Overview of Process Trend Analysis Methods and Applications

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ABSTRACT: This paper surveys trend analysis methods and their applications in process industry. Basic principles of several methods are presented together with known applications in process monitoring, diagnosis and control. In the first place, the methods presented analyse process measurements or some calculated quantities as time series using various pattern recognition methods. Also computationally much more lighter methods such as linear regression based methods are included.

KEYWORDS: Process trend analysis, temporal pattern, monitoring, diagnosis, control

INTRODUCTION

For slow processes, temporal reasoning is a very valuable tool to diagnose and control the process. Manual process supervision relies heavily on visual monitoring of characteristic shapes of changes in process variables, especially their trends. Although humans are very good at visually detecting such patterns, for control system software it is a difficult problem. The aim of this paper is to present basic principles of systems that are able to detect meaningful temporal shapes from process data, analyse them and use this information in process monitoring, diagnosis and control. In knowledge based control systems of special interest are the methods that are capable to reason about the recent process history (Konstantinov and Yoshida, 1992). One interpretation of the meaning of trend analysis is that they widen the temporal scope of knowledge based control system.

Researchers with different background, for example from pattern recognition, digital signal processing and data mining, have contributed to the trend analysis development and have put emphasis on different aspects of the field. At least the following issues are characteristic to the process control viewpoint employed here:

- Methods operate on process measurements or calculated values in time series which are not necessarily sampled at constant intervals.
- Trends have meaning to human experts.
- Trend is a pattern or structure in 1-dimensional data. Methods that operate on multidimensional patterns has been developed but in this context we focus on "visible" trends.
- Application area is in process monitoring, diagnosis and control.

In this review an overview of the potential of trend analysis in the chemical and biochemical industries is given. In the following section, the most promising methods and their applications are presented based on an extensive literature research. Finally, conclusions are given in the last section.

TREND ANALYSIS METHODS AND APPLICATIONS

Regression Analysis Based Methods

Linear regression, when applied to time-series data, fits the data to a model $y = mx + b$, where m represents the rate of change and b represents the y-intercept of the line.

Poirier and Meech (1993) have developed a real-time expert system utilising fuzzy logic for a copper flotation process that assists in detecting significant changes up or down in process variables. When such a change is detected, a message is passed to the operators indicating the trend and its corresponding time interval. The system is capable of screening out exceptions such as faulty assays and equipment shut downs. In the following basic characteristics and test results of their application are reviewed.

Process recovery is calculated from the metal content of the feed and tailings streams of the circuit. An on-line analyser assays each stream at constant intervals. In Figure 1 an illustrative example of the system in use is shown. The system uses linear regression and the moving average of the assay value over different time periods to reason the trend: *trending-up*, *trending-down* or *constant*. Fuzzy logic is used to attach a degree of belief in trending-up and trending-down to each new analysis value and accumulate them over the duration of the time period. After each new analysis corresponding degree of belief is added to the accumulated belief and every assay leaving the time window decreases the accumulated belief. When accumulated belief exceeds a certain threshold, an alarm is passed to the operators. This threshold value can be adjusted by the operators. After three months operation a system without belief accumulation property detected about 95% of significant assay changes and 20% of messages were false alarms. The inclusion of belief accumulation resulted in tests with simulated data 100% correct reasoning and no false alarms were generated. The application was developed using Comdale/C expert system shell marketed by Comdale Technologies, Toronto (bought by ABB on December, 1998). The authors see early detection of process upsets and the prevention of equipment failures as the main improvements gained by using trend analysis.

