+2}, \dots, p_k] \in R^{k \times (k-l)}$ refer to the primary load matrix and residual load matrix respectively. $T \in R^{n \times l}$ and $\tilde{T} \in R^{n \times (k-l)}$ are the primary score matrix and the residual score matrix, respectively. The original set of variables is reduced to l principal components through the principal component projection. The matrix is decomposed into modeled part \hat{X} and unmodeled part E . The composed matrix $[P \ \tilde{P}]$ is orthonormal and $[T \ \tilde{T}]$ is orthogonal [18].

After the PCA model has been built based on measurement noise, the new collection variable x (after normalized) is decomposed into two parts:

$$x = PP^T x + e = Pt + e \quad (12)$$

where $t = P^T x$ is primary score vector projected on the PCS and e is the error vector projected on RS. The fault detection is conducted on the two subspaces. The results corresponding to the traditional PCA model and the improved one are compared in Figure 2 and Figure 3. The fault data and normal data processed by the traditional PCA are mixed as shown in Figure 2 which results in false-alarm and false dismissal. In Figure 3, there is no overlapping portion between normal data and fault data, because the parity vector has been used in PCA modeling processes.

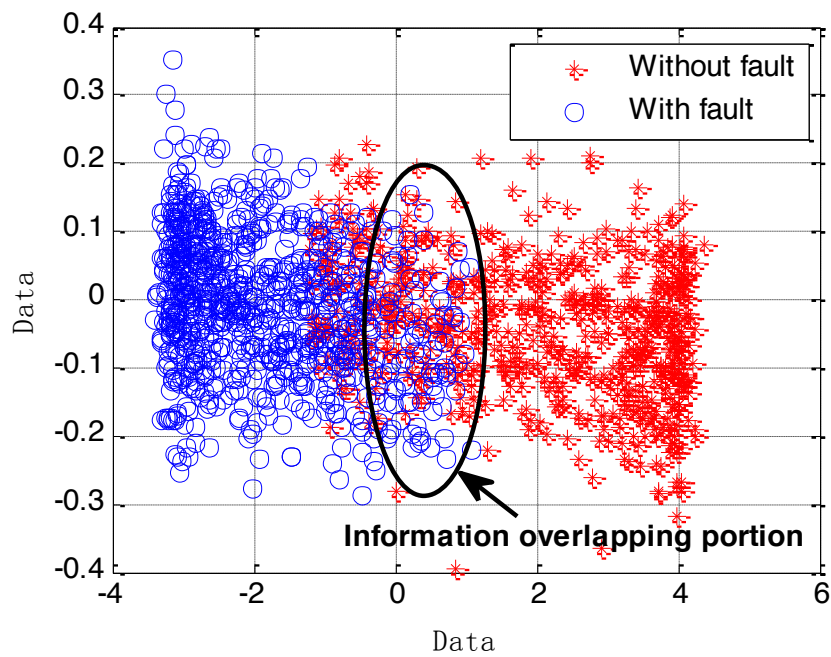


Fig. 2. Data processed by traditional PCA method

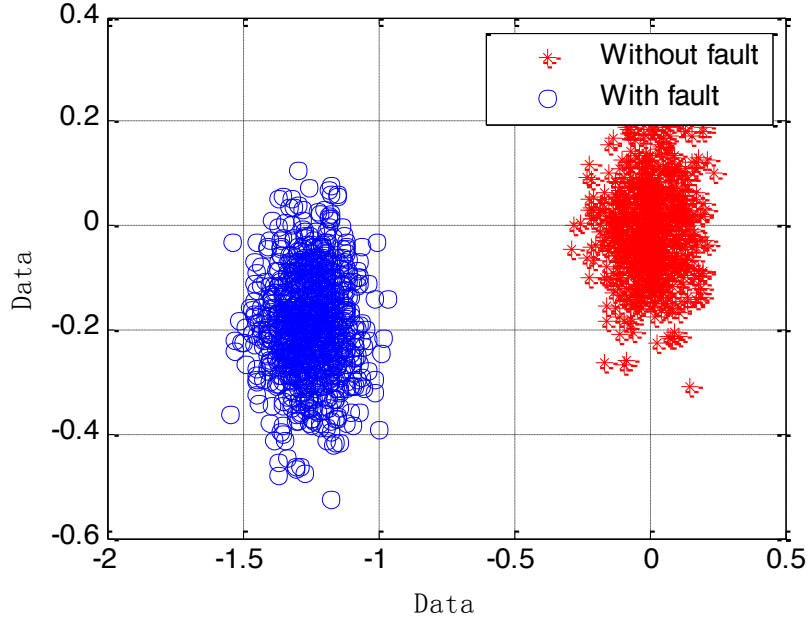


Fig. 3. Data processed by improved PCA method

3.2 Strategy of fault detection

After the establishment of PCA model, the new real-time collected data is projected onto the PCS and RS. If the data mostly falls in the main space but little falls in the residual subspace, it can be judged that the system is under a normal situation. On the contrary, if the most data falls in the residual subspace, it shows that the faults exist. In this section, we discuss the strategy of fault detection using T^2 and SPE statistics.

The T^2 statistic used in PCS reflects the distance between the sampling data and principal component, which reads:

$$\begin{aligned}
 T^2 &= X^T P \Lambda^{-1} P^T X = t^T \Lambda^{-1} t \\
 &= \sum_{i=1}^l \frac{t_i^2}{\lambda_i} : \frac{l(n^2 - 1)}{n(n - l)} F(n, n - l)
 \end{aligned} \tag{13}$$

where $t = P^T X$, Λ is the variance matrix of l principal components, which can be expressed as $\lambda_i = \text{diag}(\lambda_1, \dots, \lambda_l)$. And $F(n, n - l)$ is the distribution of F which has n and $n - l$ degrees of freedom. Giving the confidence level α , the control threshold of T^2 follows:

$$T_{\alpha}^2 = \frac{l(n^2 - 1)}{n(n - l)} F_{\alpha}(l, n - l) \quad (14)$$

