A combined canonical variate analysis and Fisher discriminant analysis (CVA–FDA) approach for fault diagnosis

Benben Jiang\textsuperscript{a,b}, Xiaoxiang Zhu\textsuperscript{b}, Dexiong Huang\textsuperscript{a}, Joel A. Paulson\textsuperscript{b}, Richard D. Braatz\textsuperscript{b,*}

\textsuperscript{a} Dept. of Automation, Tsinghua University and Tsinghua National Laboratory for Information Science and Technology, Beijing 100084, China
\textsuperscript{b} Dept. of Chemical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

\textbf{A R T I C L E   I N F O}

\textbf{Article history:}
Received 11 September 2014
Received in revised form 7 January 2015
Accepted 3 March 2015
Available online 10 March 2015

\textbf{Keywords:}
Fault diagnosis
Canonical variate analysis
Fisher discriminant analysis
Dynamic FDA
Tennessee Eastman process
Process monitoring

\textbf{A B S T R A C T}

This paper proposes a combined canonical variate analysis (CVA) and Fisher discriminant analysis (FDA) scheme (denoted as CVA–FDA) for fault diagnosis, which employs CVA for pretreating the data and subsequently utilizes FDA for fault classification. In addition to the improved handling of serial correlations in the data, the utilization of CVA in the first step provides similar or reduced dimensionality of the pretreated datasets compared with the original datasets, as well as decreased degree of overlap. The effectiveness of the proposed approach is demonstrated on the Tennessee Eastman process. The simulation results demonstrate that (i) CVA–FDA provides better and more consistent fault diagnosis than FDA, especially for data rich in dynamic behavior; and (ii) CVA–FDA outperforms dynamic FDA in both discriminatory power and computational time.

\textcopyright 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Fault diagnosis, which is the determination of the root cause of faults, is important for efficient, safe, and optimal operation of an industrial process. The task of diagnosing the faults can be rather challenging when there are a large number of process variables that are highly correlated due to the process dynamics and control systems.

For fault diagnosis based on data-driven methods, data collected from the plant during specific faults are classified into multiple classes, where data in each class indicates a particular fault. Among the methods for classifying data of multiple classes, Fisher discriminant analysis (FDA) determines a set of projection vectors that minimize the scatter within each class while maximizing the scatter between the classes. While FDA has been used for decades in pattern classification (Duda et al., 2001), its application for analyzing chemical process data began to be explored only in the last 15 years (Chiang et al., 2000, 2001; He et al., 2005).

Due to process dynamics, observations are often serially correlated, that is, the observations at one time instant are correlated with observations at past time instants. In order to handle serial correlations in the data, the FDA method for fault diagnosis can be extended by augmenting the observation vector with lagged values of process variables. This method is referred to as dynamic FDA (DFDA) (Chiang et al., 2001), which enables dynamic information to be used in classifying the observations. Since the information contained in a single observation vector is a subset of the information contained in the augmented observation vector, the augmented vector approach can lead to improved fault diagnosis. The incorporation of time lags for autocorrelated variables benefits the fault classification by decreasing the degree of overlap among the augmented data (Chiang et al., 2001). However, data stacking in DFDA significantly increases the dimensionality of the problem, proportional to the number of lags included. Another drawback is that more data may be required to determine the mean vector and covariance matrix to achieve the same level of accuracy for each class. As a result, DFDA typically has high computational requirements that hinder its application to large-scale systems. This study will focus on developing a scheme that can not only better capture the dynamic information in the data but also has reduced computational cost.

Some past studies of fault diagnosis have employed dimensionality reduction techniques followed by discriminant analysis. Raich and Činar (1995, 1996) presented a multivariate statistics approach for diagnosing abnormal behaviors by following principal component analysis (PCA) with discriminant analysis. A later study (Chiang, 2001) incorporated PCA and FDA for diagnosing both known and unknown faults. Employing partial least squares (PLS)
for discrimination has been investigated extensively, such as in Chiang et al. (2000) and Barker and Rayens (2003). In general, PCA- and PLS-based discriminant analysis are limited in their ability to quickly diagnose faults for process data that contain significant serially correlation, because the underlying PCA and PLS approaches do not generate the most accurate dynamic models, even when lagged values of process variables are augmented in the observation vectors (Chiang et al., 2001; Negiz and Çinar, 1997a; Russell et al., 2000; Ku et al., 1995; Ricker, 1988).

