# Monitoring Independent Components for Fault Detection

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*A chemical process has a large number of measured variables, but it is usually driven by fewer essential variables, which may or may not be measured. Extracting such essential variables and monitoring them will improve the process-monitoring performance. Independent component analysis (ICA) is an emerging technique for finding several independent variables as linear combinations of measured variables. In this work, a new statistical process control method based on ICA is proposed. For investigating the feasibility of its method, its fault-detection performance is evaluated and compared with that of the conventional multivariate statistical process control (cMSPC) method using principal-component analysis by applying those methods to monitoring problems of a simple four-variable system and a continuous-stirred-tank-reactor process. The simulated results show the superiority of ICA-based SPC over cMSPC.*

## Introduction

For the successful operation of any process, it is important to detect process upsets, equipment malfunctions, or other special events as early as possible, and then to find and remove the factors causing those events. In chemical processes, data-based process monitoring methods, referred to as statistical process control (SPC), have been widely used. Conventional SPC charts such as Shewhart control charts, cumulative sum (CUSUM) control charts, and exponentially weighted moving-average (EWMA) control charts are well established for monitoring univariate processes. Chemical processes are, however, multivariable systems consisting of a large number of mutually correlated variables. To monitor such multivariable processes, multivariate statistical process control (MSPC) has been developed.

The original Shewhart-type control chart for correlated variables is the Hotelling $T^2$ control chart. Jackson (1959) used principal component analysis (PCA) and proposed a $T^2$ control chart for principal components. Later, Jackson and Mudholkar (1979) and Jackson (1980) investigated PCA as a tool of MSPC and introduced a residual analysis. The control chart was introduced for the sum of squared residuals $Q$ as well as $T^2$ of principal components retained in a PCA model

$$T^2 = \sum_{r=1}^{R} \frac{t_r^2}{\sigma_{t_r}^2} \tag{1}$$

$$Q = \sum_{p=1}^{P} \left( x_p - \hat{x}_p \right)^2 \tag{2}$$

where $t_r$ is the $r$th score of principal components; $\sigma_{t_r}^2$ is the variance of $t_r$; $x_p$ and $\hat{x}_p$ are a measurement of the $p$th variable and its predicted (reconstructed) value, respectively; and $R$ and $P$ denote the number of principal components retained in the PCA model and the number of process variables, respectively. The $T^2$ statistic is a measure of the variation within the PCA model, and the $Q$ statistic is a measure of the amount of variation not captured by the PCA model. Kresta et al. (1991) demonstrated the usefulness of MSPC with applications to simulated data from a fluidized-bed reactor and an extractive distillation column. In the last decade or so, various extensions of MSPC have been proposed. For example, multiway PCA–PLS for monitoring batch processes (Wold et al., 1987), multiblock PCA–PLS for monitoring very large processes (MacGregor et al., 1994), dynamic PCA for

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including process dynamics in a PCA model (Ku et al., 1995), multiscale PCA based on wavelet analysis for monitoring signals at several different frequency ranges (Bakshi, 1998), model-based PCA for integrating a process model with PCA (Rotem et al., 2000), moving PCA that monitors changes in directions of principal components (Kano et al., 2001), a method called DISSIM that is based on the dissimilarity of process data sets (Kano et al., 2002), and a method based on constrained PCA for incorporating external information into a PCA model (Yoon and MacGregor, 2001). In addition, the integration of several advanced monitoring methods is discussed by Kano et al. (2000).

The key idea or motivation of the present work is that the monitoring performance can be improved by focusing on essential variables that drive a process. Such essential variables should be estimated from measured process variables, because they are usually unmeasured or because they are corrupted by measurement noise even if they are measurable. Independent component analysis (ICA) is an emerging technique for finding several independent variables as linear combinations of measured variables. A number of applications of ICA have been reported in speech processing, biomedical signal processing, machine vibration analysis, nuclear magnetic resonance spectroscopy, infrared optical source separation, radio communications, and so on (Girolami, 1999). In the present work, a new statistical process control method based on ICA is proposed. For investigating the feasibility of the proposed method, its fault-detection performance is evaluated and compared with that of the conventional multivariate statistical process control (cMSPC) method using PCA by applying those methods to monitoring problems of a simple four-variable system and a continuous-stirred-tank-reactor (CSTR) process.

## Independent Component Analysis

ICA (Jutten and Herault, 1991; Girolami, 1999) is a signal-processing technique for transforming observed multivariate data into statistically independent components, which are expressed as linear combinations of observed variables. In this section, an ICA algorithm is described.