T_i^2 is compared with the threshold value T_{α}^2 to judge the system state with $T_i^2 < T_{\alpha}^2$ referring to a transient normal state and $T_i^2 > T_{\alpha}^2$ referring to a failure one.

The *SPE* statistic reflects the extent to which each sampling data conforms to the PCA model. It is a measurement of the variation amount which is not captured by the principal component model. It can be calculated as:

$$SPE = \|e\|^2 = e^T e = x^T (I - PP^T)x \quad (15)$$

here x is a new observation vector to be collected. *SPE* is compared with the threshold value Q_{α} when confidence coefficient is given. If the statistic value is under threshold, the system is identified as normal. Otherwise, there are some faults within the system. The upper limit Q_{α} for *SPE* statistic is given by:

$$Q_{\alpha} = \theta_1 \left[\frac{C_{\alpha} h_0 \sqrt{2\theta_2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1} \right]^{\frac{1}{h_0}} \quad (16)$$

where $\theta_i = \sum_{j=i+1}^k \lambda_j^i, i = 1, 2, 3, h_0 = 1 - 2\theta_1\theta_3 / 3\theta_2$. and C_{α} is the critical value

when the test level is α . λ_j is the j characteristic value of the covariance matrix.

We should not only detect the fault, but also isolate the fault sensor. It is effective to isolate the fault sensor in redundant system through generalized likelihood ratio test (GLRT). This method can't be influenced by the sensors' errors by using parity vector calibration [19].

4 Simulation results and analysis

By giving the five sensors' dynamic data, the measurement matrix and the decoupling matrix, the feasibility on fault detection and isolation using the improved PCA method was verified on MATLAB.

Assume that the measurement noise of the five gyros are identical, two principal components can be selected. The yaw angle in simulation simplified to be zero since the yaw angle data was collected by other auxiliary sensors, e.g. an additional compass sensor. The five gyros sampling period was 0.01s and the total time was 1min. Giving a confidence coefficient of 0.05, the upper limit of T^2 can be calculated refer

to (14) to be 6.01. Accordingly, the test level of the given normal distribution was 0.8505, C_α was 1.65, and the control limit Q_α was 12.49.

In order to validate the effectiveness of the scheme and algorithm, the fault forms were injected into the gyro at different locations in the system operation process. As shown in Table 1 and Figure 4 we inject the step fault signal $2^\circ/s$ into 2th gyro at the 6th seconds, and the step fault signal $2^\circ/s$ into 4th gyro at the 35th seconds, respectively and each fault signal lasts 10 seconds.