Canonical variate analysis (CVA) is a dimensionality reduction technique in multivariate statistical analysis which utilizes state-space representations. CVA maximizes the combination of the ‘past’ values of the process inputs and outputs and the combinations of the ‘future’ values of the outputs of the system (Larimore, 1997). This method takes serial correlations into account by employing this different augmented vector technique during the dimensionality reduction procedure.

Negiz and Çinar (1997a) discuss and demonstrate the higher accuracy of dynamic models constructed by CVA compared to dynamic PCA through application to numerical examples. CVA has been observed to have better numerical stability and parsimony than alternative identification methods, including balanced realization (BR), numerical algorithms for state space subspace system identification (N4SID), and partial least squares (PLS), in many case studies (Juricek et al., 1998; Negiz and Çinar, 1997b; Simoglou et al., 1999, 2002).

This article describes a combined CVA–FDA fault diagnosis scheme that employs CVA for pretreating the data and subsequently utilizes FDA for classifying faults. Employing CVA in the first step improves handling of serial correlations in the data, decreases the overlap among the data classes, and enables the pretreated datasets to have similar or even fewer dimensions compared with the original datasets. The rest of this article is organized as follows. Section 2 provides some background knowledge on CVA, FDA, and DFDA. Section 3 elaborates the proposed CVA–FDA approach for fault diagnosis. The effectiveness of the CVA–FDA approach is demonstrated with the Tennessee Eastman process in Section 4, followed by conclusions in Section 5.

2. CVA and FDA

The relevant methods for fault diagnosis and classification are reviewed in this section. CVA is introduced as the dimensionality reduction method, followed by a brief review of FDA, which serves as the basis of the fault diagnosis.

2.1. CVA

CVA is a dimensionality reduction technique in multivariate statistical analysis which maximizes the correlation between two selected sets of variables. Hotelling initially proposed the CVA concept for multivariate statistical analysis, which was employed to system identification by Akaike for autoregressive-moving-average model (ARMA) models (Larimore, 1997; Akaike, 1974). The CVA method was further developed for identifying state-space models by Larimore (1997).

Given time series output data \( y_t \in \mathbb{R}^m \) and input data \( u_t \in \mathbb{R}^n \), the linear state-space model is (Russell et al., 2000)

\[
\begin{align*}
\dot{x}_{t+1} &= Ax_t + Bu_t + v_t \\
y_t &= Cx_t + Du_t + Ev_t + w_t
\end{align*}
\]

where \( x_t \) is a state vector, \( v_t \) and \( w_t \) are independent white noise processes, and \( A, B, C, D, \) and \( E \) are coefficient matrices.

The CVA algorithm uses the concept of past and future vectors. At a particular time instant \( t \in \{1, \ldots, n\} \), the past vector \( p_t \) containing the past outputs and inputs is

\[
p_t = [y_{t-1}^T, y_{t-2}^T, \ldots, u_{t-1}^T, u_{t-2}^T, \ldots]^T
\]

and the future vector \( f_t \) comprising of the outputs in the present and future is

\[
f_t = [y_{t+1}^T, y_{t+2}^T, \ldots]^T
\]

For an assumed state order \( k \), the CVA algorithm computes a constant matrix \( J_k \) that linearly relates the past vector \( p_t \) to the memory \( m_t \in \mathbb{R}^k \).

\[
m_t = J_k p_t
\]

where the term “memory” is used instead of “state” since the vector \( m_t \) may not necessarily contain all of the information in the past (Larimore, 1990). The optimal matrix \( J_k \) is calculated via the singular value decomposition (SVD) to minimize the average prediction error

\[
E(||f_t - J_k p_t||_A^2) = E((f_t - J_k p_t)A^\dagger(f_t - J_k p_t))
\]

where \( E \) is the expectation operator, \( f_t \) is the prediction of \( f_t \), and the weighing \( A^\dagger \) is the pseudo-inverse of \( A \). Selecting \( A = \Sigma_k \) nearly maximizes the likelihood function for the state-space system \( 1 \) and \( 2 \) (Larimore, 1990), where \( \Sigma_k \) is the covariance of \( f_t \).

