International Journal of Control and Automation
Vol. 7, No. 11 (2014), pp. 255-262
http://dx.doi.org/10.14257/ijca.2014.7.11.25

Application of Morphological Filtering and Dynamic Time Warping in Fault Diagnosis of Complex System

Han Li and Chengli Xie

National Computer network Emergency Response technical Team/Coordination Center of China, Beijing,China
lihan@cert.org.cn, xiecl@isc.org.cn

Abstract

Pattern classification / recognition is considered as one of the frequently adopted methodology in complex system fault diagnosis. This paper studies a group of methods which can be collectively categorized as signal feature matching based fault diagnosis methodology. This proposed methodology employs dynamic programming to quantify the distance between signals which are processed by morphological filtering. The proposed methods are applied to deterministic fault classification problem in Tennessee Eastman (TE) process to demonstrate the their validity and advantages.

Keywords: *Morphological filtering, Dynamic Time Warping, Pattern classification, fault diagnosis, complex system*

1. Introduction

The main idea using pattern classification for fault diagnosis is to conduct matching processes between standard patterns which represent various known fault states and pattern which derives from observed process data. The matching procedure needs to quantify similarity and the classification result can be determined according to the selection of highest similarity. However, for homogenous fault types, their occurring moment, magnitudes may vary from time to time. Inaccurate instruments also cause measurement noise, offset translation and amplitude scaling [2]. It can be inferred that given all these reasons above, even homogeneous faults (*e.g.*, step-type fault) [3] could lead to different observed phenomena. Therefore, the performances of many Qualitative Trend Analysis (QTA) approaches could be affected because of their traditional feature extraction and matching techniques. For example, for two temporal sequences showing the same trend but different twisted waveforms, employing Euclidean distance metric to measure the similarity can cause undesirable performance[4-5].

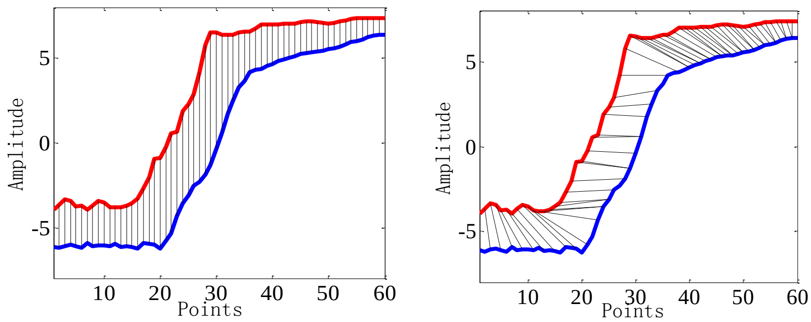
Ref. [1] presented a pattern classification method based on adaptive rank-order morphological filter. Based on the property of adaptive rank-order morphological filter, a measurement signal is transformed into a certain number of signals possessing different waveforms under different supervisory signals respectively. Then identification of the state represented by original measurement signal is realized according to the matching degrees between transformed signals and corresponding supervisory signals. In this paper, we refer to the approach proposed in Ref. [1] as pattern classification based on adaptive rank-order morphological transform I and pattern classification I for short (also denoted as EA). In pattern classification I, Euclidean distance is used to quantify the difference between two signals. In speech recognition, DTW (Dynamic Time Warping) technique is one important pattern match technique [6, 7]. Dynamic programming in DTW technique manages to align temporal landmarks shared by two patterns, which minimizes their difference. This feature of DTW creates better matching performance when applied to temporally similar signals implying the same fault type. This paper combines DTW technique and pattern classification I to develop new approaches. We alter Euclidean

ISSN: 2005-4297 IJCA

distance for measuring the difference between signals in the framework of pattern classification based on adaptive rank-order morphological transform I, and propose pattern classification based on DTW distance and adaptive rank-order morphological transform, classification based on DTW-distance-convergence adaptive rank-order morphological transform and classification based on DTW-distance-feedback adaptive rank-order morphological transform respectively. The three pattern classification methods above are collectively named as pattern classification based on adaptive rank-order morphological transform II. We also use deterministic fault diagnosis problem in Tennessee Eastman process as a case study to demonstrate the effectness of the proposed approaches.