Table 1. Injection fault information

Fault form	Gyro number	Fault injection time	Fault size
1	#2	6~16s	$2^\circ/s$
2	#4	35~45s	$2^\circ/s$

In Figure 5 and Figure 6, the vertical axis express the value of T^2 and SPE , the horizontal axis express the simulation time. Figure 5 shows the traditional PCA method has a low detection rate that can only detect the fault at 35s. In Figure 6, it is obvious that both T^2 and SPE plots generated by improved PCA model can detect the faults appeared at 6th and 35th seconds. It is a normal phenomenon that the value exceeds the threshold but soon disappears at certain moments due to the interference of experimental. In Figure 7, we can see GLRT of fault isolation decision curve, it can accurately determine the fault sensor for 2th and 4th. The simulation results show that the improved one significantly reduces missing detection rate.

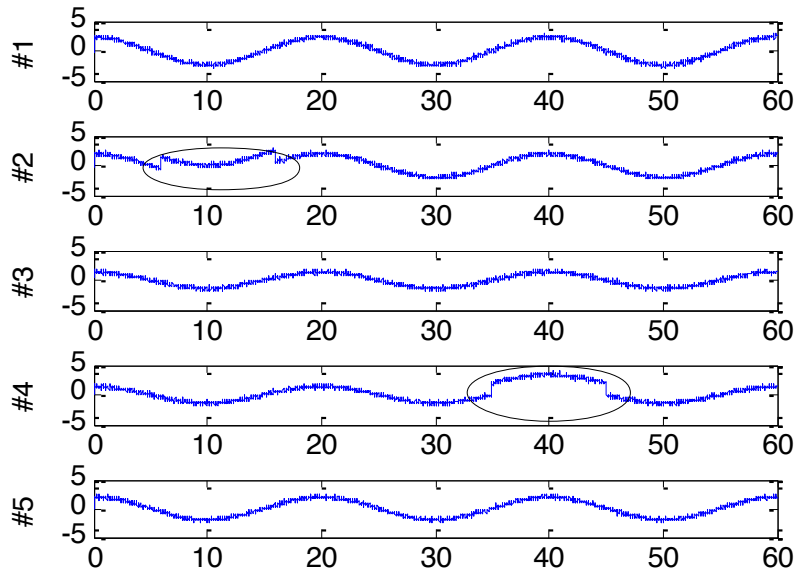


Fig. 4. Gyro output with fault under the dynamic condition

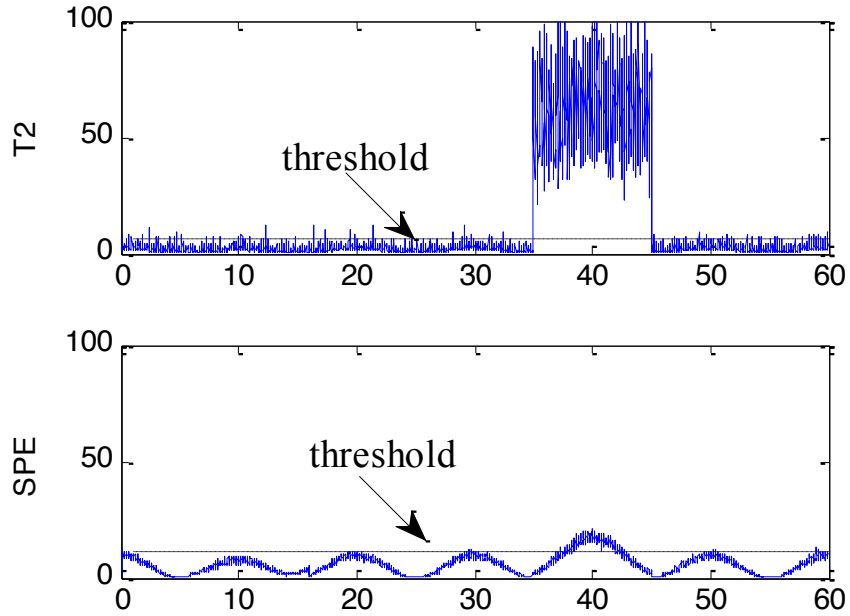