The SVD algorithm calculates the optimal value for \( J_k \) as

\[
\Sigma_k^{-1/2} \Sigma_f^{-1/2} = U S V^T
\]

where \( U \) is the diagonal matrix of nonnegative singular values with descending order, \( U \) and \( V \) are matrices of the right and left singular vectors, and the matrices \( J_k \) are obtained by

\[
J_k = U_k \Sigma_k^{-1/2}
\]

where \( U_k \) contains the first \( k \) columns of \( U \) in (7).

2.2. FDA

For fault diagnosis, data collected from the process during specific faults are categorized into classes, where each class contains data indicating a particular fault. FDA is widely used as a technique of pattern classification. The basic idea of FDA is to determine a set of projection vectors that optimize the Fisher criterion (He et al., 2005). A brief mathematical description is provided here.

Given \( n \) observations of \( m \) measurement variables, an \( n \) by \( m \) matrix \( X \) is constructed to stack the training data for all classes, and the \( n \)th row of \( X \) is represented as the column vector \( x_i \), the total-scatter matrix is given by (Duda and Hart, 1973; Chiang et al., 2004)

\[
S_t = \sum_{i=1}^{n} (x_i - \bar{x}_{mean})(x_i - \bar{x}_{mean})^T
\]

where \( \bar{x}_{mean} \) indicates the total mean vector, elements of which are the means of the columns of \( X \). Define \( X_j \) as the set of vectors \( x_i \) belonging to the class \( j \), then the within-class scatter matrix for class \( j \) is defined by

\[
S_j = \sum_{x_i \in X_j} (x_i - \bar{x}_{j,mean})(x_i - \bar{x}_{j,mean})^T
\]
where \( \mathbf{x}_{j,\text{mean}} \) indicates the mean vector of class \( j \). Given that the number of classes is \( c \), then the within-class-scatter matrix is given by

\[
S_w = \sum_{i=1}^{c} S_i
\]

and the between-class-scatter matrix is

\[
S_b = \sum_{i=1}^{c} n_i (\mathbf{x}_{j,\text{mean}} - \mathbf{x}_{\text{mean}}) (\mathbf{x}_{j,\text{mean}} - \mathbf{x}_{\text{mean}})^T
\]

where \( n_i \) is the observation number of class \( i \).

The objective is to provide a set of projection vectors \( \mathbf{W} \) that optimize the Fisher criterion:

\[
\max_{\mathbf{W}} \frac{\mathbf{W}^T S_b \mathbf{W}}{\mathbf{W}^T S_w \mathbf{W}}
\]

FDA vectors can be derived to be equivalent to the eigenvectors \( \mathbf{w}_k \) of the generalized eigenvalue problem

\[
S_b \mathbf{w}_k = \lambda_k S_a \mathbf{w}_k
\]

where \( \lambda_k \) is the generalized eigenvalue.

At most \( p - 1 \) eigenvalues will be nonzero, because the rank of \( S_b \) is less than \( p \). Define the matrix \( \mathbf{W} \) with the \( a \) FDA vectors as columns, where \( a \leq p - 1 \). Then the linear transformation of the data from \( m \)-dimensional space to \( a \)-dimensional space is represented by

\[
\mathbf{z}_i = \mathbf{W}^T \mathbf{x}_i
\]

Observations are then classified in the \( a \)-dimensional space of FDA using the discriminant function (Chiang et al., 2001)

\[
g_j(\mathbf{x}) = -\frac{1}{2} (\mathbf{x} - \mathbf{x}_{j,\text{mean}})^T \mathbf{W}_a \left( \frac{1}{n_j-1} \mathbf{W}_a^T S_a \mathbf{W}_a \right)^{-1} \mathbf{W}_a^T (\mathbf{x} - \mathbf{x}_{j,\text{mean}})
\]

\[
-\frac{1}{2} \ln \left[ \det \left( \frac{1}{n_j-1} \mathbf{W}_a^T S_a \mathbf{W}_a \right) \right].
\]

