MULTI-SCALE EXTENSION OF DISCRIMINANT PLS FOR FAULT DETECTION AND DIAGNOSIS

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ABSTRACT
A new approach based on the Partial Least Squares (PLS) and Wavelet Transform is presented for the industrial process monitoring. A different scheme for applying PLS for multiple faults diagnosis is used in this approach. Because of multi-scale nature of the variable measurements in the most of industrial processes the Discrete Wavelet Transform (DWT) is applied to extract the multi-scale features of these measurements. Comparison of the ability of this Multi-Scale PLS (MSPLS) algorithm with the PLS to diagnosis the multiple faults in the Tennessee Eastman process (TEP) benchmark, demonstrates the efficiency of the proposed approach and indicates that this MSPLS algorithm can be useful for process monitoring and detection and diagnosis multiple faults.

Keywords: fault, detection, diagnosis, discriminant PLS, MSPLS

1. INTRODUCTION
P Partial Least Squares (PLS) structure is one of the Statistical Process Monitoring (SPM) methods that widely used for monitoring the abnormal situations that happen in the processes. PLS projects the input-output data down into a latent space, extracting a number of main factors with an orthogonal structure, while capturing most of the variance in the original data (Geladi and Kowalski 1986; Wold et al. 1984). A popular application of PLS is to select the predictor block X, containing the variables measurements and the predicted block Y, containing the product quality data (Raich and Cinar 1995). This model can be used for detecting, identifying and diagnosing the faults (Piovoso and Kosanovich 1994). Another application of PLS mainly focusing on fault diagnosis is to define Y as class membership (Chaing Russell, and Braatz 2000). This PLS model is known as discriminant Partial Least Squares. To diagnosing the multiple faults in the process, discriminant Partial Least Squares is applied in this study.
Similar to the other statistical process monitoring methods, there are some limitations for applying PLS on process monitoring. Most processes in modern industrial plants are typically complex, and such a complexity seems reflected in collected data, which contain the cumulative effect of many underlying phenomena and disturbances, with different form in the time and frequency domain (Reis Saraiva and Bakshi 2008).Therefore, the overall systems are composed of processing units that have different time scales and frequency bands (Reis Saraiva and Bakshi 2008).For detecting, identifying and diagnosing events in these systems using statistical (data-driven) methods, the collected data blocks, containing the measured variables should be assayed and treated in several scales. In discriminant Partial Least Squares, all of the process variables data and quality variables will be gathered into one data block. Therefore the other limitation is the autocorrelation of variables.
Wavelet Transform is able to decompose the variables into different scales representation. Also, the online wavelet decomposition (includes downsampling) is useful to decorrelate the autocorrelation between the measurements (Ganesan Das and Venkataraman 2004).
In this study, an online Wavelet Transform is applied to the discriminant Partial Least Squares to build a MSPLS model for process monitoring. The Tennessee Eastman Process (TEP) data with multiple faults is used to examine the ability of the proposed MSPLS algorithm to diagnosis these multiple faults.

2. TENNESSEE EASTMAN PROCESS
The Tennessee Eastman Process (TEP) was created by the Eastman Chemical Company to provide a realistic industrial process for evaluating process control and monitoring methods (Downs and Vogel 1993).
The test process is based on a simulation of an actual industrial process where the components, kinetics, and operating conditions have been adjusted for specific aims. The process consists of five major units: a reactor, condenser, compressor, separator, and stripper; and, it contains eight components: A, B, C, D, E, F, G, and H (Chaing Russel and Braatz 2001).

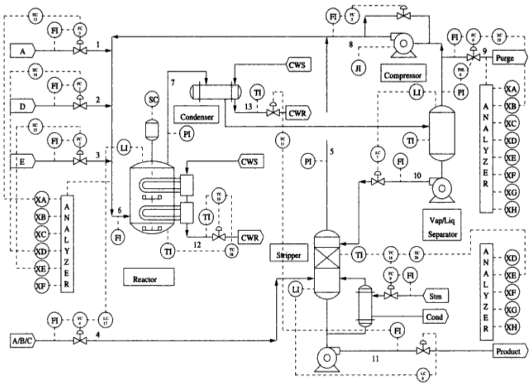

Figure1: Tennessee Eastman Process (Lyman 1995)

