Process Monitoring Using Canonical correlation analysis

Shakir Muhammad SHAIKH³, Yin SHEN¹, Shahid KARIM⁴, VISHAL KUMAR¹

¹ Department of Control Science and Engineering, Harbin Institute of Technology, Harbin, China

hit.shakir12@yahoo.com, shen.yin@hit.edu.cn, vishal@stu.hit.edu.cn,

² School of Computer Science and Technology, Harbin Institute of Technology

asiflaghari@hit.edu.cn

⁴ School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin, 150001, China shahidhit@yahoo.com

Abstract: Principal component analysis (PCA) and partial least square (PLS) used for fault diagnosis and process monitoring for systems. It is expected that the information to be examined isn't self-connected. However, the most large-scale chemical industrial plants are nonlinear in nature so these techniques do not cope with them, invalid in nature. To fulfil the gap, there is need to develop an algorithm which can manage these nonlinearities of the process. The demands of industrial products are increasing rapidly so different adaptable techniques are being proposed. Canonical Correlation Analysis (CCA) is multivariate data-driven methodology which takes input-output both process data into consideration. Most industrial systems assumed that the data to be analysed is Gaussian in nature. However, it is not due to the non-linearity's real systems in nature. In this work, an algorithm is developed that can monitor the system process using CCA with control limit that is achieved from the kernel density estimation by estimating probability density function (pdf).

Keywords: Canonical correlation Analysis, Process Monitoring, Kernel Density Estimation, Tennessee Eastman Process.

1. Introduction

In industrial systems data-driven techniques have extensively used for fault detection, and identification (FDI). In order to ensure safe and reliable operation and maintain product-quality, industrial process monitoring gained prominence in research and academia [1]. There owned technique multivariate analysis (MVA) is normally used to handle these kinds of problems [2]. Principal component analysis (PCA) and partial least square (PLS) are Multivariable analysis techniques. It explores the correlation between interrelated variables that represent the system parameters. These techniques demonstrate several improvements against the univariate techniques [3]. Mostly industrial systems operate under changing operational conditions. Process monitoring aims to determine that fault has occurred or not. It is known as fault detection. A Fault is characterized as: 'any deviation of a boundary from ordinary condition' [4]. There are two steps in multivariate analysis technique (MVA): off-line training and online monitoring. PCA technique considers variables in both procedures and monitors deviation, occurs in usually process and actuator. PLS technique focuses on quality variables which are difficult to measure on-line or measure with a large delay. Process data is used to extract the latent variable in an off-line procedure, while in an online training process variables used to sense faults. When the opportunity arises to take into consideration both input and output data, CCA technique [5] is worthy to model fault diagnosis (FD) system. It is representative MVA technique but unfortunately seldom used

for fault detection. CCA is extended form of PCA and PLS [6]. Canonical variate analysis (CVA) is generalised form of CCA. Fault has been diagnosed with CVA which is published in [7]. It depends upon CVA variables reported in [8]. Fault detection residual signal is generated by CCA by considering input and output process data. Considering into account the connection between the incoming data and outgoing data variables, CCA technique come into being static and dynamic both process in steady state [9],[10]. A numerical example has been stated which generates random data to show the effectiveness of proposed algorithm. Later this algorithm tested on Tennessee Eastman process data. CCA algorithm with probability density estimation generates control limit which process variable cross and fault occurs. Normally control limit accepts that the cycle information follows the Gaussian information however in genuine the greater part of the interaction information are non-Gaussian in nature. CCA with KDE algorithm shows effectiveness and performance is evaluated. Mostly performance in these types of systems is evaluated by fault detection rate (FDR).

The remainder of paper is organized as follows. Area II exhibits the connected work. Section III demonstrates the implementation of CCA technique. Section IV is based on a numerical example. In section V TE process description and results are discussed. Finally section VI covers conclusion and future work.