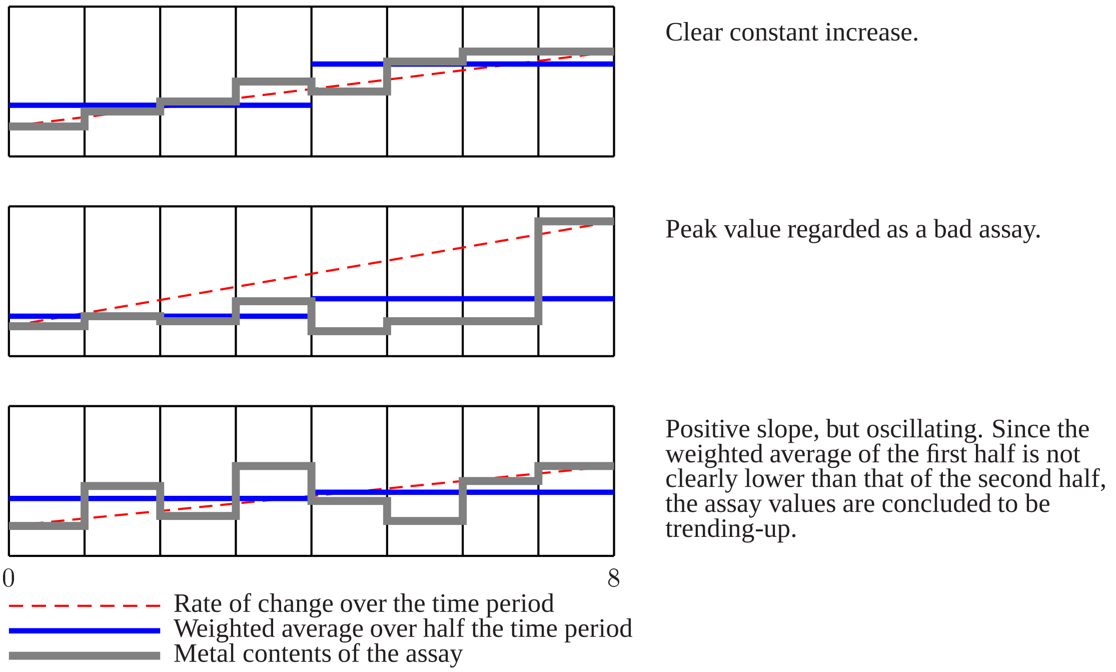

Figure 1: An example of trend analysis with Comdale/C in the flotation circuit of a mineral processing plant. Three different cases over eight sampling intervals are presented. Adapted from Poirier and Meech (1993).

Physiological signals contain normally outliers and artifacts and therefore advanced methods are needed in their analysis. Avent and Charlton (1990) have made an extensive review of trend analysis methods for biomedical monitoring systems. Sittig *et al.* (1992) have used linear regression in fuzzy classification of heart rate trends and artifacts. They found that by minimising the mean absolute deviation between the data and the estimate rather than the square of differences, a more robust estimate with respect to outliers and artifacts in the data is obtained.

Triangular Episodic Presentation and Qualitative Scaling

Cheung (1992) developed a formal framework for the extraction and representation of process trends. A language called *triangular episodic representation* is formulated and used in trend extraction. It is based on temporal episodes modelled geometrically as triangles to describe the local temporal pattern in data as illustrated in Figure 2.

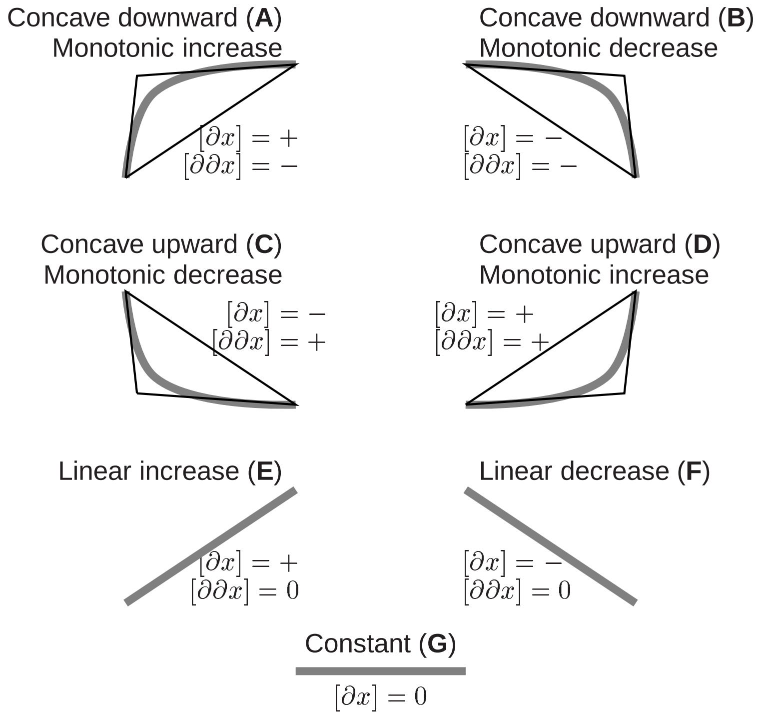

Figure 2: Triangular episodic representation. Seven basic types of episodes used for interval description. Each episode type is denoted by a letter from the set {A, B, C, D, E, F, G}. Adapted from Cheung and Stephanopoulos (1990) and Cheung (1992).

