A new Threshold Algorithm based PCA Method for Fault Detection in Transient State Processes

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Abstract

Multivariate Statistical Process Control (MSPC) approaches are now widely used for performance monitoring, fault detection and diagnosis in industrial processes. Conventional MSPC approaches are based on latent variable projection methods such as Principal Component Analysis (PCA). These methods are suitable for steady-state processes. For the systems where transient values of the processes must be taken into account, the usage of conventional PCA method causes false alarms and missing data that significantly compromise the reliability of the monitoring systems. In this paper a method is proposed to overcome false alarms which occur in the transient states according to changing process conditions and the missing data problem. The proposed monitoring method is implemented and validated experimentally on an electromechanical process. The monitoring results confirm that the proposed methodology affords credible fault detection for both the steady-state and transient operations.

1. Introduction

The demand for effective quality monitoring and safe operation in the modern industry has propelled research into statistical based fault detection and diagnosis methods over the past few decades [1, 2]. One of the most common multivariate statistical process control (MSPC) methods used for this purpose is principal component analysis (PCA) [3].

PCA method initially proposed in 1901 by Pearson [4] and later developed in 1947 by Hotelling [5]. PCA method is used to extract a few independent components from highly correlated process data and use the components to monitor the process operations. Typically, two major monitoring indices are calculated, the squared prediction error (SPE) and the Hotteling T^2 index. An abnormal situation will cause at least one of the two indices to exceed the control limit.

Conventional PCA methods for the fault detection have largely focused on the steady-state operations and are not directly applicable during the transitions [6]. Applying a PCA method to such a transient process can produce excessive number of false alarms or missed detection of process faults, that is significantly compromise the reliability of the monitoring system. Therefore, a novel PCA fault detection method is required that explicitly caters to the non-steady states and wide operating condition changes during transitions.

In the present article, a new monitoring approach is proposed based on PCA method that covers both the steady-state and transient operating conditions for the stationary signals with the variance sensitive adaptive threshold (T_{vsa}). The method is implemented and validated experimentally on a dc motor system using on-line data and provides much better fault detection for the servo systems in the transient operation.

The paper is organized as follows. Section 2 provides a theoretical background to PCA analysis and application in FDD. Section 3 describes the proposed variance sensitive adaptive threshold algorithm. Section 4 introduces the experimental setup and preliminaries. Experimental results are presented in Section 5 which is followed by a Conclusion in Section 6.

2. Principal Component Analysis

Principal Component Analysis (PCA) is a powerful tool used in MSPC [7] and in Fault Detection and Isolation (FDI) tasks [8]. This analysis is based on a linear transformation that produces new uncorrelated variables (components) from the original correlated measured variables. PCA provides a method of extracting relevant information from huge noisy data sets. This transformation implies a dimensionality reduction of the original data; so, a few of these components are sufficient to represent adequately the hidden sources of variability in the process.

Let X, $X \in \Re^{nxm}$ represent a data matrix, n denotes number of measurements; m denotes number of physical variables. The data matrix must be normalized to zero mean and unity variance with the scale parameter vectors $\bar{x}$ and ϵ as the mean and variance vectors respectively. Using PCA, the data matrix X can be decomposed as:

$$X = \hat{X} + E \quad (1)$$

$$\hat{X} = \hat{T}\hat{P}^T \quad (2)$$

$$E = \tilde{T}\tilde{P}^T \quad (3)$$

where, X is Principal Component Subspace (PCS), it represents the correct direction of the measured vectors. E represents residual subspace (RS), it is the direction of faulty measurements. E is noise or uncertain disturbance mostly, when the measurements are fault free. $\hat{T}$ is score matrix, $\hat{T} \in \Re^{nxa}$, $\hat{T} = X\hat{P}$. $\hat{P}$ is *loading* matrix, $\hat{P} \in \Re^{mxa}$. "a" is principal components (PCs) number of the model. The columns of $\hat{P}$ are eigenvectors of the correlation matrix associated with the "a" largest eigenvalues and the columns of $\tilde{P}$ are the remaining $m - a$ eigenvectors.

PCA modeling process is composed of the following steps:

1. The normalization of the original variables.
2. Calculation of the covariance matrix Σ :

$$\Sigma = \frac{1}{n-1} X^T X \quad (4)$$

3. Singular Value Decomposition (SVD) is performed as:

$$\Sigma = V \Lambda V^T \quad (5)$$

where Λ is a diagonal matrix that contains the eigenvalues (λ_i) of the covariance matrix Σ sorted in decreasing order $(\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0)$ in the diagonal locations. Columns of the matrix V are the eigenvectors of Σ.