2. Fundamentals of DTW

When two time sequences show the same trend but have different time lengths, or they have the same time length while their similar features misalign temporally, distance calculation between two sequences with the constraint of precise alignments of each timestamp would bring about a large distance, which is not a desirable result. DTW, an effective technique to deal with this problem, manage to optimally map the time axis of one sequence to that of another sequence under certain restrictions. This procedure determines an optimal combination of correspondence relationships between elements in two sequences. In this procedure, a measure of difference between two elements corresponding to a new timestamp correspondence is called local distance. The summation of local distances forms total distance. In Figure 1, Figure 1(a) demonstrates the element correspondence relationships with strict temporal alignment; Figure 1(b) an optimized element correspondence relationships which was defined by a DTW warping function. Kassidas *et. al.*, [3] employed DTW technique for deterministic fault diagnosis in TE process. Colomer *et. al.*, [8] represented signal as a series of episodes and used DTW for episode matching. Zhou and Wong [9] pointed in similarity-based query, traditional DTW may cause waveform distortion. Then Segment-wise Time Waring (STW) was proposed. Ref. [3] analyzed STW was very time-consuming. Srinivasan and Qian [10] used Dynamic Programming (DP) to search pattern to best match the current multivariate signal pattern, which realize fault diagnosis and state identification in chemical process.



(a) (b)

Figure 1. Two Different Sequence Matching Methods (a) Element Correspondence Relationships with Strict Temporal Alignment (b) An Optimized Element Correspondence Relationships which was Defined by a DTW Warping Function

3. Three Methods of Pattern Classification based on DTW and Adaptive Rank-order Morphological Transform

In Pattern classification I, sequence matching techniques for quantifying the difference are both needed in the feature construction and feature classification [1]. Figure 2 gives the basic scheme of Pattern classification I. The role, function and connections to other parts of sequence matching can be clearly identified in the scheme. In the scheme, x is the measurement signal. d1, d2, d3,……, dNp are Np signal templates (collectively denoted as d) and they are used as supervisory signals. y1, y2, y3,……, yNp are called transformed signal deriving from adaptive rank-order morphological transform (collectively denoted as y). yt1, yt2,……, ytNp (collectively denoted as yt) are transient transformed signal during the iterations. In this schematic diagram, there are three circumstances needing to calculate the signal difference for sequence matching, namely the one for the distance between d and y (denoted as e1), the one for the distance between d and yt (denoted as e2) and the one for distance or local distance between d and yt (denoted as e3). e1 is used as the criteria for classification. The convergence of e2 is used to determine when iterative adaptive rank-order morphological transform stops. For e3, it is used for calculation updates of parameter of rank-order morphological transform.

In Pattern classification I, calculation of e1 and e2 both use Euclidean distance for quantifying difference between two signals. e3 is defined as local difference between supervisory signal and transient transformed signal because every element may correspond different rank-order morphological transform parameter[1]. All the three calculation procedures above adopt Euclidean distance based quantification principle. However, if transformed signal and supervisory signal still misalign temporally in terms of their homogeneous features, adoption of Euclidean distance would result in large difference. Thus, pattern matching degree would degrade unexpectedly and incorrect classification rate rises.

If we employ matching function of DTW technique, minimal distance between two signals can be achieved through determination of optimal correspondence between timestamps. One distinct feature is DTW manages to greatly reduce distance between homogenous signals while just lightly reduce that between heterogeneous signals. This feature could help pattern classification I to reducing the misclassification rate. On the other hand, DTW technique imposes constraint conditions on time axis mapping in order to prevent the excessive warping. For two signals sharing important features which are not temporally aligned, we could firstly apply adaptive rank-order morphological transform to reduce their difference, and then use DTW matching to further gain a smaller difference. The combination application of adaptive rank-order morphological transform and DTW broadens the original scope of pattern matching which DTW deals with.