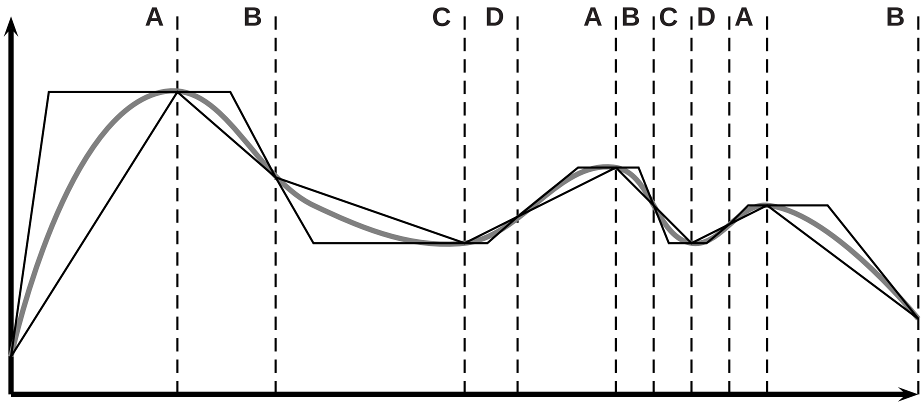

Figure 3: Example of triangular representation of process trends. Episodes are separated by vertical dashed lines.

The actual trend extraction method is called qualitative scaling. It generates a hierarchical multiscale structure of trend descriptions over different time scales from process data.

Stephanopoulos *et al*. (1997) have applied the methodology in fermentation process data analysis. Their system consists of a wavelet signal decomposition that acts as a noise removing filter, a triangular representation of smoothened process variables, and a search algorithm that uses decision trees comparing Shannon's entropy for each branch in the tree. The methodology has been implemented as a part of *dbminer* tool aimed at fermentation data mining, diagnosis and control. As a result, their approach gives a decision tree that can be converted to rules for process improvement. Another, quite similar approach to fermentation data analysis from the same research group is presented in Bakshi *et al*. (1994).

German MIT GmbH markets ProcessAnalyzer PlugIn, user-defined function block extending the basic software, to their DataEngine tool (MIT GmbH, 1999). They see especially batch process analysis as a potential application area of the system. Fochem *et al*. (1998) have described an idea of using the multi-scale trend extraction method to electronic nose for classifying odours.

Dynamic Time Warping

Dynamic time warping (DTW) uses dynamic programming to align the time series under study and a given template so that some total distance measure is minimised (Rabiner and Juang, 1993). This technique has been widely used in the area of speech recognition. DTW algorithm alings the time axis of a template Y with the time axis of observation sequence X:

$$X = x_1, x_2, \ldots, x_i, \ldots x_n \qquad \text{and} \qquad Y = y_1, y_2, \ldots, y_j, \ldots y_m \tag{1}$$

A warping path, W, aligns the elements of X and Y, such that the selected distance measure between them is minimised.

$$W = w_1, w_2, \ldots w_p \tag{2}$$

W is a sequence of grid points, where each w_k corresponds to a point $(i, j)_k$. For example, in point w_3 in Figure 4, x_2 is aligned with y_3. If no timing difference exists, the warping path follows the diagonal line $i = j$.

In the formulation of a dynamic programming problem an appropriate distance measure $\delta(i, j)$ is needed. Obvious candidates are (Berndt and Clifford, 1996)

$$\delta(i, j) = |x_i - y_j| \quad \text{and} \quad \delta(i, j) = (x_i - y_j)^2 \tag{3}$$

Normally the search space is reduced by several local and global constraints. This is necessary due to the computational efficiency needed in applications.

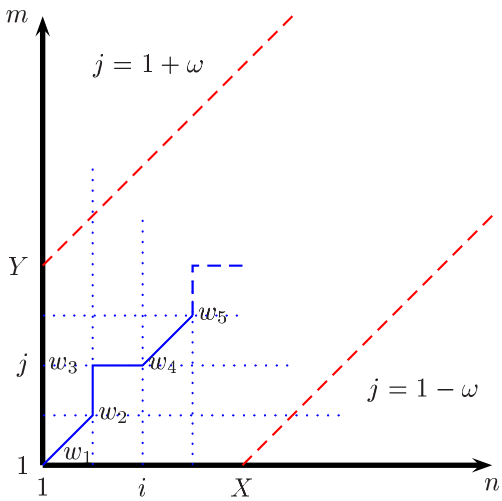

Figure 4: Example of DTW. A limiting window $|i_k - j_k| \leq \omega$ also shown.