Fig. 5. The traditional PCA method for fault detection

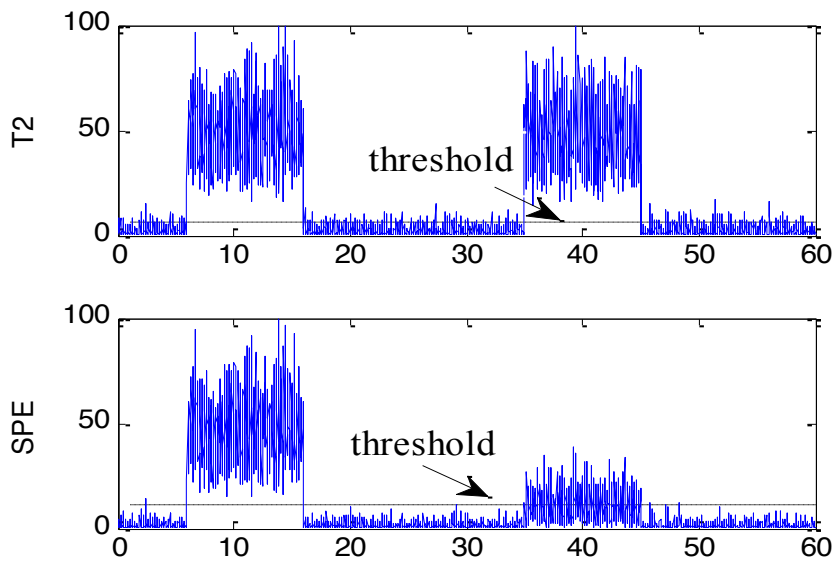


Fig. 6. The improved PCA method for fault detection

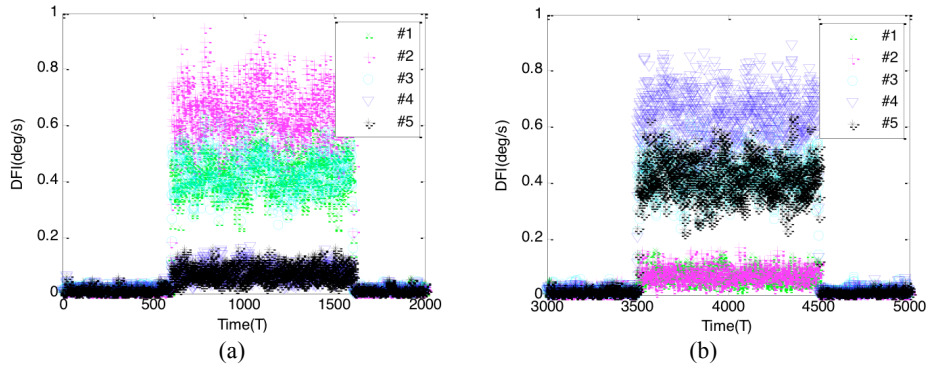


Fig. 7. Improved PCA method for fault isolation decision curve

1 Experiment verification

As shown in Figure 8, the experimental platform includes a measuring module consisting of five digital MEMS single axis gyroscopes (ENC03), a collection module and a computer. The measuring range of gyroscope is $\pm 250^\circ / s$. The angular velocity rate is obtained via the experimental platform. The gyroscope original data collected by the embedded processor (STM32) was processed on the MATLAB to verify the performance of the improved algorithm. On the practical operation, in order to obtain the real-time running state of the robot, the data collected by the embedded processor was connected to the computer by using the wireless module whose transmission distance is 100 meters. Thus, it's convenient to monitor the robot's operation state in the distance.