2. Related work

Over last eras, the prominent work on fault detection has received significant attention. Thus, automatic industrial process monitoring is an active area to study until now [11]. Extensively used data-driven based fault detection approaches, namely Multivariate Statistical Process Monitoring (MSPM) method which separates abnormal process from normal process conditions by forming statistical thresholds around feature variables take out from the process historical data [12]. Thus, early detection is valued for preemptive preservation of equipment and harmless operations. Two common categories of FD methods are model-based data-driven and others. Data-driven FD techniques have been extensively applied in industrial applications because these techniques take modest form and low demands on design effort. Instead, the industrial uses are commonly distinctive dynamic processes so might work on dissimilar functioning conditions in industrial situation. But, the multivariate statistical approaches could not be productively applied due to their assumption under stationary ideal operating conditions. The model-based systems need a priori mathematical knowledge of a process. Based on first principles process model is designed, the firm model-based techniques could be successfully applied. Then again, the information driven plans fill in as an effective way, wherein the fundamental cycle data can be taken out straightforwardly from the colossal measures of recorded interaction information. By considering the association between input-output variables, CCA methods have been established newly for static and dynamic both processes in steady state. The procedure whose center is the arrangement of the connection between two interaction factors, typically measure data sources and yields, may be seen as an expansion of the PLS and PCA techniques. These methods are dissimilar than CVA-based methods which rely on canonical variable [13]. CCA procedure for the most part settled by what strategy for standard connection based (RG) residual generation. The CCA techniques mainly considered by its expressively modest scheme because of avoiding the necessity for system identification which is required by CVA. Furthermore, the

beneficial application of CCA method is based on the supposition that the process noises and subsequently the residual signal monitor a Gaussian distribution. In practice, fault detection considerably puzzles when the process under monitoring is non-Gaussian [14]. To deal with its challenges, few variants of the standing MVA techniques have been proposed. For the analysis of multimode nonlinear non Gaussian batch process, a novel model migration method has been proposed. In that method, PCA and ICA methods are combined [15]. An easy to implement method has been proposed in [16], which uses statistical method to diagnosis the fault and improve the system. Similar to this, another method is proposed in which fault relevant independent components extracted and fault commands in non-Gaussian and nonlinear processes [17]. Mutual information and ICA techniques together established for non-Gaussian process [18]. This method is to estimate the signal and then set threshold for fault detection by estimated distribution and this comes in the category of estimation-based. Gaussian mixture models (GMM) related methods [19], [20], Based on kernel methods [21], and consecutive quantile estimation [22] are illustrative examples. Although these methods have been applied effectively in complex system processes, their performance in FD are partial by choosing of appropriate kernel parameters and other quantified parameters. Hence, there is essential need to follow well-organized method based on the available measurements and threshold setting for non-Gaussian processes. Keeping in view above discussion, this paper focuses on CCA approach to detect faults in non-Gaussian processes. In this work control limit is achieved by kernel density estimation to cope with non-Gaussian and this techniques is applied on CCA to generate residual signal, for fault diagnosis that proposed technique effectively have high fault detection rate (FDR) than of standard algorithm.

3. Methodology

A. Canonical correlation analysis (CCA)

CCA is a technique to capture the linear combinations of two vectors by maximizing correlations between them [23]. Suppose we have input-output data, that data is from process which is collected from the sensors of

the system. Input is represented as u and output as y . These input and output can be normalized as:

$$u = (u_{\text{obs}} - u_u) \quad (1)$$

$$y = (y_{\text{obs}} - u_y) \quad (2)$$

$$U = [u_1, u_2, \dots, u_N] \in \mathcal{R}^{1 \times N} \quad (3)$$

$$Y = [y_1, y_2, \dots, y_N] \in \mathcal{R}^{m \times N} \quad (4)$$

u_i , and y_i , $i = 1, \dots, N$ are normalized to mean and their estimates are:

$$u_u \approx \frac{1}{N} \sum_{i=1}^N u_{\text{obs}}(i), \quad (5)$$

$$u_y \approx \frac{1}{N} \sum_{i=1}^N y_{\text{obs}}(i), \quad (6)$$

Furthermore, the covariance (Σ_u), (Σ_y) and (Σ_{uy}) calculated as:

$$\Sigma_u \approx \frac{1}{N} \sum_{i=1}^N (u_{\text{obs}}(i) - u_u) \quad (7)$$

$$\Sigma_u \approx (N-1)^{-1} \sum_{i=1}^N (u_{\text{obs}}(i) - u_u)(u_{\text{obs}}(i) - u_u)^T = \frac{UU^T}{N-1} \quad (8)$$

$$\Sigma_y \approx (N-1)^{-1} \sum_{i=1}^N (y_{\text{obs}}(i) - u_y)(y_{\text{obs}}(i) - u_y)^T = \frac{YY^T}{N-1} \quad (9)$$

$$\Sigma_{uy} \approx (N-1)^{-1} \sum_{i=1}^N (u_{\text{obs}}(i) - u_u)(y_{\text{obs}}(i) - u_y)^T = \frac{UY^T}{N-1} \quad (10)$$

with CCA technique, it turns out that:

$$\begin{aligned} & \left(\frac{UU^T}{N-1} \right)^{-\frac{1}{2}} \left(\frac{UY^T}{N-1} \right) \left(\frac{YY^T}{N-1} \right)^{-\frac{1}{2}} \\ &= \Sigma_u^{-\frac{1}{2}} \Sigma_{uy} \Sigma_y^{-\frac{1}{2}} \\ &= \Gamma_s \Sigma Y_s^T, \end{aligned} \quad (11)$$