To sum up, combing the features of adaptive rank-order morphological transform and DTW matching, we use DTW distance metric as an alternative of Euclidean distance metric for three sequence matching circumstances in Figure 2. Thus, we firstly apply DTW distance for quantifying e1 to propose pattern classification based on DTW distance and adaptive rank-order morphological transform, secondly apply DTW distance for quantifying e_2 to propose pattern classification based on DTW-distance-convergence adaptive rank-order morphological transform and lastly apply DTW distance for quantifying e_3 to propose pattern classification based on DTW-distance-feedback adaptive rank-order morphological transform. The three proposed pattern classification methods are collectively referred as to Pattern classification based on adaptive rank-order morphological transform II and Pattern classification II for short. They are explained in more details as follows.

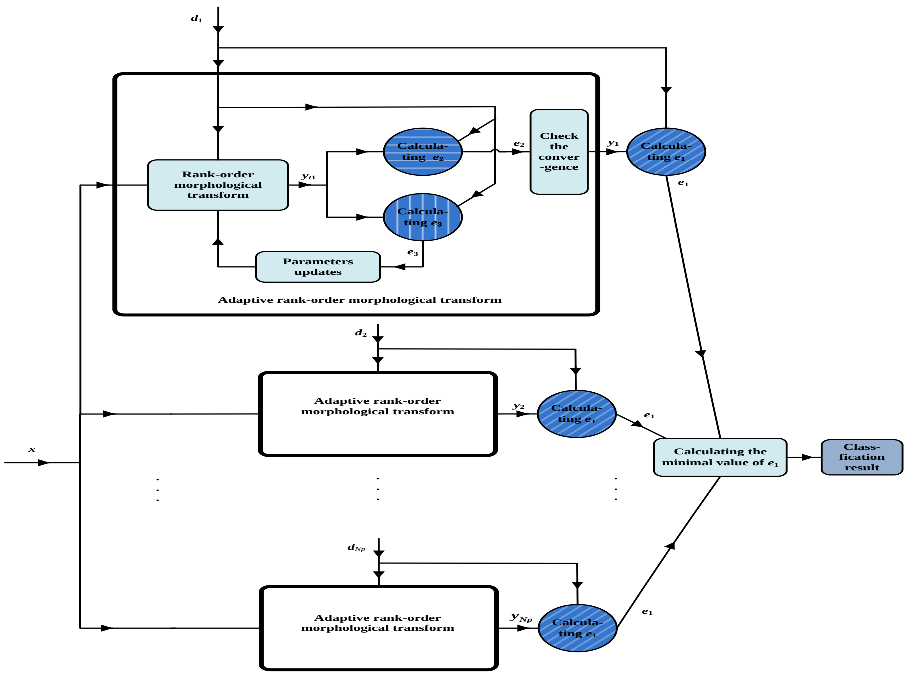


Figure 2. The Schematic Diagram of Pattern Classification based on Adaptive Rank-order Morphological Transform

Method 1: Pattern classification based on DTW distance and adaptive rank-order morphological transform (DA)

It substitutes Euclidean distance by DTW distance for e1 in Pattern classification I while quantification of e2 and e3 are still Euclidean distance. Transformed signal is defined as the transient transformed signal which generates the minimal value of e2 over the entire iterations.

Method 2: Pattern classification based on DTW-distance-convergence adaptive rank-order morphological transform (DC)

Besides e1, we also apply DTW distance to also quantify e2 on the basis of the method above. Transformed signal is with the same definition previously. The parameter update procedures remain the same as those in Pattern classification I.

Method 3: Pattern classification based on DTW-distance-feedback adaptive rank-order morphological transform (DF)

This method quantifies e3 as DTW distance between selected segments of yt and d and uses it for related parameters updates.