### *Problem definition*

It is assumed that $m$ measured variables $x_1, x_2, \ldots, x_m$ are given as linear combinations of $n(\leq m)$ unknown independent components $s_1, s_2, \ldots, s_n$. The independent components and the measured variables are zero mean. The relationship between them is given by

$$\boldsymbol{x} = \boldsymbol{A}\boldsymbol{s} \tag{3}$$

$$\boldsymbol{x} = [x_1\ x_2\ \cdots\ x_m]^T \tag{4}$$

$$\boldsymbol{s} = [s_1\ s_2\ \cdots\ s_n]^T \tag{5}$$

where $\boldsymbol{A} \in \Re^{m \times n}$ is an unknown full-rank matrix, called the mixing matrix. When $k$ samples are available, the preceding relationship can be rewritten as

$$\begin{aligned} &\boldsymbol{X} = \boldsymbol{A}\boldsymbol{S} \\ &\boldsymbol{X} \in \Re^{m \times k}, \qquad \boldsymbol{S} \in \Re^{n \times k} \end{aligned} \tag{6}$$

The basic problem of ICA is to estimate the original components $\boldsymbol{S}$ or to estimate the mixing matrix $\boldsymbol{A}$ from the measured data matrix $\boldsymbol{X}$ without any knowledge of $\boldsymbol{S}$ or $\boldsymbol{A}$. Therefore, the objective of ICA is to calculate a separating matrix $\boldsymbol{W} \in \Re^{n \times m}$ so that components of the reconstructed data matrix $\boldsymbol{Y}$, given as

$$\boldsymbol{Y} = \boldsymbol{W}\boldsymbol{X} \tag{7}$$

become as independent of each other as possible. The limitations of ICA are: (1) only non-Gaussian independent components can be estimated (just one of them can be Gaussian); and (2) neither signs, powers, nor orders of independent components can be estimated.

It should be noted here that these limitations have little influence on the monitoring performance of ICA-based SPC. The first limitation means that original independent components cannot be reconstructed when they are Gaussian. In such a situation where two or more variables follow normal distribution, independent components can be selected arbitrarily and used for monitoring. Therefore, reconstruction of the original independent components is not necessary. In addition, signs, powers, or orders of independent components do not have to be estimated when independent components are used for monitoring. Estimation of them is crucial only when exact reconstruction of unknown original independent components is the final objective.

### *Sphering with PCA*

Statistical independence is more restrictive than uncorrelation. Therefore, for performing ICA, measured variables $x_i$ are first transformed into uncorrelated variables $z_j$ with unit variance. This pretreatment can be accomplished by PCA, and it is called sphering or prewhitening.

By defining the sphering matrix as $\boldsymbol{M}$ and then $\boldsymbol{B} = \boldsymbol{M}\boldsymbol{A}$, the relationship between $z$ and $\boldsymbol{s}$ is given as

$$z = \boldsymbol{M}\boldsymbol{x} = \boldsymbol{M}\boldsymbol{A}\boldsymbol{s} = \boldsymbol{B}\boldsymbol{s} \tag{8}$$

Since $s_i$ are mutually independent and $z_j$ are mutually uncorrelated

$$E[zz^T] = \boldsymbol{B}E[\boldsymbol{s}\boldsymbol{s}^T]\boldsymbol{B}^T = \boldsymbol{B}\boldsymbol{B}^T = \boldsymbol{I} \tag{9}$$

is satisfied. Here $E[\cdot]$ denotes expectation. It is assumed here that the covariance matrix of $s_i$, $E[\boldsymbol{s}\boldsymbol{s}^T]$, is an identity matrix, because signs and powers of $s_i$ remain arbitrary. Equation 9 means that $\boldsymbol{B}$ is an orthogonal matrix. Therefore, the problem of estimating a full-rank matrix $\boldsymbol{A}$ is reduced to the problem of estimating an orthogonal matrix $\boldsymbol{B}$ through the sphering.

### *Fixed-point algorithm for ICA*

For performing ICA, the fourth-order cumulant or its normalized form, kurtosis, is usually used. The fourth-order cumulant of zero-mean random variable $y$ is defined as

$$\kappa_4(y) = E[y^4] - 3E[y^2]^2 \tag{10}$$

The fourth-order cumulant is widely used in statistics as a measure of the heaviness of tails of a distribution (Girolami, 1999). The fourth-order cumulant is zero for a Gaussian variable. It is negative for a sub-Gaussian variable whose distribution is flat or multimodal; and it is positive for a super-Gaussian variable whose distribution tends to be spiky with heavy tails. By minimizing or maximizing the fourth-order cumulant $\kappa_4(\boldsymbol{b}^T\boldsymbol{z})$ under the constraint of $\|\boldsymbol{b}\| = 1$, columns of the orthogonal matrix $\boldsymbol{B}$ are obtained as solutions for $\boldsymbol{b}$. Finding the local extrema of the fourth-order cumulant is equivalent to estimating the non-Gaussian independent components (Delfosse and Loubaton, 1995).