As shown in Figure 1, the gaseous reactants A, C, D, and E and the inert B are fed to the reactor where the liquid products G and H are formed and the species F is a by-product of the reactions. The labels in Figure 1 represent flow meters (FI), thermometers (TI), pressure gauges (PI), level detectors (LI), agitator speed control (SC), steam supply (Stm), and cooling water supply/recycle (CWS/CWR) (Wilson and Irwin 2000).
The process contains 53 variables containing 41 measured and 12 manipulated variables. The measurements of these 53 variables, is generated from the open-loop and the closed-loop simulations for the Tennessee Eastman process (TEP) as well as the training and testing data files used for evaluating the statistical methods (PCA, PLS, FDA, and CVA).
The training set used in this study consists of 500 observations for each variable which was generated with no fault and 1440 observation generated under three programmed faults. Fault 1 is connected to the step change in the cooling water. Fault 2 is a low drift in the reaction kinetics, and Fault 3 is associated with one of the sticking valves. The testing set contains of 3840 observations which starts with normal operation. Then, each of the faults mentioned above occurs to the system at determinate times.

3. MODEL DESCRIPTION

3.1. Discriminant PLS modeling

Discriminant PLS selects the matrix X, containing all process variables and selects the matrix Y, to focus PLS on the task of fault diagnosis (Chaing, Russell and Braatz 2000). To determine the predicted class in the prediction step, discriminant analysis is used (Nouwen et al. 1997).

To apply discriminant PLS for multiple fault diagnosis, the model is trained with observations of normal operation and also with faulty observations. The output (Y) of the training data is no longer the quality variables, the predicted variables are dummy variables (0 or 1), where 0 is corresponds to the faultless observation and the 1 is faulty observation. In the case that there is only one possible fault in the process, the predicted block is one column vector. In this study, however there are 3 possible faults and discriminant PLS model needs to be built for each of those faults as shown in Figure 2.

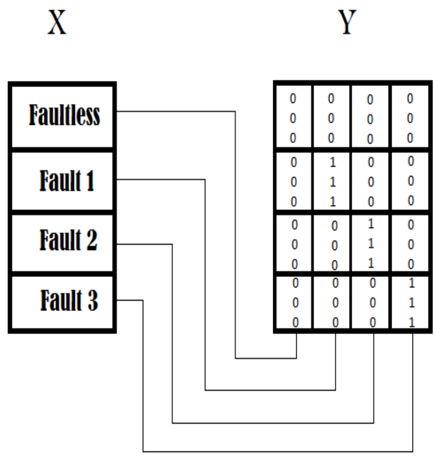

Figure2: Discriminant PLS structure. Each sub block of x is corresponds to one sub mode in predicted block.

One problem about this model is that the predicted outputs are not exactly 0 and 1, and need to be assigned to 0 or 1. One way to do that is to assign the nearest value to the predicted value.

3.2. Wavelet Transform and multi-scale modeling

Wavelet Transform analyses the signal containing multi-frequency content at different resolutions. The family of wavelet basis functions may be represented as:

$$\psi_{su}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{1}$$

Where, s and u represent the dilation and translation parameters, respectively. $\psi\ (t)$ is the mother wavelet.
Any signal may be decomposed to its contribution at multiple scales by convolution with the corresponding filters. Using online Wavelet compels the translation parameters to be discretized dyadically as $u = \left(2^m k\right)$ and so the wavelet decomposition downsamples the coefficients at each scale. This approach permits the use of orthonormal wavelets, which approximately decorrelate autocorrelated measurements (Ganesan Das and Venkataraman 2004).
To construct the MSPLS structure, in this study, the Wavelet Transform is used to decompose the measurements to its contribution at multiple scales, and the discriminant PLS is applied to each scale to diagnosis the multiple faults mentioned earlier. Scales at which the current coefficient detects the faults are selected as being relevant at the current time. The signal and covariance at the selected scales are reconstructed by the inverse wavelet transform. The schematic diagram of MSPLS algorithm is shown in Figure 3.

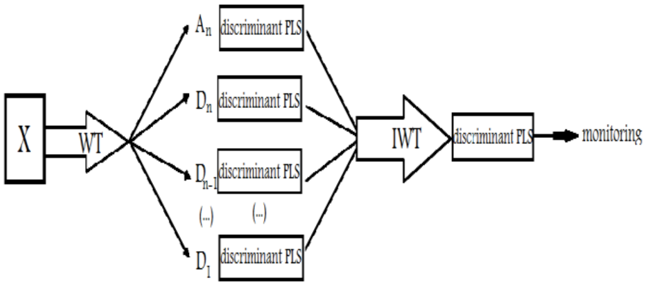

Figure3: Multi-scale PLS for process monitoring

The type of mother wavelet and the optimum decomposition level are two important selective items that should be first determined for the implementation of the online DWT (Lee Lee and Park 2009). Choosing a proper mother Wavelet usually depends on the purpose of its application. As mentioned above, an orthonormal Wavelet can approximately decorrelate the autocorrelated measurements. Based on a systematic approach proposed by Maulud (Maulud Wang, and Romagnoli 2006) for selecting the optimum decomposition level, the 'Haar' wavelet with level three is used in this study. The 'Haar' Wavelet has a simple mother function and is a common Wavelet which is applicable in discrete signal processing and also doesn't make the non-causality problems (Aradhye et al. 2003).