Where $\Sigma = \begin{bmatrix} \Sigma_u & 0 \\ 0 & \Sigma_y \end{bmatrix}$ rank $\Sigma_{uy} = q$, and $\Sigma_q = \text{diag}(p_1, \dots, p_q) \Gamma = (w_1, \dots, w_{d_1}) Y = (V_1, \dots, V_{d_2})$

Let:

$$J_s = \Sigma_u^{-\frac{1}{2}} \Gamma(:, 1:q), \quad (12)$$

$$L_s = \Sigma_y^{-\frac{1}{2}} Y(:, 1:q) \quad (13)$$

$$J_{\text{res}} = \Sigma_u^{-\frac{1}{2}} \Gamma(:, q+1:l), \quad (14)$$

$$L_{\text{res}} = \Sigma_y^{-\frac{1}{2}} Y(:, q+1:m) \quad (15)$$

Relationship between L_s^T and J_s^T break down into:

$$L_s^T y(k) = \Sigma_q J_s^T u(k) + V_s(k) \quad (16)$$

V_s is measurement noise, dimly correlated with $J_s^T u$. As a result, residual vector define as:

$$r(k) = L_s^T y(k) - M_s^T u(k) \quad (17)$$

$$M_s^T = \Sigma_q J_s^T \quad (18)$$

Where r will follow a normal distribution. $r(k)$'s covariance is estimated by :

$$(N-1)^{-1} (L_s^T Y - \Sigma_q J_s^T U) (L_s^T Y - \Sigma_q J_s^T U)^T = \frac{I_e - \Sigma_q^2}{N-1} \quad (19)$$

Test Statistics

$$T_{\text{cca}}^2(k) = (N-1) r^T(k) (I_e - \Sigma_q^2)^{-1} r(k) \quad (20)$$

The Threshold value T^2 for a given level of significance α like $P(T^2 < T_{\text{th}}^2(\alpha)) = \alpha$. Normally these threshold values follow along with Gaussian distribution. However, this assumption is invalid due to the most industrial process are nonlinear. An eminent strategy built up that adapt to this matter of conflict by first assuming the (pdf) probability density function of the factual estimations with the assistance of (kdf) kernel density estimations.. The likelihood x with $p(x)$ i.e arbitrary variable with (pdf) probability density function to be lesser than a guaranteed esteem s is decide as:

B. Calculation of CCA based process monitoring control limit

Kernel density estimation is proposed in this work in order to cope with Gaussian assumption. Mostly control limit is calculated by Gaussian assumption in this work. We propose an algorithm that uses probability density function using kernel density estimation to evaluate nonlinearities in the process.

$$p(x < s) = \int_{-\infty}^s p(x) dx \quad (21)$$

Where $p(x)$ can be predicated from K , kernel function:

$$p(x) = \frac{1}{Mh} \sum_{k=1}^M K\left(\frac{x-x_k}{h}\right) \quad (22)$$

$$k(g) = \frac{e^{-\frac{g^2}{2}}}{\sqrt{2\pi}} \quad (23)$$

In the equation, h is the calculated bandwidth and x_k is sample of x . By substituting x_k with T_k^2 obtained from (19). The corresponding threshold for these data correspond to s in (20), acquired by solving $P(x < s) = \alpha$. The T^2 cadent means necessary deviation of sanctioned factors exhibit change in the expansion of head subspace. T^2 Metric is important; faults can source an inconsistent growth in the principal space and other will be revealed as; an increase in the residual variability space. A Fault could happen if the statistics exceed the threshold value. Following the way, the quantities of the measurements determined at the hour of preparing stages which are agent for the ordinary framework when no shortcoming had occur. The edge is assessed for an ostensible

move of effect by seeing at the likelihood thickness capacity of these insights, arriving at the edge and vulnerability occurs. Any deviancy in the lead of framework elements delivered by pass, will influence an expansion in the measure of these insights traversing the edge and making an alarm [23]. In an internet preparing information is prototypal, the calculation be sufficient to oblige estimation of measurements beneath the edge in the event that if no issues are accessible. And in testing phase of the algorithm the new data is generated which is not included in training model could be or not faulty. However two procedures are there for testing data, one is on-line and other is off-line. In this work we will focus on off-line training and testing data, later one is adaptive approach.