A gradient method is used to obtain $\boldsymbol{b}$ that minimizes or maximizes the fourth-order cumulant

$$\kappa_4(\boldsymbol{b}^T\boldsymbol{z}) = E\left[(\boldsymbol{b}^T\boldsymbol{z})^4\right] - 3E\left[(\boldsymbol{b}^T\boldsymbol{z})^2\right]^2 = E\left[(\boldsymbol{b}^T\boldsymbol{z})^4\right] - 3\|\boldsymbol{b}\|^4 \quad (11)$$

A learning algorithm based on the gradient method has the form

$$\boldsymbol{b}(k+1) = \boldsymbol{b}(k) \pm \mu\left\{E\left[4\left(\boldsymbol{b}(k)^T\boldsymbol{z}\right)^3\boldsymbol{z}\right] - 12\|\boldsymbol{b}(k)\|^2\boldsymbol{b}(k) + 2\lambda\boldsymbol{b}(k)\right\} \quad (12)$$

where $\mu$ denotes a learning-rate parameter and $\lambda$ a Lagrange multiplier. For finding the local extrema of the fourth-order cumulant, a fixed-point algorithm can be used instead of the learning algorithm given earlier. In this article, the fixed-point algorithm developed by Hyvarinen and Oja (1997) is briefly described. For more details and convergence proof of the algorithm, refer to their article.

The fixed points $\boldsymbol{b}$ of Eq. 12 satisfy

$$E\left[4(\boldsymbol{b}^T\boldsymbol{z})^3_z\right] - 12\|\boldsymbol{b}\|^2\boldsymbol{b} + 2\lambda\boldsymbol{b} = 0 \quad (13)$$

and are obtained with the following iteration scheme

$$\boldsymbol{b}(k+1) = \lambda'\left\{E\left[\left(\boldsymbol{b}(k)^T\boldsymbol{z}\right)^3\boldsymbol{z}\right] - 3\|\boldsymbol{b}(k)\|^2\boldsymbol{b}(k)\right\} \quad (14)$$

Since the constraint $\|\boldsymbol{b}\| = 1$ must be satisfied, $\boldsymbol{b}$ is normalized at each iteration step.

For estimating $n$ independent components that are different from each other, the following orthogonal conditions are imposed

$$\boldsymbol{b}_i^T\boldsymbol{b}_j = 0 \qquad (i \neq j) \quad (15)$$

Thus, the current solution $\boldsymbol{b}_i$ is projected on the space orthogonal to previously calculated $\boldsymbol{b}_j (j = 1, 2, \ldots, i-1)$. By defining

$$\boldsymbol{B}_{i-1} = [\boldsymbol{b}_1\ \boldsymbol{b}_2\ \cdots \boldsymbol{b}_{i-1}] \quad (16)$$

the fixed-point algorithm for ICA is summarized as follows:

(1) Transform measured variables $\boldsymbol{x}$ into uncorrelated variables $\boldsymbol{z}$. This linear transformation is expressed as $\boldsymbol{z} = \boldsymbol{Mx}$ and can be accomplished by PCA. Here, each uncorrelated variable $z_j$ has unit variance. Let $i = 1$.

(2) Take a random initial vector $\boldsymbol{b}_i(0)$ of unit norm. When $i \geq 2$, $\boldsymbol{b}_i(0)$ is projected through the following operation

$$\boldsymbol{b}_i(0) = \boldsymbol{b}_i(0) - \boldsymbol{B}_{i-1}\boldsymbol{B}_{i-1}^T\boldsymbol{b}_i(0) \quad (17)$$

and then it is normalized so that $\|\boldsymbol{b}_i(0)\| = 1$. Let $k = 0$.

(3) $\boldsymbol{b}_i$ is updated through the following operation

$$\boldsymbol{b}_i(k+1) = E\left[\left(\boldsymbol{b}_i(k)^T\boldsymbol{z}\right)^3\boldsymbol{z}\right] - 3\boldsymbol{b}_i(k) \quad (18)$$

The expectation can be estimated by using a large number of samples.

(4) $\boldsymbol{b}_i(k+1)$ is projected through the following operation

$$\boldsymbol{b}_i(k+1) = \boldsymbol{b}_i(k+1) - \boldsymbol{B}_{i-1}\boldsymbol{B}_{i-1}^T\boldsymbol{b}_i(k+1) \quad (19)$$

and then it is normalized so that $\|\boldsymbol{b}_i(k+1)\| = 1$.

(5) If $|\boldsymbol{b}_i(k+1)^T\boldsymbol{b}_i(k)|$ is close enough to one, then go to the next step. Otherwise, let $k = k+1$ and go back to step 3.

(6) Let $\boldsymbol{b}_i = \boldsymbol{b}_i(k+1)$, $i = i+1$, and then go back to step 2. This iteration ends when $i = n$.

Independent components $\boldsymbol{Y}$ can be obtained from

$$\boldsymbol{Y} = \boldsymbol{B}^T\boldsymbol{Z} = \boldsymbol{B}^T\boldsymbol{MX} \quad (20)$$

where $\boldsymbol{B} = \boldsymbol{B}_n$.