4. Case Study: Deterministic Fault Diagnosis in TE Process

Tennessee Eastman (TE) process was a simulated complex industry model firstly proposed by Downs and Vogel [11]. Since its launching, it has been used as a typical example for verifying the new control, identification and supervision methods. Ref. [12] provided the schematic diagram of TE process. This paper adopts the second control plan proposed in Ref. [13] because this plan keeps TE process operating in the best state [14]. Ref. [12] also shows the adopted control plan consists of 19 control loops and all the control parameters are listed in Ref. [14]. The simulated codes of TE process in FORTRAN adopted in this paper are provided form URL: http://web.mit.edu/braatzgroup/links.html.

This paper adopts Method 1 and Method 2 of Pattern classification II (DA and DC) to study deterministic fault diagnosis problem and compares their performances with those of Pattern classification I and direct DTW matching. Ref. [15] expounded the basic framework of fault diagnosis using pattern classification based on rank-order morphological transform, including the procedure of signal templates and simulation data generation and parameter selection. In this paper, we adopt the same procedure and parameters for generating signal templates. The training data contains 10 simulations data for each deterministic fault scenario to generate 60-points signal template and there are total 7 fault scenarios (IDV(1) ~ IDV(7)). Every fault is introduced the 12th hr after the simulation started. For testing data, each fault type includes 10 simulation data, but their fault occurring moments are stochastic within 24 hrs. The signal patterns to be identified also have 60 points. In this paper, we employ DTW matching methods with Itakura constraint [16] and Sakoe-Chiba constraint conditions [17] respectively to give a comparative study. The window length in the adjustment window condition [17] is chosen 30, half of the signal pattern length, which guarantees the inclusion of the max possible occurring timestamp difference of shared feature in two signals. All the adaptive rank-order morphological transforms adopt the flat structuring element. The initial length of flat structuring element is chosen 29. Other parameters are selected randomly. The maximum number of iterations is chosen 200 and the iterations are not allowed to stop prematurely. Table 1 lists the results obtained by the proposed methods and existing methods.

Table 1. Comparative Study of Multi Methods Applied to Deterministic Fault Classification in TE Process

Constraint condition of DTW employed	Method adopted	Correct classification rate							
		IDV(1) (%)	IDV(2) (%)	IDV(3) (%)	IDV(4) (%)	IDV(5) (%)	IDV(6) (%)	IDV(7) (%)	Ave (%).
-	E	5.00	80.00	15.00	10.00	0	100.00	15.00	32.14
-	EA	55.00	90.00	0	25.00	55.00	80.00	55.00	51.43
I	D	50.00	80.00	30.00	30.00	35.00	80.00	35.00	48.57
	DA	65.00	90.00	10.00	25.00	55.00	75.00	60.00	54.29
	DC	70.00	90.00	5.00	25.00	50.00	70.00	60.00	52.86
symmetric S no scc	D	80.00	80.00	45.00	15.00	65.00	95.00	60.00	62.86
	DA	70.00	90.00	0.00	25.00	50.00	95.00	60.00	55.71
	DC	80.00	90.00	0.00	25.00	55.00	90.00	45.00	55.00
asymmetric S no scc	D	90.00	80.00	45.00	20.00	60.00	15.00	85.00	56.43
	DA	55.00	90.00	0	10.00	25.00	45.00	10.00	33.57
	DC	60.00	85.00	0	10.00	30.00	35.00	10.00	32.86
symmetric S scc: [1/3,3]	D	65.00	85.00	40.00	15.00	55.00	90.00	35.00	55.00
	DA	65.00	90.00	0	25.00	50.00	95.00	55.00	54.29
	DC	70.00	90.00	5.00	25.00	50.00	80.00	50.00	52.86
asymmetric S scc: [1/3,3]	D	65.00	80.00	45.00	15.00	50.00	70.00	55.00	54.29
	DA	65.00	85.00	5.00	25.00	50.00	80.00	40.00	50.00
	DC	70.00	90.00	5.00	15.00	50.00	75.00	40.00	49.29
symmetric S scc:[1/2,2]	D	55.00	85.00	30.00	20.00	30.00	95.00	35.00	50.00
	DA	65.00	90.00	0	25.00	50.00	90.00	60.00	54.29
	DC	65.00	90.00	0	25.00	50.00	85.00	60.00	53.57
asymmetric S scc:[1/2,2]	D	55.00	85.00	30.00	20.00	40.00	80.00	45.00	50.71
	DA	65.00	90.00	5.00	25.00	55.00	75.00	60.00	53.57
	DC	70.00	90.00	5.00	20.00	55.00	75.00	45.00	51.43
symmetric S scc:[2/3,3/2]	D	40.00	85.00	30.00	20.00	30.00	90.00	30.00	46.43
	DA	60.00	90.00	0	25.00	55.00	90.00	55.00	53.57
	DC	65.00	90.00	5.00	25.00	55.00	90.00	55.00	55.00
asymmetric S scc:[2/3,3/2]	D	85.00	85.00	30.00	20.00	25.00	95.00	25.00	45.71
	DA	90.00	90.00	0	25.00	55.00	95.00	55.00	54.29
	DC	90.00	90.00	0	25.00	50.00	85.00	50.00	52.14