4. A Numerical Example

In this section numerical supposition has been studied. The effectiveness of CCA algorithm with KDE has been demonstrated on randomly generated data. These methods provide that algorithms working well and later it will be shown to industrial benchmark. To train model, two thousand samples are generated. It is establish that $L^T y$ and $J^T u$ have strong correlation the confidence limit is 0.01. A fault has occurred after 1000 samples, which is apparently shown in *figure 1*. An input output linear relationship is given in a numerical example which is modeled as:

$$y(k) = \Psi u(k) + b_{obs} + v(k) \quad (24)$$

Where $u \in \mathcal{R}^l$, $y \in \mathcal{R}^m$ are input and output variables Ψ is system parameter

Figure 1: Random fault scenario

5. Description of Tennessee Eastman process

The TEP is designed to simulate that create real time chemical producing process. It has been used a lot in many academic and research work as a benchmark to show various algorithms. [25,26]. A test system is created, subtleties is in [26]. In this piece of paper, CCA with KDE which is proposed calculation for issue conclusion exhibit on Tennessee Eastman measure (TEP) to. It is a down to earth modern cycle. TE measure filled in as received benchmark. The fundamental model of TE measure is apply to assess the essential Multivariate Statistical Process Monitoring strategies under ideal fixed working conditions. Figure 2 shows stream of interaction with 5 significant sections. Cycle has four reactants and 2 items. Alongside a latent and a result are likewise accessible, detailing an aggregate of 8 segments. The interaction own altogether 52 measurements out of which 11 are controlled factors and 41 are measure factors. In noticed deficiencies, which can turn out all the while.

A. Application to TEP

The proposed algorithm of CCA with KDE is applied to Tennessee Eastman process (TEP) in this section. It contains the data that is received from sensors, 52 variables and also 960 measurements. In this case study fault no 1, 3 and 5 are under consideration.

B. Test setup and Training

Inputs are in this work, the manipulated variables, and for outputs (XMEAS1-XMEAS31) are selected as given in table 2. In the training phase these variables are chosen for input-output patterns which are used for training with CCA.

C. Test results

In test results, it is shown that the fault detection rate is higher for CCA with KDE than for standard CCA. As a representative fault no 1, 3 and 5 simulated and results are shown in figure 3, 4 and 5 respectively. In this dataset, 960 samples of 52 variables, fault occurred at 160 sample of data set.

$$FDR = \frac{\text{Number of samples}(j > j_{th} | \text{fault free})}{\text{total number of sampling}}$$

Figure 2. Tennessee Eastman Process [27]

Table 1. List of process and manipulated Variables

Tag	Description
XMV(1)	D feed flow
XMV(2)	E feed flow
XMV(3)	A feed flow
XMV(4)	A and C feed flow
XMV(6)	Purge Valve
XMV(7)	Separator pot liquid flow
XMV(8)	Stripper liquid product flow
XMV(10)	Reactor Cooling water flow
XMV(11)	Condenser Cooling water flow
XMEASV(1)	A feed (Stream 1)
XMEASV(2)	D feed (Stream 2)
XMEASV(3)	E feed (Stream 3)
XMEASV(4)	A and C feed
XMEASV(5)	Recycle flow
XMEASV(6)	Reactor feed rate
XMEASV(7)	Reactor Pressure
XMEASV(8)	Reactor level
XMEASV(9)	Reactor temperature
XMEASV(10)	Purge rate
XMEASV(11)	Separator temperature
XMEASV(12)	Separator level
XMEASV(13)	Separator pressure
XMEASV(14)	Separator underflow
XMEASV(15)	Stripper level
XMEASV(16)	Stripper pressure
XMEASV(17)	Stripper underflow
XMEASV(18)	Stripper temperature
XMEASV(19)	Stripper steam flow
XMEASV(20)	Compressor work
XMEASV(21)	Reactor water temperature
XMEASV(22)	Separator water temperature