### *Example of ICA*

An example of ICA is shown in Figure 1. Original variables are a sine wave and a random variable. These two variables $s_1$ and $s_2$ are transformed into measured variables $x_1$ and $x_2$ by using a mixing matrix $\boldsymbol{A}$. The original variables and the mixing matrix are assumed to be unknown. First, $x_1$ and $x_2$ are sphered or prewhitened by using PCA. As a result, uncorrelated variables $z_1$ and $z_2$ are obtained. It should be

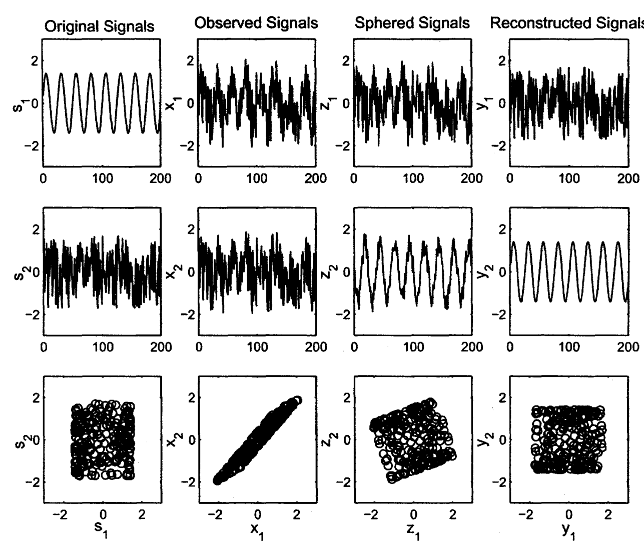


**Figure 1. Simple example of independent component analysis (ICA).**

noted that $z_1$ and $z_2$ are not independent of each other. To obtain independent variables $y_1$ and $y_2$, ICA is applied to $z_1$ and $z_2$. The fixed-point algorithm just described is used here. Figure 1 clearly shows that the original variables can be reconstructed by ICA without any knowledge of the original variables or the mixing matrix. The only assumption used here is that original variables are independent of each other and measured variables are linear combinations of the original variables.

## Monitoring of Independent Components

The procedure of ICA-based SPC is the same as univariate SPC (USPC). The only difference involves the variables to be monitored. That is, independent components are monitored in ICA-based SPC, although correlated measured variables are monitored in USPC.

A separating matrix $\boldsymbol{W}$ in Eq. 7 and control limits must be determined in order to apply the proposed ICA-based SPC method for monitoring problems. For this purpose, the following procedure is adopted.

(1) Acquire time-series data when a process is operated under normal conditions. Normalize each row (variable) of the data matrix, that is, adjust it to a zero mean and unit variance, if necessary.

(2) Apply ICA to the normalized data, determine a separating matrix $\boldsymbol{W}$, and calculate independent components.

(3) Determine control limits of all independent components.

For on-line monitoring, a new sample of monitored variables is scaled with the mean and the variance obtained at step 1. Then, it is transformed to independent components through the separating matrix $\boldsymbol{W}$. If one or more of the independent components are outside the corresponding control limits, the process is judged to be out of control.

In order to realize an advantage in using independent components for process monitoring, the fitness of control limits for monitored variables is illustrated in Figure 2. The control limits for measured variables $x_1$ and $x_2$ form a rectangle, but it is far from the region representing a normal operating condition because the two measured variables are highly correlated. In order to cope with the correlation between those variables, PCA can be used. The sphered variables $z_1$ and $z_2$ are uncorrelated, and, thus, the ellipsoidal control limit fits nicely for the normal region. In Figure 2 (center), two types of control limits are drawn. The control limits become rectangular when sphered variables are monitored independently. On the other hand, the control limits are integrated into an ellipse when sphered variables are monitored together. The fit, however, is not perfect. As usually pointed out from a practical viewpoint, the monitored variables should be normally distributed for good monitoring if PCA-based MSPC is used. This characteristic limits the achievable monitoring performance of PCA-based MSPC. On the other hand, the fitness of control limits for independent components $y_1$ and $y_2$ is perfect. The monitoring of independent components functions very well and better than the others.

In the following sections, the proposed ICA-based SPC is compared with other conventional SPC methods in order to clarify the usefulness of the ICA-based SPC. For this purpose, average run length (ARL) is used as a measure of fault-detection performance. The ARL is the average number of points that must be plotted before a point indicates an out-of-control condition (Montgomery, 1997). For any Shewhart control chart, the ARL is calculated from $\mathrm{ARL} = 1/p$, where $p$ is the probability that any point exceeds the control limits. For example, the ARL is 100 under normal operating conditions when the control limit represents the 99% confidence limit.