4. Determine the optimal number "a" of PCs.
5. Choose loading matrix $\hat{P}$ according to the PCs number "a".
6. The projection matrix C and $\tilde{C}$ are calculated using the loading matrix $\hat{P}$ as:

$$C = \hat{P}\hat{P}^T, \tilde{C} = \tilde{P}\tilde{P}^T = (I - C) \quad (6)$$

The original m dimension data space is substituted by the "a" PCS and "*m-a*" RS, and then the correlations of variables are removed.

After the PCA model has been built, when new measurements are collected, the PCA model can be used for the fault detection.

2.1. T^2 Charts

Normal operations can be characterized by employing T2-statistic method proposed by Hotelling in 1947 [5]:

$$T^2 = x^T \hat{P} \Lambda_a^{-1} \hat{P}^T x \quad (7)$$

where Λ_a is a squared matrix formed by the first "*a*" rows and columns of Λ. The process is considered *normal* for a given confidence level $(100(1-\alpha)\%)$ if:

$$T_\alpha = \frac{(n^2-1)a}{n(n-a)} F_\alpha(a, n-a) \quad (8)$$

where $F_\alpha(a, n-a)$ is the critical value of the Fisher-Snedecor distribution with n and $n - a$ degrees of freedom and α the level of significance. α takes the values between 95% and 99% as recommended in [9]. The T^2-statistic with Eq. (8) defines the normal process behavior, and an observation vector outside this region indicates that a fault has occurred.

3. Proposed Threshold For T^2 Charts

Considering the variation of the T^2 signal defined in Eq. (7) with the data matrix X which consist of all measured data, the mean and variance of the T^2 signal can be expressed according to the stochastic theory [10]:

$$\mu(X,t) = \frac{1}{n}\sum_{i=1}^{n} T_i^2(t) \quad (9)$$

$$\sigma^2(X,t) = \frac{1}{n-1}\sum_i^n T_i^2(t) - \mu(X,t)^2 \quad (10)$$

where μ, σ^2 and n are the mean, variance and sample data respectively. From the statistical theory [11] the confidence limits of the mean that represent a confidence of $(1-\alpha)$ is

$$P\{\bar{\mu} - z\sigma < \mu < \bar{\mu} + z\sigma\} = 1 - \alpha \quad (11)$$

where α is the confidence level, and z is the coefficient related to the confidence level. From Eq. (11), the adaptive threshold of the mean for the T^2 signal can be calculated as [11]:

$$T_{adp} = \mu(T^2, t) \pm z\sigma(T^2, t) \quad (12)$$

Fixed threshold T_α in Eq. (8) provides the chosen confidence limit. However it causes the false alarms in the transient state of the system. The fixed (T_α) and adaptive (T_{adp}) thresholds are combined to overcome the false alarms and to provide the confidence limit it is given as T_{comb} [12]:

$$T_{comb} = \begin{Bmatrix} T_\alpha & if & T_\alpha \geq T_{adp} \\ T_{adp} & if & T_\alpha < T_{adp} \end{Bmatrix} \quad (13)$$

where, T_{comb} eliminates the false alarms arising from the transient state. But the high variance which occurs during the variations of the states in transient conditions and measurements noise results in very high T_{comb}. This causes to produce the missing fault signal components.

To overcome the outlined drawbacks the threshold should be sensitive to the size of the variance. High variance is obtained if $\sigma(T^2, t) \geq \mu(T^2, t)$. Instead, if the variance $\sigma(T^2, t)$ is taken to be equal to the mean $\mu(T^2, t)$ the high variance will be reduced to a reasonable level:

$$T_{adp} = \mu(T^2, t) \pm z\mu(T^2, t) = \mu(T^2, t)(1 \pm z) \quad (14)$$

New threshold T_{vsa} called "variance sensitive adaptive threshold" can be given as [12]:

$$T_{vsa} = \begin{cases} T_\alpha & if \quad T_\alpha \geq T_{adp} \\ T_{adp} = \mu(T^2,t) \pm z\sigma(T^2,t) & if \quad T_\alpha < T_{adp} \ and \ \mu \leq \sigma \\ T_{adp} = \mu(T^2,t)(1 \pm z) & if \quad T_\alpha \leq T_{adp} \ and \ \mu > \sigma \end{cases} \quad (15)$$

Where the parameter T_α in (Eq.15) provides the confidence limit, the relation $\mu(T^2, t) \pm z\sigma(T^2, t)$ overcomes the false alarm in the transient state and the last relation $\mu(T^2, t)(1 \pm z)$ reduces high variance effect and eliminates missing fault signal component.

4. Experimental Set-Up and Preliminaries

General diagram of the experimental set-up illustrated in Fig. 1 is used in the experiments.

