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Adaptive monitoring of the process operation based on symbolic episode representation and hidden Markov models with application toward an oil sand primary separation☆

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ABSTRACT

This paper presents a novel procedure for classification of normal and abnormal operating conditions of a process when multiple noisy observation sequences are available. Continuous time signals are converted to discrete observations using the method of triangular representation. Since there is a large difference in the means and variances of the durations and magnitudes of the triangles at different operating modes, adaptive fuzzy membership functions are applied for discretization. The expectation maximization (EM) algorithm is used to obtain parameters of the different modes for the durations and magnitudes assuming that states transit to each other according to a Markov chain model. Applying Hamilton's filter, probability of each state given new duration and magnitude is calculated to weight the membership functions of each mode previously obtained from a fuzzy C-means clustering. After adaptive discretization step, having discrete observations available, the combinatorial method for training hidden Markov models (HMMs) with multiple observations is used for overall classification of the process. Application of the method is studied on both simulation and industrial case studies. The industrial case study is the detection of normal and abnormal process conditions in the primary separation vessel (PSV) of an oil sand industry. The method shows an overall good performance in detecting normal and risky operating conditions.

1. Introduction

In general, a fault diagnosis problem can be divided into several sub-problems (Pernestal, 2007).

- Fault detection: determination of presence of the faults in the system.
- Fault isolation: determination of location of the fault
- Fault estimation: determination of size of the fault

In order to achieve safe production and decrease manufacturing cost, fault diagnosis along with process monitoring is becoming increasingly important. There are three main approaches for process monitoring: the knowledge-based approach, the model-based approach and the data-driven approach. The knowledge based approach is based on qualitative models. The model based approach is based on analytical models which are complex for large systems. The data driven framework is appropriate for large multivariate processes (Verron et al., 2010). Most of the approaches based on qualitative models use pattern recognition techniques to extract features from historical process data, e.g., signal directed graphs, fault trees, fuzzy systems, neural networks or qualitative trend analysis (D'Angelo et al., 2011).

Wong et al. (1998) introduce a strategy for detection of abnormal trends using important process features and qualitative information from a signal. They use the method of triangular representation, initially developed by Cheung and Stephanopoulos (1990a,b) and Bakshi and Stephanopoulos (1994), in order to discretize the continuous time observation sequences using appropriate fuzzy membership functions and rules. In their study, first, the high frequency noise is removed using wavelet analysis. Second, continuous time observations are converted to discrete numbers using the method of triangular representation and appropriate fuzzy membership functions and rules. In the overall decision making step, each variable is classified based on its corresponding HMM

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and the overall classification is based on a Back Propagation Neural Network (BPNN) which uses the generated probabilities of each HMM as the input (Wong et al., 2001).

The main disadvantage of the method of triangular representation is the loss of information when providing symbolic observations. Fixed fuzzy membership functions might provide imprecise classifications for the modes with smaller means and variances as the membership functions are biased by the modes with larger means and variances.

The proposed adaptive fuzzification method in this paper will provide more accurate discrete observations considering different modes for the durations and magnitudes of the triangles. Applying the EM algorithm, we will first divide the historical data of durations and magnitudes to different modes assuming that states can transit to each other at probabilities that obey Markov property. Fuzzy membership functions for each mode are obtained following a fuzzy C-means (FCM) clustering approach. When a new observation for the magnitude and duration is available, the probability of the observation given each mode is calculated using Hamilton's filter (Hamilton, 1988). These probabilities are then used as weights to combine means and variances of the membership functions of the different modes. Finally, using the adaptive membership functions at each time step and the method of triangular representation, the discrete observations are generated. Having the discrete observations available, a multivariate HMM approach is adopted (Li et al., 2000) for overall classification of the process.

In Sammaknejad and Huang (2014) we showed that using a multivariate scheme to train HMMs for discrete observations provides better results in comparison to the BPNN approach introduced by Wong et al. (2001). The multivariate scheme will reduce the computational time, consider the interactions between different inputs and reduce the number of false alarms.