## Application 1: Four-Variable System

In this section, univariate SPC (USPC), conventional MSPC (cMSPC), and ICA-based SPC (ICA-SPC) are applied to fault-detection problems of a simple four-variable system

$$\boldsymbol{x} = \boldsymbol{A}\boldsymbol{s} + \boldsymbol{v}$$

$$\boldsymbol{A} = \begin{bmatrix} 0.445 & 0.846 \\ 0.932 & 0.525 \\ 0.466 & 0.203 \\ 0.419 & 0.672 \end{bmatrix}$$

$$\boldsymbol{s} = [s_1 \quad s_2]^T \tag{21}$$

where $s_1$ and $s_2$ are uncorrelated random signals following uniform distribution within [0, 1]. The output $\boldsymbol{x}$ is corrupted by measurement noise $\boldsymbol{v}$ following normal distribution with standard deviation $\sigma_v = 0.05$ or 0.1. For evaluating the monitoring performance, mean shifts of $s_1$ are investigated.

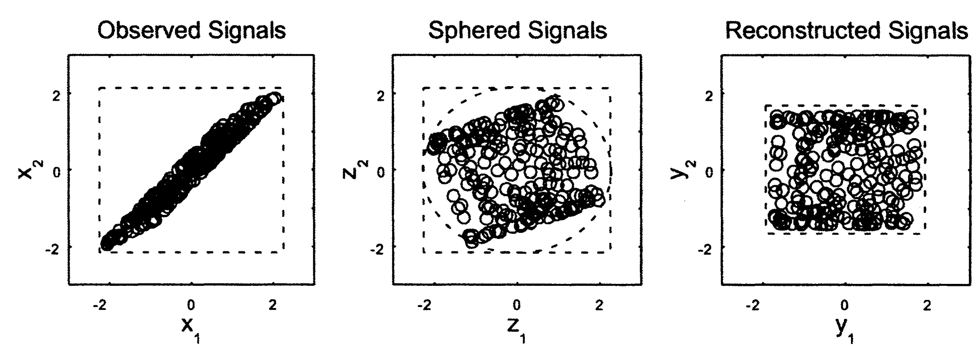


**Figure 2. Comparison of univariate SPC (left), conventional MSPC (center), and ICA-based SPC (right).**

Observed signals $x_1$ and $x_2$ are plotted with their control limits (left). Sphered signals, that is, scores, $z_1$ and $z_2$ are plotted with their control limits (center). Reconstructed signals, that is, independent components, are plotted with their control limits (right).

**Table 1. Average Run Length in Detecting Mean Shifts.***

| Noise: Shift Size | USPC | $\sigma_v = 0.05$ cMSPC | ICA-SPC |
|---|---|---|---|
| 0 | 93.6 | 95.1 | 94.8 |
| 0.01 | 92.0 | 96.7 | 89.9 |
| 0.02 | 91.8 | 93.7 | 84.4 |
| 0.05 | 73.0 | 75.3 | 55.4 |
| 0.1 | 41.1 | 44.7 | 25.0 |
| 0.2 | 16.4 | 15.9 | 8.4 |
| 0.5 | 3.6 | 3.0 | 2.4 |
| Noise: | | $\sigma_v = 0.1$ | |
| 0 | 95.0 | 96.4 | 97.0 |
| 0.01 | 93.7 | 98.1 | 96.2 |
| 0.02 | 94.9 | 96.7 | 95.7 |
| 0.05 | 80.5 | 87.1 | 78.4 |
| 0.1 | 52.7 | 67.1 | 47.9 |
| 0.2 | 21.8 | 32.0 | 17.9 |
| 0.5 | 4.3 | 5.4 | 3.3 |

*Comparison of USPC, cMSPC, and ICS-SPC at different sizes of noises and mean shifts.

One data set, including 100,000 samples, obtained from the normal operating condition was used to build a PCA model for the conventional MSPC, to determine a separating matrix for the ICA-based SPC, and also to determine control limits. In addition, in order to calculate ARL, 10,000 data sets were generated by changing seeds of the random signals $\boldsymbol{s}$ and $\boldsymbol{v}$ in each case shown in Table 1.

The control limit of each index or each variable is determined so that the number of samples outside the control limit is just 1% of all the samples while the process is operated under normal conditions. Therefore, the control limits represent 99% confidence limits. The monitored indexes for cMSPC are $T_2^2$ and $Q_2$. The subscript 2 means that two principal components are retained in the PCA model. On the other hand, each independent component is independently monitored in ICA-SPC.

The fault-detection results are summarized in Table 1. The ARL decreases as the shift size increases, irrespective of the type of monitoring method. The results have clearly shown the advantage of ICA-SPC over both USPC and cMSPC. ICA-SPC can detect faults faster than the others. In this example, cMSPC does not work well even in comparison with USPC, because the distribution of measured variables is quite different from the normal distribution that cMSPC expects.