An observation is categorized to class \( j \) that has the maximum value of discriminant function,

\[
g_j(\mathbf{x}) > g_i(\mathbf{x}), \quad \forall i \neq j
\]

2.3. Dynamic FDA

The FDA method can be extended to take the serial correlations in the data into account, by augmenting the observation vector and stacking the data matrix as

\[
X(l) = \begin{bmatrix}
\mathbf{x}_l & \mathbf{x}_{l-1} & \cdots & \mathbf{x}_{l-l} \\
\mathbf{x}_{l-1} & \mathbf{x}_{l-2} & \cdots & \mathbf{x}_{l-l-1} \\
\vdots & \vdots & \ddots & \vdots \\
\mathbf{x}_{l-l-n} & \mathbf{x}_{l-l-n-1} & \cdots & \mathbf{x}_{l-n}
\end{bmatrix}
\]

The observation vector for (18) with \( l \) lags corresponds to \( p_l \) with \( l+1 \) lags (Chiang et al., 2001). This approach is referred to as dynamic FDA (DFDA) (Chiang et al., 2001), which enables more information used in the pattern classification system to classify the observations. The augmented vector approach can lead to better performance, because the information comprised in the augmented observation vector is a superset of the information comprised in a single observation vector. However, the dimensionality of the problem is considerably increased by the data stacking in DFDA, which implies that, in order to determine the same level of accuracy of the mean vector and covariance matrix for each class, more data may be required. In practice, better performance can be expected by augmenting the observation vector under the condition with both significant serial correlation and enough data to justify the larger dimensionality.

3. CVA–FDA

This section describes the CVA–FDA method, which implements CVA as a first step for pretreating the data, and then utilizes FDA for diagnosing faults. The objective of employing CVA in the first step is to handle serial correlations in the data as well as decrease the overlap between the data with the added dimensions by utilizing the time lag technique inherently contained in CVA. In addition, the dimensionality reduction procedure provided by CVA results in similar or lower dimensions of the CVA-treated datasets compared with the original datasets, which can reduce the computational time of CVA–FDA as compared with DFDA.

Misclassification generally results from the data falling in the overlapping region among different classes (Chiang et al., 2001). Two parameters in CVA can affect the degree of overlap in the projected data with reduced dimensionality: time lag \( l \) and CVA dimensionality reduction order \( a_{CVA} \). Incorporating time lags into autocorrelated variables increases the dimension of the data vectors and can reduce overlapping among the datasets. The order of model reduction \( a_{CVA} \) represents the dimensionality of the reduced space. A value of \( a_{CVA} \) that is too low or too high will result in a poorer characterization of the process dynamics, which would likely result in a larger overlap in the CVA-treated data. A rational method for selecting values of the time lag \( l \) and dimensionality reduction order \( a_{CVA} \) is to minimize overlap in the resulting CVA-treated data. Many overlap measures have been defined in terms of means and/or covariance matrices of individual classes, such as Raich and Cinà (1996, 1993); this section uses a method that is more widely used in the statistical learning literature (Bredensteiner and Bennett, 1999; Smith, 1968).

Given \( n \) faults \( C_i (i = 1, 2, \ldots, n) \), the overlap ratio between Fault \( C_i \) and Fault \( C_j \) is defined by (Chiang, 2001; Bredensteiner and Bennett, 1999; Smith, 1968)

\[
R(C_i, C_j) = \frac{N_{C_i \cap C_j}}{N_{C_i} + N_{C_j}}
\]

where \( N_{C_i \cap C_j} \) is the number of data points falling in the intersection of the Fault \( C_i \) and Fault \( C_j \) elliptical confidence regions, as illustrated in Fig. 1. \( N_{C_i \cap C_j} \) is the total number of data points in Fault \( C_i \) and Fault \( C_j \), and the elliptical confidence region for Fault \( C_i \) is given by (Chiang et al., 2001)

\[
T^2_{i} = \sum_{t} (\mathbf{x}_t - \mathbf{x}_{t,\text{mean}})^T S_t^{-1} (\mathbf{x}_t - \mathbf{x}_{t,\text{mean}}) \leq T^2_{s,\alpha}
\]

where \( \mathbf{x}_t = J_t \mathbf{p}_t \) and \( S_t \) is defined in (10), and \( T^2_{s,\alpha} \) follows the distribution

\[
T^2_{s,\alpha} = \frac{k(n^2 - 1)}{n(n - k)} F_{\alpha}(k, n - k)
\]

The \( T^2_{s,\alpha} \)-statistic specifies the threshold, with each elliptical confidence region in Fig. 1 drawn for a significance level of \( \alpha = 0.05 \). If the statistic of the data point falls within this threshold, the data point is classified as being fault class \( C_i \).