Kassidas *et al*. (1998a) have applied DTW to batch process trajectories syncronisation in order to reconcile timing differences among them. They used data from an industrial emulsion polymerisation reactor to demonstrate the method. The same group (Kassidas *et al*., 1998b) has also studied off-line diagnosis of faults in continuous processes using DTW.

Wavelets

Recently, wavelet based signal processing methods have gained popularity for example in denoising, data compression and feature extraction. Wavelet analysis preserves both the time domain and the frequency domain information of the signal.

Vedam and Venkatasubramanian (1993) have developed a wavelet theory based nonlinear adaptive system for identification of trends from sensor data named W-ASTRA. It identifies primitives from sensor data (by generalising the methods presented in Rengaswamy and Venkatasubramanian (1995)) and use them as input to a knowledge base to perform fault diagnosis. They demonstrate the application of the system on a simulated fluidised catalytic cracking unit (FCCU). The results showed that W-ASTRA could perform accurate diagnosis of all the fault cases included in a historical data base and can notify the occurrence of unknown faults.

Flehming *et al*. (1998) have applied wavelet based approach to identification and localisation of polynomial trends in noisy measurements. Their method yields both the least-squares polynomials for the identified intervals and a quantitative measure for their goodness of fit. Subsequent to a wavelet transformation and denoising of the measurement, candidate intervals are identified by a hierarchical search in the time-frequency plane. The coefficients of the trend polynomials are determined by least squares approximation in the time-frequency representation. In testing the method they have used measurement data from an industrial multi stage flash (MSF) desalination plant. They present two examples, one for steady-state detection using the Haar wavelet and one for detection of linear trend using the Daubechies 4 wavelet. In both cases, the search algorithm succeeded in detecting the corresponding trends. The authors conclude that the algorithm is efficient enough to operate with moving time windows in on-line applications.

Qualitative temporal shape analysis

Konstantinov and Yoshida (1992) have proposed a generic methodology for qualitative analysis of the temporal shapes of process variables. Their procedure consist of three phases: analytical approximation of the process variable, its transformation into symbolic form based on the signs of the first and second derivatives of an analytical approximation function and degree of certainty calculation.

At the first step process variable $x_j(t)$ is approximated by a polynomial

$$x_j^*(t) = c_0 t^0 + c_1 t^1 + \cdots + c_m t^m, \quad t \in [t_1, t_2] \tag{4}$$

where m is the order of the polynomial and c_k, $k = 1, \ldots, m$ are the unknown coefficients. To speed up the procedure in real-time environment, the approximation equation

$$\mathbf{F}^\top \cdot \mathbf{F} \cdot \{\mathbf{c}\} = \mathbf{F}^\top \cdot \{\mathbf{x}\} \tag{5}$$

was modified. The matrix $\mathbf{F}$ is defined as

$$\mathbf{F} = \begin{bmatrix} [t_1 + 0 \cdot \Delta T]^0 & [t_1 + 0 \cdot \Delta T]^1 & \cdots & [t_1 + 0 \cdot \Delta T]^m \\ [t_1 + 1 \cdot \Delta T]^0 & [t_1 + 1 \cdot \Delta T]^1 & \cdots & [t_1 + 1 \cdot \Delta T]^m \\ \vdots & \vdots & \ddots & \vdots \\ [t_1 + (n-1) \cdot \Delta T]^0 & [t_1 + (n-1) \cdot \Delta T]^1 & \cdots & [t_1 + (n-1) \cdot \Delta T]^m \end{bmatrix} \tag{6}$$

where $[t_1 + (n-1) \cdot \Delta T] = t_2$ and ΔT is constant sampling interval. By setting $t_1 = 0$ and $\Delta T = 1$ matrix $\mathbf{F}$ can be simplified to a form where it can be calculated in advance taking into account the polynomial order and the length of the discrete time interval. Consequently, polynomial coefficients can be solved from

$$\{\mathbf{c}\} = (\mathbf{F}^\top \cdot \mathbf{F})^{-1} \cdot \mathbf{F}^\top \cdot \{\mathbf{x}\} = \mathbf{Q} \cdot \{\mathbf{x}\} \tag{7}$$

where $\mathbf{Q}$ is a constant matrix. At the second step feature strings are extracted from the analytical approximation function. The extraction of a sequence of the derivative signs is formally described by the operators

$$SD1[x_j(t)] = sd1 = (+, -, \ldots) \quad \text{and} \quad SD2[x_j(t)] = sd2 = (+, -, \ldots), \quad t \in [t_1, t_2] \tag{8}$$