One of the 10,000 monitoring results from using USPC, cMSPC, and ICA-SPC when the shift size is 0.5 and $\sigma_v = 0.05$ is shown in Figures 3, 4, and 5, respectively. The control limits, representing 99% confidence limits, are also shown in these figures. The mean shift occurs at the 101st step. The shift size of 0.5 is so large that all three monitoring methods can detect it within a few steps. The mean shift of $s_1$ affects all measured variables, $x_1$, $x_2$, $x_3$, and $x_4$. Therefore, all variables of $x$ exceed their control limits, as shown in Figure 3. This characteristic of USPC is not bad from the viewpoint of fault detection, but makes it difficult for operators to identify the cause of the fault. The cMSPC is not suitable for fault identification because $T^2$ and $Q$ themselves do not give detailed information about the cause of the fault. In fact, it can be confirmed from Figure 4 that the correlation structure does not change, because only $T^2$ exceeds its control limit. This information, however, is not sufficient for fault identification. Contribution plots (Nomikos, 1996) can be used for further investigation, but their ability is limited. ICA-SPC, however, has a very interesting and useful characteristic. As shown in Figure 5, only one independent component, $y_1$, exceeds the control limit. The other independent components do not exceed their control limits. From the off-line analysis, it is confirmed that $y_1$ and $y_2$ correspond to $s_1$ and $s_2$, respectively, and $y_3$ and $y_4$ represent measurement noise, $\boldsymbol{v}$. Therefore, Figure 5 indicates that $s_1$, which is an essential variable to

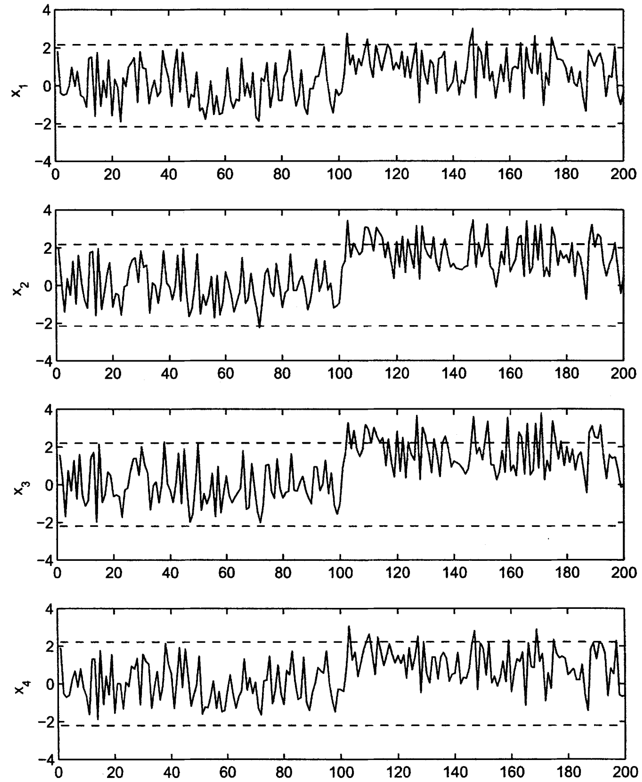


**Figure 3. Monitoring results of the four-variable system with USPC; the mean shift of 0.5 occurs at the 101st step.**

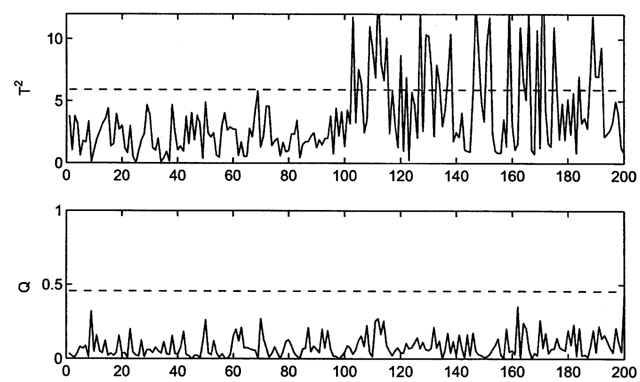


**Figure 4. Monitoring results of the four-variable system with cMSPC; the mean shift of 0.5 occurs at the 101st step.**

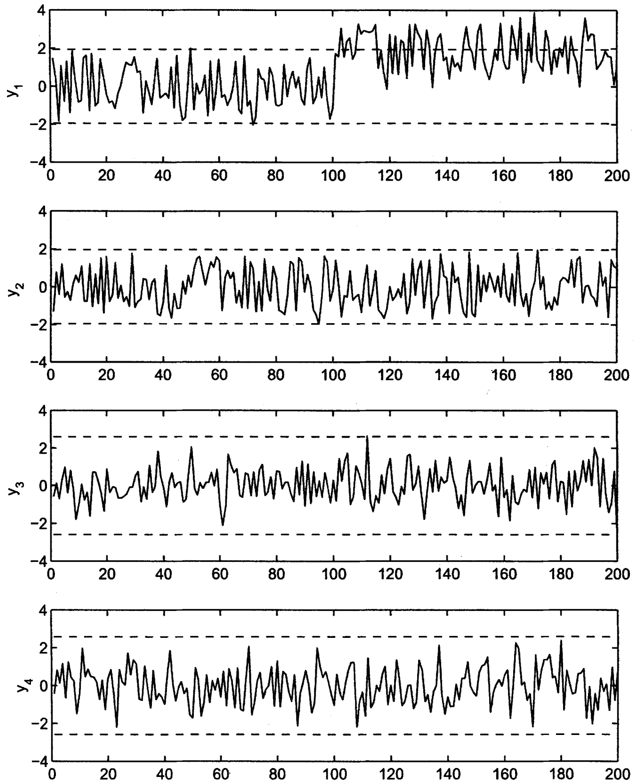

**Figure 5. Monitoring results of the four-variable system with ICA-SPC; the mean shift of 0.5 occurs at the 101st step.**

drive the system, is the key variable for identifying the cause of the fault.

