ABSTRACTION OF OPERATING DATA ON THE EPISODE MAP

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Abstract. The plant operator monitors historical data of process variables and recognizes features of process behaviors. In this study, we propose a simple method to extract features, such as constant operation, rapid changes and process trend from time series data of process variables. For this propose, the episode map, which shows graphically each episode and connection of episodes, is introduced, and a selective scaling method which can extract patterns of flatness, changes and trends in time series data is proposed. This scaling method enables to decide appropriate scaling to satisfy the objectives.

Keywords. Time series data, signal abstraction, episode representation, episode map

1. INTRODUCTION

The plant operator monitors process variables to operate the plant safely and to produce high quality products. He understands the plant behavior by extracting the abstracted pattern from the historical process data. He manipulates the process variables based on the pattern using heuristic knowledge such as cause and effect reasoning.

Time series data of process variables sampled at constant time interval is not always useful for the operator. The operator usually sees significant features, such as set-point changes, sudden spikes, fluctuations, and so on. These features are extracted with local scope from the time series data. On the other hand, the process trend is a globally abstracted pattern of historical data. From the fact that set-point changes and process upsets by disturbances often happen in plant operation, the features extracted with both local and global scopes are more useful to the operator.

The features must be extracted so as to preserve the important properties of data, such as the occurrence time and the magnitude of the corresponding event. Preserving only significant features in the historical data can reduce the size of stored data than that of original data. The abstracted data can be used as an index to retrieve quickly desired data from the original data.

In this study, a simple method is proposed to extract features from time series data, such as stationary operation, set-point changes and process trend, and the method is applied to an actual process time series data.

2. FEATURE EXTRACTION BY EPISODE REPRESENTATION

To extract the process trend *triangular episodic representation* of a time function was developed by Cheung et al.(1990a,1990b) and Stephanopoulos(1991). They also provided a scaling algorithm to merge episodes. In their method, a specified scale was used to adjust resolution of abstraction. The minimum episode is found and merged with two adjacent episodes in the series of episodes. This procedure is repeated until the minimum episode becomes less than the specified scale. Since the method was developed to extract the process trend, significant features are lost in the merging process.

The objective in this paper is to extract local significant features as well as process trend. In our approach, the features are represented by a set of inflection points of the continuous function. Only the significant points are remained in the historical data and the other points are removed.

First, the continuous function is made from time series data by the spline interpolation and inflection points are determined. An *episode* is defined as a time interval between two adjacent inflection points and its *base* is defined by the segment between these two inflection points. The episode is characterized by four parameters, i.e. the interval denoted by a, the altitude difference of the episode base denoted by b, the area surrounded by the function and the base denoted by c, and the slope of the function at the left inflection point of each episode denoted by d as shown in Fig.1. The value of c has physical meaning and it should be conserved when episodes are merged.

To remove the unimportant inflection points, three adjacent episodes are merged into a larger episode. The resultant episode shown in Fig.2 has the parameter values as follows:

$$a = \sum_{i=1}^{3} a_i \tag{1}$$

$$b = \sum_{i=1}^{3} b_i \tag{2}$$

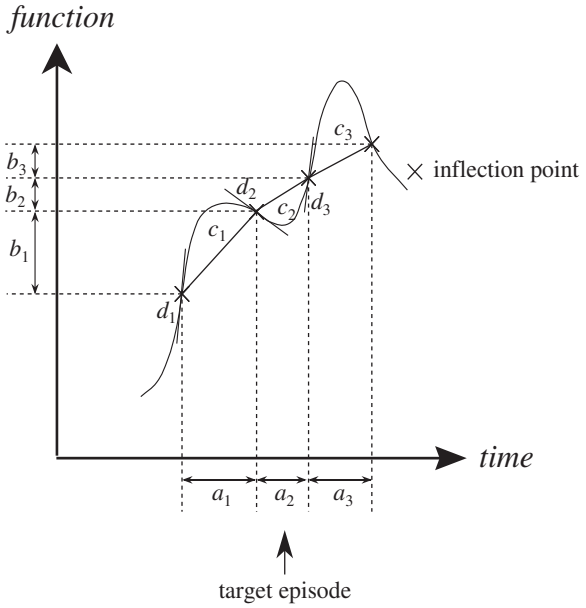

Fig. 1. Property of episodes

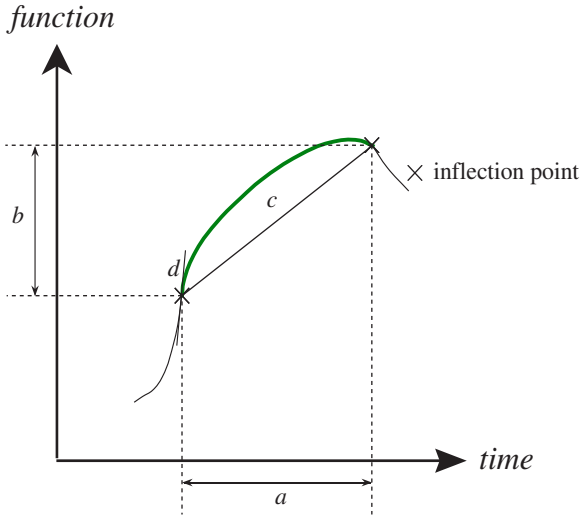

Fig. 2. Resultant episode

$$c = \sum_{i=1}^{3} c_i + \frac{1}{2}\{(a_2+a_3)(b_1+b_2)-(a_1+a_2)(b_2+b_3)\} \quad (3)$$

$$d = d_1 \quad (4)$$

This merging process is performed only when the following condition is satisfied:

$$c_1 c_2 < 0 \quad \& \quad c_2 c_3 < 0 \quad \& \quad c c_2 < 0 \quad (5)$$

This means signs of c_1,c_3 and c are same, and only the sign of c_2 is different from the others. In our approach, it is unnecessary to determine a curve shape of the function in the resultant episode.