Some simple patterns can adequately be presented only by $sd1$. The qualitative shape of process variable is represented by combining these strings

$$qshape[x_j(t)] = SD1[x_j(t)]; SD2[x_j(t)] = (+, -, \ldots); (+, -, \ldots), \quad t \in [t_1, t_2] \tag{9}$$

The third step, degree of compatibility calculation is formulated as follows:

$$dc = cmp1(sd1, sd1^L) \cdot \left(1 - k_1 \frac{cmp2(sd2, sd2^L)}{R} - k_2 \frac{dev}{dev_{\max}}\right), \; cmp1(sd1, sd1^L) = \begin{cases} 0 \text{ if } sd1 \neq sd1^L \\ 1 \text{ if } sd1 = sd1^L \end{cases} \tag{10}$$

where $cmp2(sd2, sd2^L)$ gives the relative number of the symbols in the second derivative string that do not match. Parameters k_1 and k_2 are user adjustable weights and $dev_{\max}$ sets limit to the maximal allowed deviation. From the equation above it can be seen that the first derivative string must match perfectly to give a degree of certainty above zero. In this way it is given a higher priority than to the second derivative.

In Figure 5 the communication of the shape analyser and an inference engine is presented. The shape analyser was implemented as a server which run after receiving a request message from the inference engine. The message contains information about the time interval, shape descriptor and variable. The shape analyser replies with the evaluated degree of certainty.

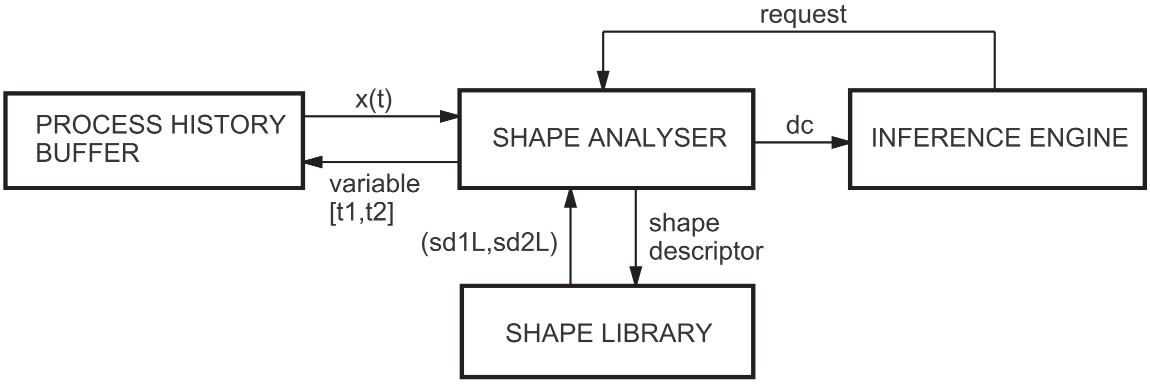

Figure 5: Communication in the shape analysing system.

The authors have applied the shape analysing scheme to the supervision of a recombinant amino acid production in laboratory scale. They tested the system in handling of process phase transitions, detection of foaming, automatic termination of the process and monitoring of instrumental failures. Their main conclusion was that the use of temporal shapes together with current values of process variables and their derivatives in a rule based supervisory system provides for a natural representation of process dynamics by eliminating nonessential quantitative details and allows for more abstract and robust knowledge representation.

Kivikunnas *et al*. (1996) have modified this shape analyser and applied it to continuous lactic acid fermentation process diagnosis. In experimenting with the method they found the behaviour of its function approximation stage unsatisfactory with noisy or corrupted data. FIR-Median Hybrid filtering was used for pretreating process measurements before template matching procedure. The filtered data was used directly for shape analysis. Further, the system has been expanded with simple, interval algebra based, temporal reasoning capabilities (Kivikunnas , 1998).

CONCLUDING REMARKS

This paper has been devoted to presenting some promising approaches to process trend analysis. Although the methodological background varies considerably in the presented approaches, certain common features can be found:

1. Most of the authors refer to the emulation of human perception and reasoning capabilities in motivating their work.
2. Trend analysis operates as a complementing, not as stand alone system and normally provides information to some reasoning mechanism.
3. Computational efficiency issues play an essential role in development towards on-line systems.
4. No firm design methodologies can be found.

One perspective is to integrate trend analysis with systems providing for adequate temporal reasoning capabilities. Another direction for further research could be the investigation of possibilities of trend information in supervisory control.

In conclusion: Trend analysis has found its place in process monitoring, diagnosis and control but is still in its infancy. To date, only demonstrations with industrial data have been published.

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