In conclusion of this section, the proposed ICA-based SPC is advantageous to univariate SPC and to conventional MSPC. The ARL analysis has shown that ICA-SPC can detect faults faster than the other monitoring methods. In addition, ICA-SPC has the potential for fault identification. An invisible cause of a fault might be identified by monitoring independent components, which represent independent inputs to a system. It should be noted, however, that derived independent components should be related with physical phenomena of a process to identify faults by using ICA. It would be difficult to interpret the meaning of independent components and to relate them with process operation in the real world.

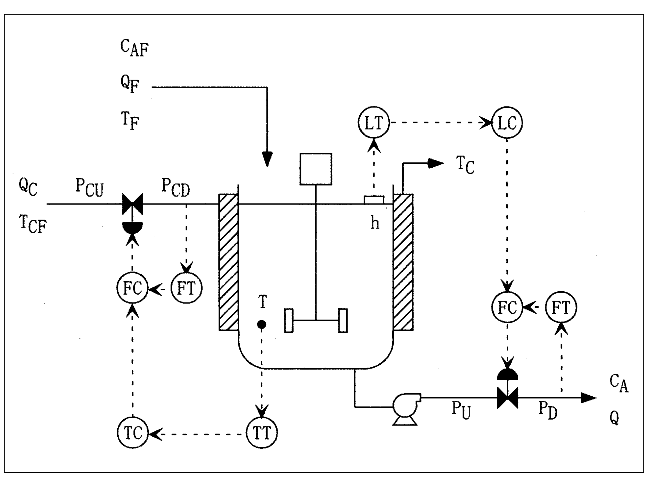


**Figure 6. CSTR with feedback control.**

**Table 2. Process Variables Used for Monitoring**

| | |
|---|---|
| $x_1$ | Reactor temperature |
| $x_2$ | Reactor level |
| $x_3$ | Reactor outlet flow rate |
| $x_4$ | Coolant flow rate |
| $x_5$ | Reactor feed flow rate |
| $x_6$ | MV of level controller |
| $x_7$ | MV of outlet flow controller |
| $x_8$ | MV of temperature controller |
| $x_9$ | MV of coolant flow controller |

## Application 2: CSTR Process

In this section, USPC, cMSPC, and ICA-SPC are applied to monitoring problems of a CSTR process (Johannesmeyer and Seborg, 1999). The objective of this section is to show the usefulness of ICA-SPC with its application to a more realistic example.

The CSTR process used for dynamic simulations is shown in Figure 6. The process has two manipulated variables (valves) and five continuous process measurements. A total of nine variables used for monitoring are listed in Table 2. Process data are generated from a normal operating condition and nine abnormal operating conditions listed in Table 3. All variables are measured every 5 s.

The control limit of each index or variable is determined so that the number of samples outside the control limit is 1% of all the samples while the process is operated under normal conditions. The fault-detection performance is evaluated on the basis of ARL.

The fault detection results are summarized in Table 4. In addition, Figure 7 shows the success rate of fault detection in all cases. The success rate is defined as the percentage (%) of the realizations in which each monitoring method can successfully detect the fault at each time step. Therefore, the monitoring method with the highest success rate is the best of all. In Figure 7, each fault or disturbance occurs at the first step.

In this application, there is little or no difference in ARL among the three monitoring methods, as shown in Table 4.

**Table 3. Process Disturbances and Faults for the CSTR Process**

| Case | Operation |
|---|---|
| N | Normal operation |
| F1 | Catalyst deactivation—ramp |
| F2 | Heat-exchanger fouling—ramp |
| F3 | Dead coolant flow measurement |
| F4 | Bias in reactor temperature measurement |
| F5 | Coolant valve sticking |
| F6 | Feed flow rate—step |
| F7 | Feed concentration—ramp |
| F8 | Feed temperature—ramp |
| F9 | Coolant feed temperature—ramp |

**Table 4. Average Run Length of USPC, cMSPC, and ICA-SPC Applied to the CSTR Process**

| Case Method | N | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|---|---|---|---|---|---|---|---|---|---|
| USPC | 84.3 | 64.0 | 47.0 | 6.2 | 1.0 | 7.5 | 1.0 | 56.8 | 62.7 | 60.7 |
| cMSPC | 111.4 | 77.1 | 51.2 | 1.5 | 1.0 | 2.7 | 1.0 | 61.0 | 70.5 | 60.2 |
| ICA-SPC | 95.3 | 70.3 | 45.0 | 1.1 | 1.1 | 1.4 | 1.0 | 57.4 | 59.5 | 58.6 |