Table 2. List of Process Manipulated Variables in Tennesseans Eastman Process

Variable name	Number	Base Value (%)	Units
D feed flow	XMV(1)	63.053	$kg h^{-1}$
E feed flow	XMV(2)	53.980	$kg h^{-1}$
A feed flow	XMV(3)	24.644	$kscmh$
A and C feed flow	XMV(4)	61.302	$kscmh$
Compressor recycle valve	XMV(5)	22.210	%
Purge valve	XMV(6)	40.064	%
Separator pot liquid flow	XMV(7)	38.100	$m^3 h^{-1}$
Stripper liquid product flow	XMV(8)	46.534	$m^3 h^{-1}$
Stripper steam valve	XMV(9)	47.446	%
Reactor cooling water flow	XMV(10)	41.106	$m^3 h^{-1}$
Condenser	XMV(11)	18.114	$m^3 h^{-1}$

D. Algorithm for CCA with KDE fault detection

Off-line design

Step 1: Collect input-output data u and y

Step 2: centre the process input output data (1-6)

Step 3: Doing SVD on input output data using (11)

On-line implementation

Step 1: Collect the input- output (online)

Step 2: Calculate the residual statistics using eq (17)

Step 3: Calculate the T^2 statistics using eq (20)

Step 4: Based on decision logic take decision:

Step 5: $T_{kde}^2 > j_{th} \Rightarrow \text{faulty, otherwise faultfree}$

Table 3. List of Faults in Tennessee Eastman Process

Fault number	Process Variable	Type
IDV(1)	A/C feed ratio, B composition constant	Step
IDV(2)	B composition, A/C ration constant	Step
IDV(3)	D feed temperature	Step
IDV(4)	Reactor cooling water inlet temperature	Step
IDV(5)	Condenser cooling water inlet temperature	Step
IDV(6)	A feed loss	Step
IDV(7)	C header pressure loss-reduced availability	Step
IDV(8)	A, B C feed composition	Random variation
IDV(9)	D feed temperature	Random variation
IDV(10)	C feed temperature	Random variation
IDV(11)	Reactor cooling water inlet temperature	Random variation
IDV(12)	Condenser cooling water valve	Random variation
IDV(13)	Reaction Kinetics	Slow Drift
IDV(14)	Reactor cooling water valve	Sticking
IDV(15)	Condenser cooling water valve	Sticking
IDV(16)	Unknown	Unknown
IDV(17)	Unknown	Unknown
IDV(18)	Unknown	Unknown
IDV(19)	Unknown	Unknown
IDV(20)	Unknown	Unknown
IDV(21)	The valve fixed at steady state position	Constant Position

Table 4: Detection results in terms of FDR

Fault IDs:	CCA with KDE	CCA
IDV(1)	99.12%	88.62%
IDV(2)	99.13%	93.24%
IDV(5)	99.75%	99.62%

It is shown in above results that the CCA with KDE have higher FDR than CCA standard algorithm.

Figure 3. Fault scenario 1

Figure 4. Fault scenario 2

Figure 5. Fault scenario 5

6. Conclusion and future work

In this paper, improved CCA based issue analysis methods have been examined. At that point, standard CCA strategy applied on arbitrary information to show the adequacy of the calculation. The prevailing methods for the first time have been dealt with Gaussian and non-Gaussian assumption of industrial process data. Despite the achievements of data-driven algorithms in the application of fault detection and diagnosis using industrial simulated system based on the assumption of Gaussian, there is lack of non-Gaussian work. This work is presented with aim to cope with real simulated data from industries which are usually non Gaussian in nature and effectiveness of these algorithms applied on Tennessee Eastman industrial simulated plant. In this case study three faults have been simulated. The faults are effectively detected using the T^2 statistics. These outcomes approve that CCA can be proficiently applied for shortcoming location and analysis in genuine complex frameworks working under adaptable working conditions. The CCA system when contrast a presentation and CCA-KDE it is perfect that the strategy is better than the others as far as fault detectin rate (FDR). It is worthy to note that the procedure of KDE is essential for threshold estimation otherwise Gaussian assumption was impractical due to nonlinearities in the process plant system. Despite of quite satisfactory

performance demonstrated by CCA along with KDE, the fault detection in highly dynamic nonlinear is fairly challenging, which force to develop improved algorithms for these particular faults in future.