E-Direct matching using Euclidean distance metric, EA-Pattern classification I, D-DTW matching, I- Itakura constraint, S-Sakoe-Chiba constraint. ssc-slope constraint condition.

Table 1 shows direct matching using Euclidean distance metirc (E) gains the poorest performance. Among all the 9 DTW slope constraint conditions, 7 are turned out to be helpful for enhancing the performance of EA except asymmetric DTW with no slope constraint condition and asymmetric DTW with slope constraint condition [1/3,3]. As slope constraint condition becomes more and more intensified, performances of direct DTW matching degrade and are outperformed by EA, DA and DC. Taking no account of unobservable fault IDV(3) [14], Table 1 shows DA and DC generally outperform direct DTW matching for faults which can be represented by relative steady waveforms. In conclusion, DA and DC are verified to have advantages on deterministic fault classification.

5. Conclusions

This paper analyzes three circumstances for quantifying signal difference in the framework of pattern classification method proposed in Ref. [1] (Pattern classification I or EA). With the employment of DTW matching, three new pattern classification methods are proposed. Method 1(DA) adopts DTW distance to quantify the difference between supervisory signal and transformed signal derived from adaptive rank-order morphological transform. Method 2(DC) adopts DTW distance to quantify the difference between supervisory signal and transient transformed signal. Method 3(DF) quantifies the difference as method 2 dose and uses the quantified difference for parameters updates.

We use deterministic fault diagnosis in TE process to verify the validity of proposed methods. Method 2 not only generates specified transformed signal according to the given waveform of supervisory signal but also avoids excessive warping under the convergence constraint of Euclidean distance. This feature is the distinct advantage of Method 2 and it reduces misclassification rates compared to EA. Method 1 performs nearly the same as EA. Method 3 is too time-consuming because of its high computational complexity. Besides, it is apt to cause unstable signal waveforms and therefore performs more poorly than Method 1.

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Authors

Li Han Ph.D. He is now an engineer in National Computer network Emergency Response technical Team/Coordination Center of China, Beijing, China. He received his doctor degree in 2013 from Tsinghua University, Beijing, China. His research interests now are data mining in information and network security, pattern recognition and fault diagnosis in complex system.

Xie Chengli Ph.D. He is now a researcher in National Computer network Emergency Response technical Team/Coordination Center of China, Beijing, China. He received his doctor degree in 2013 from University of Chinese Academy of Sciences. His interests now are big data research, pattern recognition and internet-of-things.