In other words, these three methods can detect disturbances and faults at a similar speed. Figure 7, however, shows the crucial difference between them. In abnormal cases F2, F3, F5, F7, F8, and F9, the success rate of fault detection with ICA-SPC is considerably higher than the others. This result indicates that the judgment made by ICA-SPC is more reliable than by USPC or cMSPC. The higher reliability is a very nice characteristic that any monitoring method should have. In cases F4 and F6, the success rate reaches 100% within one or two steps, regardless of the methods used. On the other hand, the success rate of ICA-SPC is much lower than the others in case F1. At this stage of the development of the ICA-based SPC method, the reason why the reliability of ICA-SPC deteriorates in some cases has not yet been determined. In addition, the performance of ICA-SPC will depend on the types of ICA algorithms.

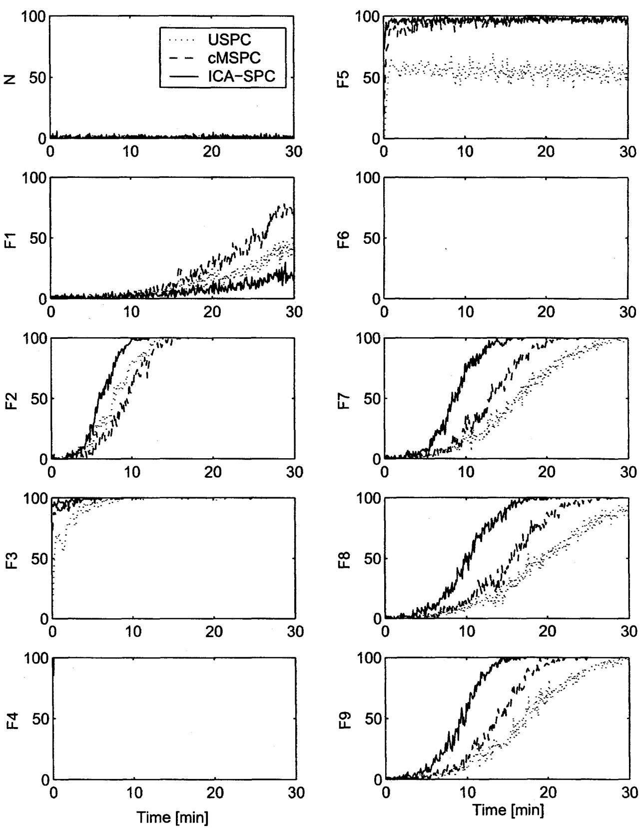


**Figure 7. Time-series plots of success rate of fault detection.**

Comparison of USPC (dotted line), cMSPC (dashed line), and ICA-SPC (solid line) with applications to the CSTR process.

## Conclusions

The key idea of the present work is that the process monitoring performance can be improved by focusing on essential variables that drive a process, and such essential variables can be estimated from measured process variables by using independent component analysis (ICA). ICA is an emerging signal-processing technique for transforming observed multivariate data into statistically independent components, which are expressed as linear combinations of observed variables.

To investigate the feasibility of the proposed ICA-based statistical process control (ICA-SPC) method, its fault-detection performance is evaluated and compared with that of the univariate statistical process control (USPC) method and the conventional multivariate SPC (cMSPC) method using principal component analysis (PCA) by applying those methods to monitoring problems of a simple four-variable system and a continuous-stirred-tank-reactor (CSTR) process. The simulated results of the four-variable system show that ICA-SPC can detect faults faster than the others and also that ICA-SPC has the potential for fault identification. However, it would be very difficult to interpret the meaning of independent components and to relate them with process operation in the real world. Further investigation is indispensable in this area, because fault identification is a difficult but crucial task in process operation. In addition, the application results of the CSTR process show that the success rate of fault detection with ICA-SPC is considerably higher than that of the others, and, thus, the judgment made by ICA−SPC is more reliable than by the other methods.

ICA-SPC is still under development. Criteria for selecting a proper algorithm are needed, because the performance of ICA-SPC is affected by the algorithm used. In the present work, a well-known fixed-point algorithm based on the fourth-order cumulant is used. But it is not clear if the algorithm used here is the best one for process monitoring. However, it has been pointed out in this article that ICA-SPC has the potential for fault identification, because essential variables, which drive the process, can be monitored. In order to make an ICA-based fault-identification method useful and practical, independent components reconstructed from measured process variables must be linked to measured or unmeasured process inputs that can be physically interpreted. As requirements imposed on process monitoring become severer, the development of new methods that can cover data rectification, fault detection, and fault identification in a unified framework is needed more than ever for the improvement of process operation. From this viewpoint, ICA-SPC would be promising, and further efforts need to be focused in this research area.

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