Fig. 1. A scene from the laboratory.

The armature current and output shaft speed are measurable. A computer (Pentium IV, 2 GHz in speed, 1 GB RAM) is used to implement the proposed PCA method. Output shaft speed is measured from a tachogenerator (as volts) connected to the motor shaft. A data acquisition card (DAQ-Advantech, Model: PCI-1716, 250 kHz in speed and 0.03% of accuracy, 16 bit) is used to communicate between the plant and the computer. The proposed PCA method is implemented in Simulink of Matlab software [13]. The produced control input (armature voltage) is sent to the power amplifier. The sampling period is taken to be 5 msec. for all experimental tests.

A functional diagram of the overall PCA fault detection method is demonstrated in Fig. 2. Two measurements are chosen for calculating the PCA detection algorithm: the motor shaft speed and the motor armature current Using the cumulative percent variance (CPU) approach [14], one principal component (a = 1) is found adequate to capture major correlations (%98) in the process variable. T^2-statistic is computed in order to monitor behavior of the process.

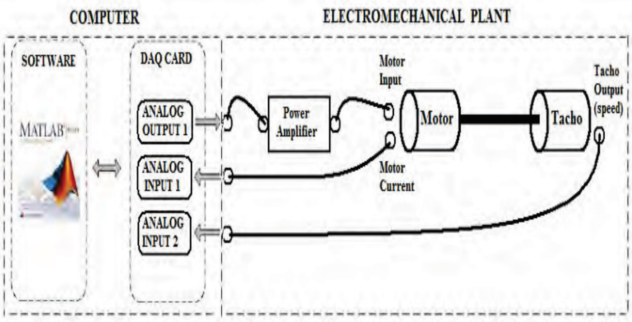

Fig. 2. General diagram of the laboratory equipment.

Then, the fixed threshold T_α (from Eq. (8)) is calculated for %95 confidence limit. The combination of fixed and adaptive threshold T_{comb} and the proposed variance sensitive adaptive threshold T_{vsa} are calculated using Eq. (13) and Eq. (15). For the 97% confidence level (i.e. $\alpha = 0.03$) (100(1-0.03)%=97%) , and the coefficient z is calculated from Eq. (11) to be 2.17.

5. Experimental Results

In order to demonstrate the efficacy of the proposed PCA method, experimental test is performed. The experiment is carried out in open-loop conditions to test both the steady-state and transient operating conditions for the actuator fault under the constant load conditions. The results in experimental test using fixed threshold-based T^2-statistic (T_α), combination of fixed and adaptive threshold-based T^2-statistic (T_{comb}) and proposed variance sensitive adaptive threshold-based (T_{vsa}) methods are presented for PCA monitoring.

A signal shown in Fig. 3 is applied to the system as an actuator fault during the time that the plant is running.

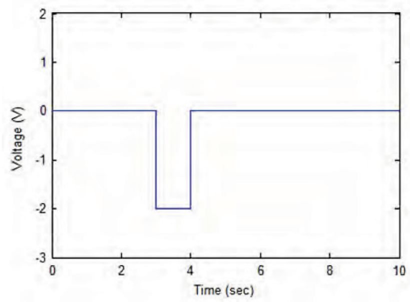

Fig. 3. Applied fault signal to input of the actuator.

The results are plotted with their alarm signals in which Fig (a) shows PCA method with their threshold values and the Fig (b) shows alarm signals produced. T^2-statistic methods based on the fixed thresholds illustrated in Fig. 4(a) and (b) produce false alarm signals during the transient state of the fault signal applied.

The false alarm is eliminated but this time, the missing fault signal components appear in the combination of fixed and adaptive threshold-based T^2-statistic (T_{comb}) method as shown in Fig. 5 (a) and (b).

The alarm signal produced from the proposed variance sensitive adaptive threshold method (T_{vsa}) is illustrated in Fig. 6 (a) and (b) such that both the false alarm caused during the transient state and the missing data are eliminated.