4. MONITORING AND RESULTS

The training data set used in this process contains data which are generated under different conditions. After the modeling with MSPLS, the model is applied to monitoring the TE process. To show the ability of MSPLS to diagnosis multiple faults in process, the testing data used in this study contains three different faults which occur at determinate times. Fault1 start at the sample time 1100 and is connected to the step change in the cooling water. Fault2 start at the sample time 2100 and is a low drift in the reaction kinetics. Fault3 start at the sample time 3000 and is associated with one of the sticking valves.

Table 1: Table1: The percent variance captured by MSPLS and discriminant PLS for the simulated faults.

	PLS	MSPLS	Scales			
		Global level	A3	D3	D2	D1
Fault1	0.50	0.89	0.81	0.12	0.04	0.08
Fault2	0.53	0.92	0.88	0.09	0.18	0.22
Fault3	0.44	0.74	0.55	0.23	0.28	0.71

To compare the monitoring ability of the MSPLS algorithm and PLS algorithm, the monitoring diagrams of the PLS and MSPLS are shown in the Figure 4 and Figure 5 respectively. In these figures the predicted variable for each fault is drawn. This value is between '0' and '1' where '0' indicates the faultless observation and '1' a faulty observation. Different colors for different faults have been used. The blue sketch is for Fault1, red is for Fault2 and green is for Fault3.

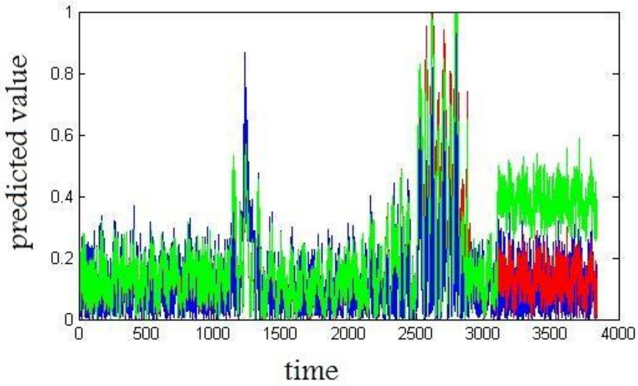

Figure4: Monitoring results of discriminant PLS. The blue graph is relevant to fault1, red is for fault2, and green is corresponds to fault3.

As shown in Figure 5 the MSPLS can detect all of three faults at acceptable time delay, while PLS could not do this adequately. This issue also is emphatic in table 1 where the percent of variance captured by PLS and MSPLS at each scale is shown for each fault, and the final MSPLS algorithm. It is obvious that this value for MSPLS is more than PLS.

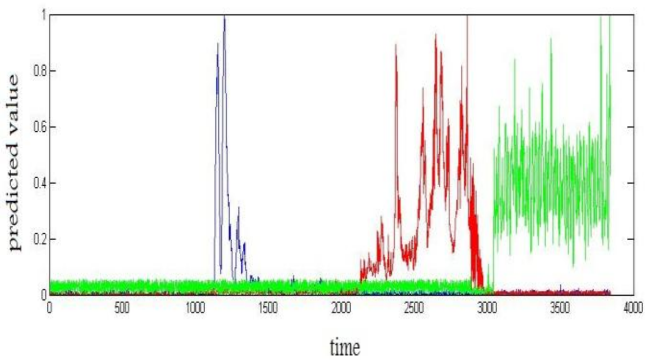

Figure5: Monitoring results of MSPLS. The blue graph is relevant to fault1, red is for fault2, and green is correspond to fault3.

5. CONCLUSIONS

In this paper, a discriminant PLS is used for constructing a new MSPLS algorithm for monitoring on the processes with multiple possible faults. This methodology has the potential of detection and diagnosing each abnormal event, denoting the time and frequency location of each event. In addition to exploiting the useful properties of Wavelet Transform, a MSPLS model which could separately construct a sub model for each possible fault and can detect each of these faults separately. The presented MSPLS algorithm can do this job adequately.

Future works can bring into focus on use of other types of mother wavelet, with the aim of improving detection, diagnosis and identification capabilities. The application of this methodology to other processes is also visualized as an interesting field for future research activities to be carried out.

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