Combination of adaptive fuzzification to discretize the continuous observations and multivariate HMM modeling show a good performance in detection of normal and faulty operating conditions in both simulation and industrial case studies. The industrial case study is selected as abnormal operating condition diagnosis in the primary separation vessel (PSV) of an oil sand industry.

Fig. 1a is a summary of the proposed process monitoring strategy in this paper where state recognition, adaptive fuzzification and multivariate HMM modeling are added to the previous studies. The procedure of state recognition and adaptive fuzzification is presented in Fig. 1b. The multivariate HMM modeling step is adopted from Li et al. (2000).

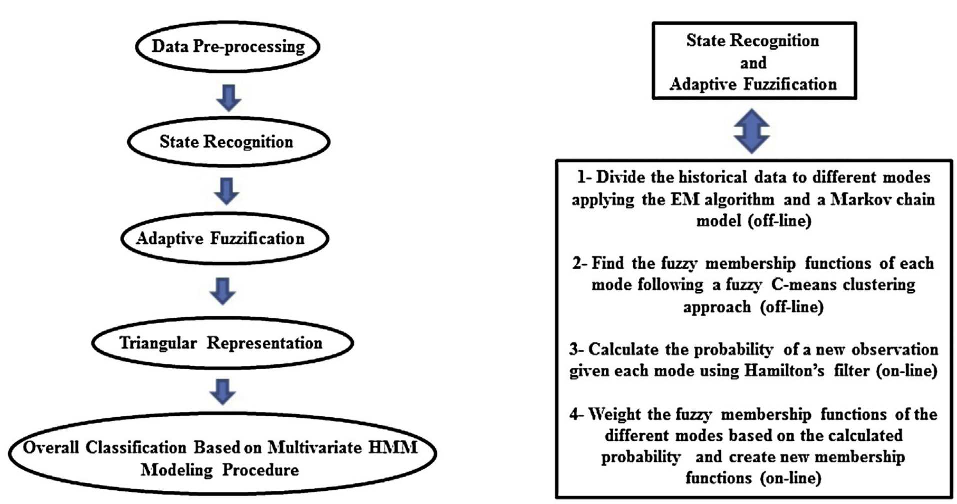
The remainder of this paper is organized as follows: Sections 2 and 3 are a review on the data pre-processing based on wavelet analysis and the method of triangular representation. Section 4 reviews state recognition applying the EM algorithm and Hamilton's filter. In Section 5, the procedure of adaptive fuzzification is explained. Section 6 briefly reviews the multivariate scheme adopted here to train HMMs for multiple observation sequences. Section 7 is the simulation case study. Section 8 is the industrial case study, and Section 9 concludes the paper.

2. Data preprocessing

The first step in representation and classification of a signal is data filtering. Typically, a filter removes nuisance information over a range of frequencies, which is determined by filter parameter. Several methods are available in order to filter a signal, e.g., moving average, Gaussian filter, Fourier transform or wavelet analysis. Compared with moving average, Gaussian filtering and Fourier analysis, the wavelet analysis possesses excellent time–frequency properties since it uses a time-scale region. Therefore, using wavelet analysis, we can get a multi-scale description of trends and features, which enables us to analyze the data efficiently. Using wavelet analysis, the original signal emerges as two signals, the low frequency part of the signal which is called approximation and the high frequency part of the signal which is called the detail. This process is called decomposition in wavelet and can be performed iteratively (Daubechies, 1990; Mallat, 1989).

3. Triangular representation

Cheung and Stephanopoulos treat the problem of trend representation graphically by using the simple idea that at the extrema and inflection points, the first and second derivatives are zero respectively. Thus, an episode is described as any part of a signal or process trend with a constant sign of the first and second derivative. This leads to the set of triangles and lines that are defined using seven letters of the alphabet (Bakshi and Stephanopoulos, 1994).



a) The proposed process monitoring approach in this study

b) The procedure of adaptive fuzzification and state recognition

Fig. 1. Comparison of the proposed methodology in this paper with the previous studies.