Choosing too large of the time lag and the dimensionality reduction order would lead to overfitting of the training data, which would give small overlap ratio in the training data but can lead to large overlap ratio in the validation data; choosing too small of the time lag and the dimensionality reduction order would underfit
the data overlap, which would have too large of a degree of overlap in both the training and validation data.

In order to select the optimal time lag \( l \) and CVA dimensionality reduction order \( a_{\text{CVA}} \), the objective function

\[
\min_{l, a_{\text{CVA}}} \sum_{1 \leq i < j \leq n} (R_{\text{train}}(C_i, C_j) + R_{\text{val}}(C_i, C_j))
\]  (22)

is used for optimization during the first CVA step based on the training and validation data, where \( R_{\text{train}}(C_i, C_j) \) and \( R_{\text{val}}(C_i, C_j) \) indicate the overlap ratios (19) of the training data and validating data between fault classes \( C_i \) and \( C_j \) respectively. This choice of objective function selects the best \( l \) and \( a_{\text{CVA}} \) in terms of facilitating the subsequent classification by FDA.

The optimization in (22) selects \( l \) and \( a_{\text{CVA}} \) for CVA to provide the least overlap in the dimensionality reduced datasets. The procedure

---

**Fig. 1.** 95% confidence regions (red ellipses) for three different fault classes (Chiang et al., 2001), with significant overlap between Faults \( C_i \) and \( C_j \). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

---

**Fig. 2.** Flowsheet for the Tennessee Eastman process (Chiang et al., 2001).
Fig. 3. Projections of the training, validation, and testing data for the three faults onto the first two FDA loading vectors by standard FDA: (a) training data, (b) validation data, and (c) testing data.

benefits the subsequent FDA algorithm for diagnosing faults where the misclassification rates are reduced as a result of reduced overlap (Chiang et al., 2004).

4. Application to Tennessee Eastman process

In this section, the proposed CVA–FDA fault diagnosis approach is evaluated for the Tennessee Eastman process (TEP). The TEP simulates an industrial process with the properly modified kinetics, components, and operating conditions. The process flowsheet of TEP with closed-loop control is shown in Fig. 2. The plant-wide control structure of Lyman and Georgakis (1995) was employed to produce the simulated process data for each fault, including normal operating conditions (Fault 0) together with 21 faulty conditions (Faults 1–21). More details about the TEP are given in Chiang et al. (2001); Downs and Vogel (1993) and McAvoy (1998).

For each fault, three sets of data (training, validation, and testing data) were generated with a sampling time of 3 min. The training and validation data were used to build the models and the testing data were used for model testing. The training, validation, and testing data each contain 400, 400, and 800 observations, respectively. Each observation contains 52 process variables, including all the manipulated and measurement variables except for the agitation speed of the reactor’s stirrer. The data were auto-scaled before the application of CVA–FDA, FDA, and DFDA, that is, each variable was subtracted by the sample mean and then divided by its standard deviation (Chiang et al., 2000).

4.1. Case Study 1: Faults 3, 4, and 11

In this case study, the performance of CVA–FDA, FDA, and DFDA for classifying multiple classes with overlap is investigated and compared for Faults 3, 4, and 11 (as specified for the TEP in Table 1). These three faults are used for the evaluation of the performance of methods for fault classes with overlapping data. Faults 4 and 11 are selected which are both related to reactor cooling water inlet temperature but are different in the fault type (step change for Fault 4 versus random variation for Fault 11) (Chiang et al., 2004; He et al.,...
When the data from these two faults are projected onto the first two FDA loading vectors, overlap is observed (see Fig. 3). Fig. 3 also includes data from Fault 3, which is related to step variation in D feed temperature – a different process variable than for Faults 4 and 11.