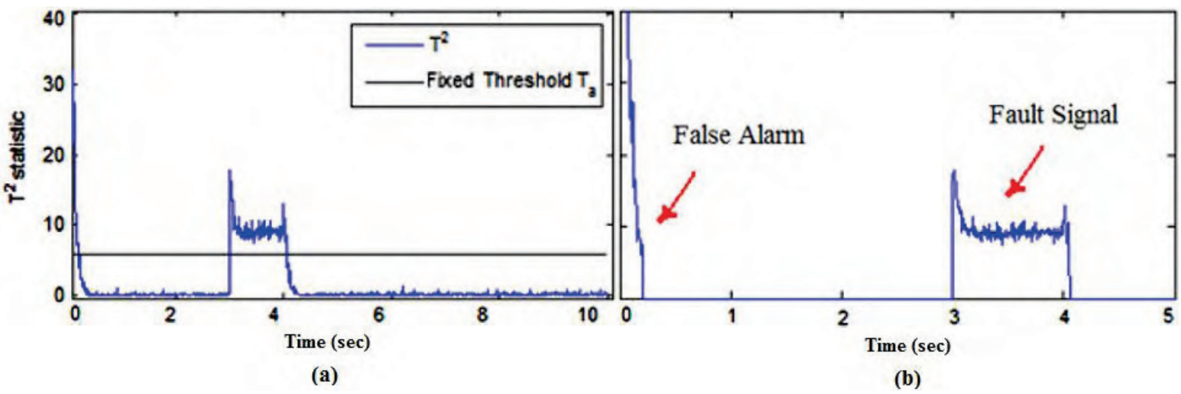

Fig. 4. a) PCA monitoring with fixed threshold-based T2-statistic (T_α). b) Alarm signal.

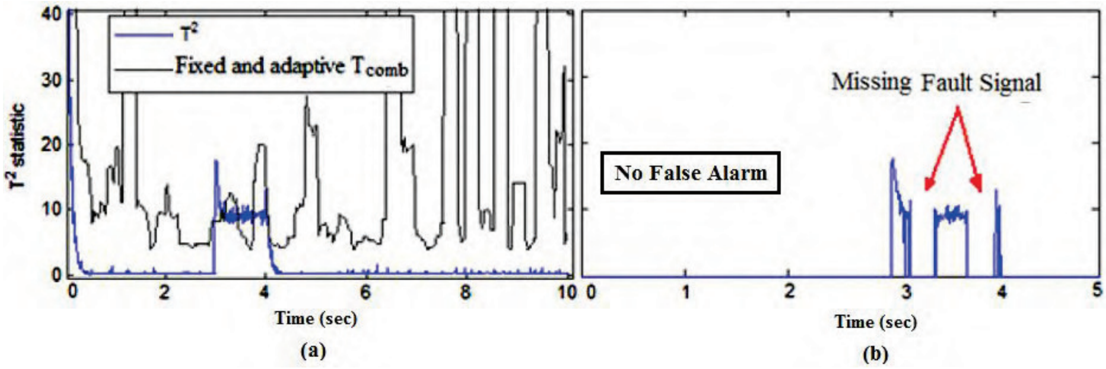

Fig. 5. a) PCA monitoring with combination of fixed and adaptive threshold-based T2-statistic (T_{comb}). b) Alarm signal.

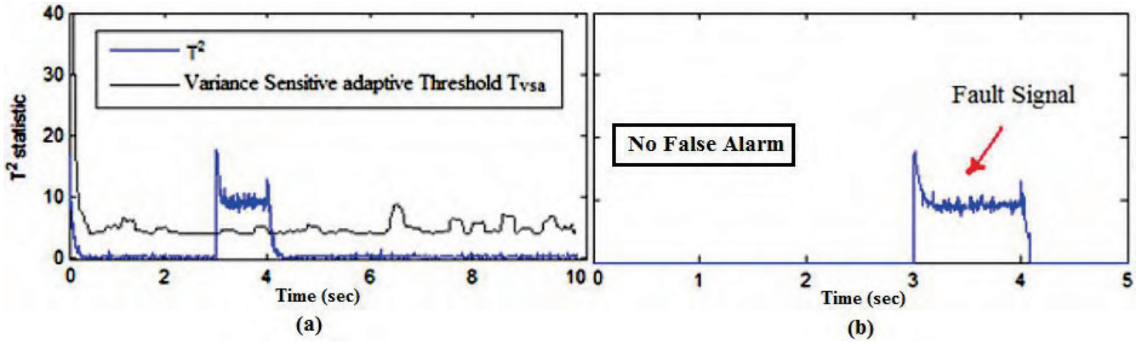

Fig. 6. a) PCA monitoring with variance sensitive adaptive threshold-based (T_{vsa}). b) Alarm signal.

6. Conclusions

Applying a Conventional PCA method to such a transient process can produce excessive number of false alarms or missed detection of process faults, which is significantly compromise the reliability of the monitoring system. Therefore, a novel PCA fault detection method is required that explicitly caters to the non-steady states and wide operating condition changes during the transitions.

The proposed method, variance sensitive adaptive threshold for confidence limit of Hotelling's T^2 is presented, prevents false alarms appearing in the transient conditions and overcomes missing fault signal problem. Experimental test confirms the fact that the proposed method is applicable and effective for both the steady-state and transient operations and gives early warning to operators.

7. References

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