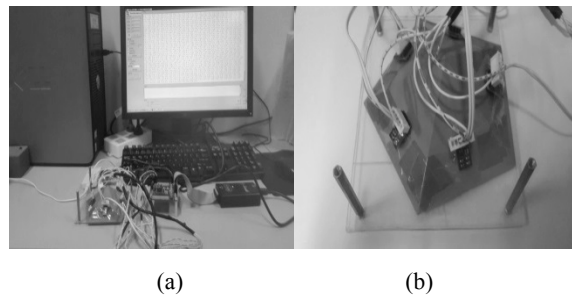


Fig. 8. The experimental platform

The measuring module installed on the experimental platform was able to simulate the actual operation of the two wheeled self-balancing robot. The angular velocity rate data of five gyroscopes is shown in Figure 9 and Figure 10. The horizontal axis of Figure 9 and 10 represents the time and the vertical axis represents the angular velocity rate of five gyroscopes. Notice that in Figure 10 the 4th gyro is injected failure after a period of time on operation.

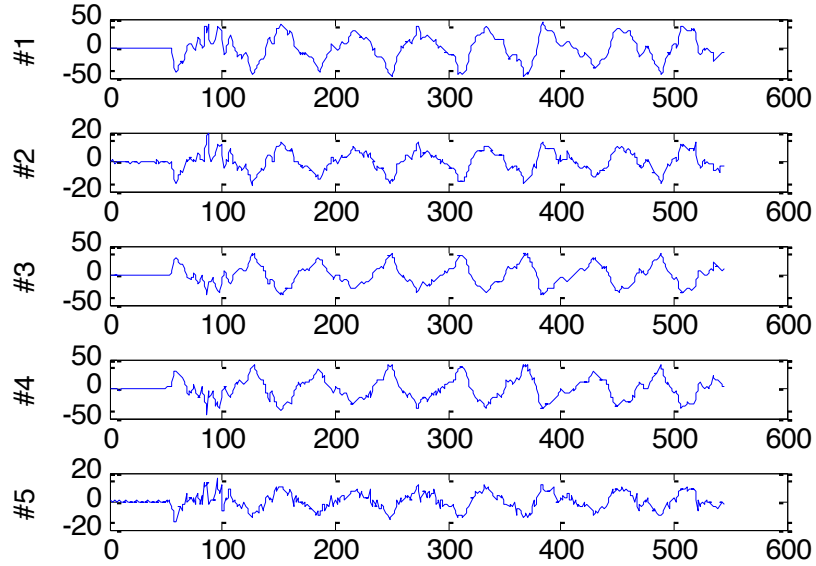


Fig. 9. the output of five gyroscopes

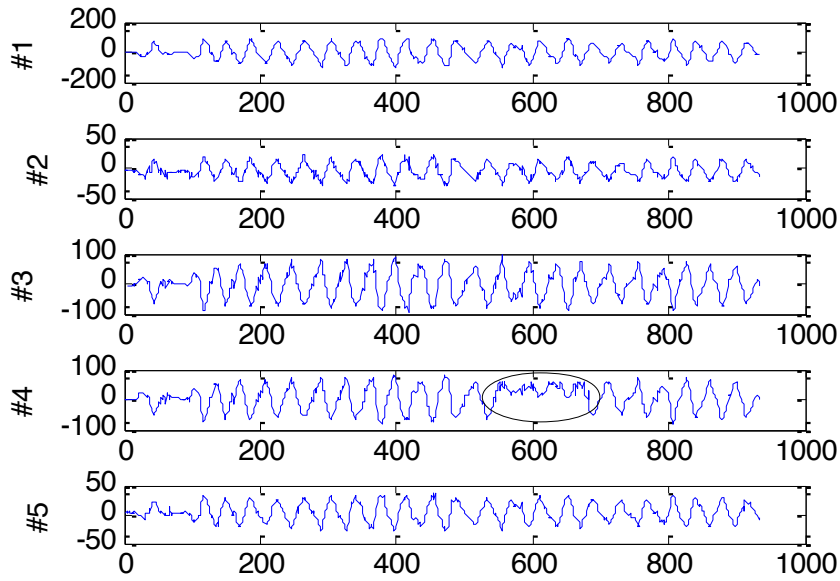


Fig. 10. The 4th Gyro output with fault

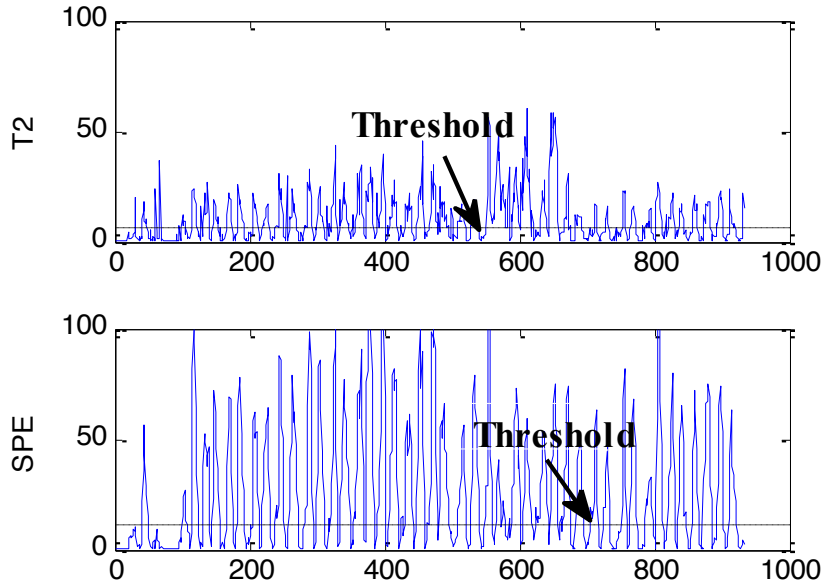


Fig. 11. The traditional PCA method for fault detection

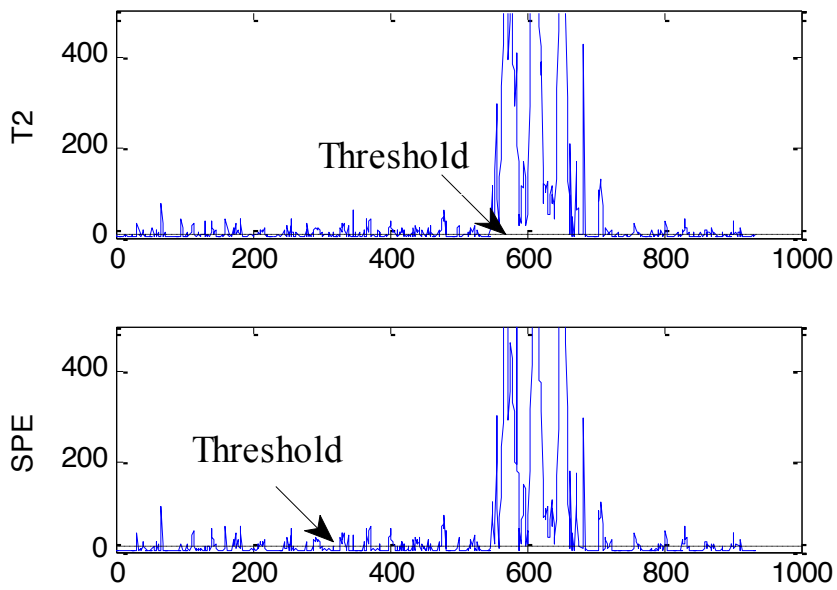


Fig. 12. The improved PCA method for fault detection

The experimental result of the traditional PCA is shown in Figure 11. When the system is in the dynamic condition, both T^2 and SPE values calculated by the traditional one are always exceed the threshold. It means that the system is in a state of fault all the time, which is inconsistent with the actual operation situation. Figure 12 presents the result of improved method. When the fault appears, the values of T^2 and SPE go beyond the control limit. At other times, the values are lower than the detection threshold. The experimental results meet the consistent with the simulation results.

5 Conclusion

In this paper, the improved PCA method was proposed to adapt for the dynamic system. Compared with the traditional one, the model based on the parity vector was able to isolate the dynamic data from the original data. The difference between two methods was as follows:

According to Eq.1, the measurement data with fault consists of dynamic data, measurement noise and fault signal in a dynamic system. The traditional PCA can't draw a clear distinction between fault data and dynamic data which result in false-alarm and false dismissal. The method proposed in this paper preprocessed the data by parity vector to obtain new data structure with measurement noise and fault signal. We used noise data to build PCA model due to the characteristic that measurement noise frees to the movement of system.

The improved method was applied to a redundant system with five gyroscopes. The simulation and experiment demonstrated that the improved method performs better than the traditional one in dynamic condition which enhanced the accuracy and reliability of multi-sensors system.

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