Fault 11 data overlap with a large portion of the date for both Faults 3 and 4, while Faults 3 and 4 have a good separation from each other. The observed separability is consistent with the above discussion. The first two FDA scores plotted over time for Faults 3, 4, and 11 in Fig. 4 show that the projected data contain a large amount of serial correlation that is not exploited in the standard FDA method.

The classification results for Faults 3, 4, and 11 utilizing FDA and CVA–FDA are displayed in Fig. 5a and b, respectively. FDA incorrectly classifies the Fault 11 data most of the time, and often misclassifies Fault 3 data. CVA–FDA has better classification than FDA for all three faults. The overall misclassification rate for CVA–FDA is 20.8% for the testing data (800 samples), compared to 35.2% to FDA (Table 2), which is a factor of 1.7 improved classification for CVA–FDA. The main reason for the differing performance is the inability of FDA to capture the information on dynamics from the data.

Using the same time lags as CVA–FDA, the classification results for Faults 3, 4, and 11 utilizing DFDA are shown in Fig. 5c. The overall misclassification rate of DFDA is 25.2%, indicating that the overall misclassification rate of CVA–FDA is a factor of 1.2 less than for DFDA. One reason for the improved fault diagnosis performance of CVA–FDA over DFDA is that the CVA state-space representation

---

**Table 1**

Description of Faults 3, 4, and 11.

<table>
<thead>
<tr>
<th>ID</th>
<th>Fault description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault 3</td>
<td>D feed temperature</td>
<td>Step change</td>
</tr>
<tr>
<td>Fault 4</td>
<td>Reactor cooling water inlet temperature</td>
<td>Step change</td>
</tr>
<tr>
<td>Fault 11</td>
<td>Reactor cooling water inlet temperature</td>
<td>Random variation</td>
</tr>
</tbody>
</table>

**Table 2**

Summary of classification results for FDA, CVA–FDA, and DFDA for Case Study 1 ($n_{FDA} = 2$).

<table>
<thead>
<tr>
<th></th>
<th>FDA</th>
<th>CVA–FDA</th>
<th>DFDA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Misclassification rate (%)</td>
<td>35.2</td>
<td>20.8</td>
<td>25.2</td>
</tr>
<tr>
<td>Overall misclassification rate</td>
<td>35.2</td>
<td>20.8</td>
<td>25.2</td>
</tr>
<tr>
<td>Computation time (s)</td>
<td>77</td>
<td>61</td>
<td>8949</td>
</tr>
</tbody>
</table>
is better than DFDA in capturing the dynamic information from the data (Negiz and Çinar, 1997b). Furthermore, applying canonical variate analysis between the future and the past information gives the optimal predictors (Negiz and Çinar, 1997a). The predicting feature is absent in models based on DFDA.

Also, the computational time for CVA–FDA is significantly shorter than that of DFDA (more than 100 times lower, 61 s for CVA–FDA compared to 8949 s for DFDA). The lower computational cost of CVA–FDA makes it more suitable for applications in which the fault diagnosis model is updated online as process operators or engineers assign data from initially unknown faults to known fault classes as they track down the root causes of the abnormal operations. The results for CVA–FDA, FDA, and DFDA are summarized in Table 2. Superior classification in both performance and computational speed are obtained in CVA–FDA than both FDA and DFDA.
The performance of the three methods for classifying transient data is further investigated here. For the sampling time of 3 min in the TEP, the first 200 samples are rich in the initial fault signatures and the transient behaviors (He et al., 2009). The misclassification rate for the dynamic data (first 200 samples) is denoted as the dynamic misclassification rate (DMR). A summary of the classification results for the FDA, CVA–FDA, and DFDA algorithms constructed from data for the first 200 samples and the first 100 samples is depicted in Table 3. The misclassification rate in CVA–FDA decreases from 20.8% for the full dataset to 18.7% for the first 200 samples. Meanwhile, the misclassification rate of the FDA has increased from 35.2% for the full dataset to 42.3% for the first 200 samples, and that of the DFDA has only a slight increment. The contrasting results advocate the superior performance of CVA–FDA in handling data with high serial correlation.