REFERENCES

1. Isermann, Rolf. "Fault detection with Principal Component Analysis (PCA)." *Fault-Diagnosis Systems*. Springer, Berlin, Heidelberg, 2006. 267-278.
2. Ge, Zhiqiang. "Review on data-driven modeling and monitoring for plant-wide industrial processes." *Chemometrics and Intelligent Laboratory Systems* (2017).
3. Odiowei, P. P., and Y. Cao. "Nonlinear dynamic process monitoring using canonical variate analysis and kernel density estimations." *Computer Aided Chemical Engineering*. Vol. 27. Elsevier, 2009. 1557-1562.
4. Isermann, Rolf. "Model-based fault-detection and diagnosis—status and applications." *Annual Reviews in control* 29.1 (2005): 71-85.
5. Hotelling, Harold. "Relations between two sets of variates." *Biometrika* 28.3/4 (1936): 321-377.
6. Li, Gang, S. Joe Qin, and Donghua Zhou. "Geometric properties of partial least squares for process monitoring." *Automatica* 46.1 (2010): 204-210.
7. Chiang, Leo H., Evan L. Russell, and Richard D. Braatz. *Fault detection and diagnosis in industrial systems*. Springer Science & Business Media, 2000.
8. Yin, Shen, Lei Liu, and Jian Hou. "A multivariate statistical combination forecasting method for product quality evaluation." *Information Sciences* 355 (2016): 229-236.
9. Chen, Zhiwen, et al. "Canonical correlation analysis-based fault detection methods with application to alumina evaporation process." *Control Engineering Practice* 46 (2016): 51-58.
10. Chen, Zhiwen. *Data-driven Fault Detection for Industrial Processes: Canonical Correlation Analysis and Projection Based Methods*. Springer, 2017.
11. Reis, Marco S., and Geert Gins. "Industrial Process Monitoring in the Big Data/Industry 4.0 Era: From Detection, to Diagnosis, to Prognosis." *Processes* 5.3 (2017): 35.
12. Chiang, Leo H., Evan L. Russell, and Richard D. Braatz. *Fault detection and diagnosis in industrial systems*. Springer Science & Business Media, 2000.
13. Larimore, Wallace E. "System identification, reduced-order filtering and modeling via canonical variate analysis." *American Control Conference, 1983*. IEEE, 1983.
14. Yin, Shen, et al. "A review on basic data-driven approaches for industrial process monitoring." *IEEE Transactions on Industrial Electronics* 61.11 (2014): 6418-6428.
15. Zhang, Yingwei, Jiayu An, and Chi Ma. "Fault detection of non-Gaussian processes based on model migration." *IEEE Transactions on Control Systems Technology* 21.5 (2013): 1517-1526.
- Zhang, Yingwei, Nan Yang, and Shipeng Li.
16. Chenaru, Oana, et al. "Fault-Tolerant Control System Implementation Based on Parameter Analysis." *analysis* 4.6 (2016): 18.
17. "Fault isolation of nonlinear processes based on fault directions and features." *IEEE Transactions on Control Systems Technology* 22.4 (2014): 1567-1572.
18. Rashid, Mudassir M., and Jie Yu. "A new dissimilarity method integrating multidimensional mutual information and independent component analysis for non-Gaussian dynamic process monitoring." *Chemometrics and Intelligent Laboratory Systems* 115 (2012): 44-58.
19. C. M. Bishop, *Pattern Recognition and Machine Learning* (Information Science and Statistics). Secaucus, NJ, USA: Springer-Verlag, 2006.
20. Chen, Tao, Julian Morris, and Elaine Martin. "Probability density estimation via an infinite Gaussian mixture model: application to statistical process monitoring." *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 55.5 (2006): 699-715.
21. Odiowei, Pabara-Ebiere Patricia, and Yi Cao. "Nonlinear dynamic process monitoring using canonical variate analysis and kernel density estimations." *IEEE Transactions on Industrial Informatics* 6.1 (2010): 36-45.
22. Tschumitschew, Katharina, and Frank Klawonn. "Incremental quantile estimation." *Evolving Systems* 1.4 (2010): 253-264.

-
23. Hardoon, David R., Sandor Szedmak, and John Shawe-Taylor. "Canonical correlation analysis: An overview with application to learning methods." *Neural computation* 16.12 (2004): 2639-2664.
24. Chen, Zhiwen, et al. "Fault Detection for Non-Gaussian Processes Using Generalized Canonical Correlation Analysis and Randomized Algorithms." *IEEE Transactions on Industrial Electronics* 65.2 (2018): 1559-1567.
25. Yin, Shen, et al. "A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark Tennessee Eastman process." *Journal of Process Control* 22.9 (2012): 1567-1581.
26. Ricker, N. Lawrence. "Decentralized control of the Tennessee Eastman challenge process." *Journal of Process Control* 6.4 (1996): 205-221.
27. Chen, Zhiwen, et al. "Improved canonical correlation analysis-based fault detection methods for industrial processes." *Journal of Process Control* 41 (2016): 26-34.