Compared to FDA, the DMR for CVA–FDA is more than a factor of two lower overall (18.7% vs. 42.3% in Table 3), and a factor of 3.6, 3.5, and 1.7 lower for Faults 3, 4, and 11. Compared to DFDA, the DMR of CVA–FDA is a factor of 1.4 lower overall, is more than a factor of two lower for Faults 3, 4, and 4, and is the same for Fault 11. The reductions in DMRs for CVA–FDA compared to FDA and DFDA are even greater when computed for the first 100 samples (Table 3), with CVA–FDA having nearly the same DMRs for 100 and 200 samples whereas FDA and DFDA have higher DMRs for 100 samples than 200 samples, further indicating the enhanced performance of CVA–FDA during operations in which the data are rich in dynamic information.

4.2. Case Study 2: all 21 faults

In this case study, all 21 faults generated by the TEP simulator are used to further investigate the performance of the proposed CVA–FDA scheme for faulty data classification. From the optimization in (22), the selection of time lag $l$ and CVA dimensionality reduction order $a_{\text{CVA}}$ are calculated as $l=8$ and $a_{\text{CVA}}=22$.

The overall misclassification rates and the standard deviation of misclassification rates for the 21 faults utilizing the FDA and CVA–FDA methods are plotted as a function of FDA model order $a_{\text{FDA}}$ in Figs. 6a and b, respectively. As the model order increases, the misclassification rate decreases for both FDA and CVA–FDA. Fig. 6a shows that, for the same model order $a_{\text{FDA}}$, CVA–FDA always outperformed FDA, which is indicative that the superior fault diagnosis provided by CVA–FDA is inherent in the FDA procedures and is not affected by the selection of FDA model order $a_{\text{FDA}}$. The performance of the CVA–FDA method is also less sensitive to FDA model order selection than the FDA method (Fig. 6b), while consistently providing better classification results. The main reasons for the superior performance of CVA–FDA are that (i) the CVA state-space representation can capture the dynamic information from the data more effectively; and (ii) incorporating CVA between the future and the past information gives the optimal predictors (Negiz and Çinar, 1997a) while this property is absent in models based on FDA.

The computational cost of fault diagnosis for all 21 faults using FDA and CVA–FDA are around 90 min and 70 min, respectively. Compared with FDA and CVA–FDA, the computational cost of DFDA is so high that utilization of that method for diagnosis in Case Study 2 was prohibitive.

Case Study 2 demonstrates the effectiveness of the proposed CVA–FDA fault diagnosis method. Pretreating the data by the CVA approach is advantageous for the subsequent FDA algorithm for diagnosing faults.

5. Conclusions

This article describes a combined CVA–FDA scheme for fault diagnosis that employs CVA to pretreat the data in the first step and then utilizes FDA for classifying faults. Serial correlations in the data are handled and the overlap between the data is decreased in the CVA step, where an optimization technique based on the overlapping degrees of training and validation data is utilized to select an appropriate time lag $l$ and CVA dimensionality reduction order $a_{\text{CVA}}$. The proposed approach has been demonstrated by all the 21 faults in TEP, which indicated that (i) CVA–FDA provides better and more consistent fault diagnosis for various faults than FDA, particularly in diagnosing faulty data with dynamic behavior; and (ii) CVA–FDA outperforms DFDA in discriminatory power and computational time.

An idea for future work is to develop a framework to simultaneously perform dimensionality reduction for CVA and FDA. The
development of such a framework would be challenging, in that CVA consists of a projection of the input–output data onto a chosen state coordinate system followed by least-squares, which are rather different in character as FDA, which solves an optimization problem that maximizes separation between classes. Such a simultaneous approach would likely have much higher computational cost than the approach described in this article, but could have the potential of achieving even better fault diagnosis.

Acknowledgements

This work was supported by the National Basic Research Program of China (2012CB720505) and the National Natural Science Foundation of China (21276137). The first author is grateful for the financial support from China Scholarship Council. The last author’s time on the project was supported by the Edwin R. Gilliland Professorship. An anonymous reviewer is acknowledged for the idea for future work at the end of Section 5.

References