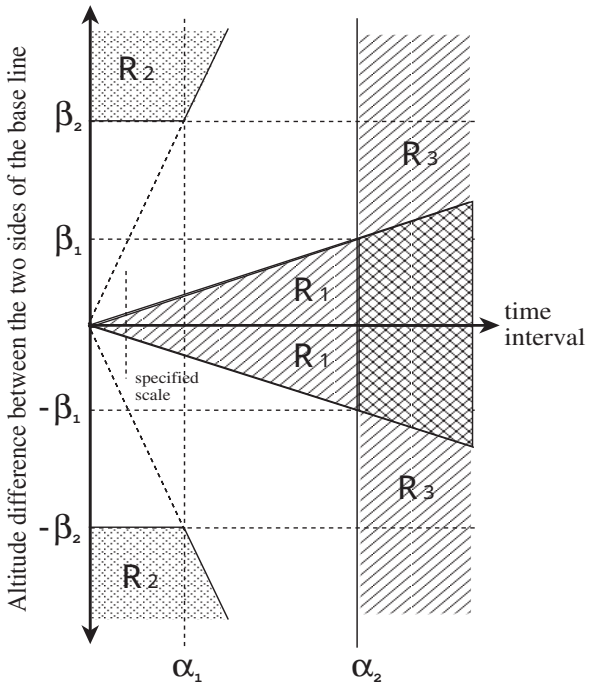

Fig. 3. Defnition of episode map

3. MERGING ON THE EPISODE MAP

To illustrate the property of each episode, the *episode map*, of which horizontal and vertical axes correspond to a and b, respectively, is defined. An episode is projected onto the episode map as a vector (a, b). Each episode is classified into the following categories using constants such as $\alpha_1, \alpha_2, \beta_1, \beta_2$, $(0 < \alpha_1 < \alpha_2,\ 0 < \beta_1 < \beta_2)$ (Fig. 3)

1. Category of flat episodes: C_1

$$\left|\frac{b}{a}\right| < \frac{\beta_1}{\alpha_2} \quad (6)$$

2. Category of rapid change episodes: C_2

$$\left|\frac{b}{a}\right| > \frac{\beta_2}{\alpha_1} \quad and \quad b > \beta_2 \quad (7)$$

3. Category of large episodes: C_3

$$a > \alpha_2 \quad (8)$$

Each category has the corresponding region; R_1, R_2 and R_3 on the episode map are shown in Fig.3. The operator can easily tune four constants according to actual data. A series of episodes is projected onto the map as a chain of vectors. The merging operation of three episodes is to generate a new vector by chaining three vectors. If three adjacent episodes are described as $-(a_1, b_1)-(a_2, b_2)-(a_3, b_3)-$, the resultant merged episode is made as $-(a_1 + a_2 + a_3,\ b_1 + b_2 + b_3)-$.

4. SELECTIVE SCALING

It is called *scaling* to make an abstracted profile by iterative episode merging. We have to select less important episodes to be merged. The minimum episode among all remaining episodes is a candidate for a target episode. A simple method is to merge the minimum episode and its two adjacent episodes. But this often loses significant points corresponding to local features. A scaling algorithm must be designed so that the features may not be lost.

In our approach, selective selection of the target episode is introduced to remain the locally significant points. The minimum episode and its two adjacent episodes are merged only when they meet either of the following three conditions:

- Condition 1: "All the bases of there three episodes are increasing or decreasing."
  If adjoining three episodes have no extreme point, the profile of the merged episode monotonously increases or decreases. No existence of an extreme point in the i-th episode can be checked as follows:

$$d_i\, d_{i+1} > 0 \tag{9}$$

  On the episode map, the new point created by merging is closer to category C_2 or C_3.
- Condition 2: "A merged episode belongs to category C_1."

$$\left| \frac{\sum_{i=1}^{3} b_i}{\sum_{i=1}^{3} a_i} \right| < \frac{\beta_1}{\alpha_2} \tag{10}$$

- Condition 3: "Both of two adjacent episodes of the target episode belong to category C_2."

$$(a_1, b_1) \in R_2 \quad \& \quad (a_3, b_3) \in R_2 \tag{11}$$

The priority order of scaling condition is from condition 1 to 3. By merging episodes based on the three conditions, many small episodes are integrated into larger episodes which belong to category C_2 or C_3. We carefully have to merge these episodes to remain features in category C_2 and C_3. Therefore, the episodes which meet the next condition are merged.

- Condition 4: "The minimum episode is less than the specified episode, and its adjacent episode does not belong to category C_2 or the other adjacent episode does not belong to category C_3."

$$\{(a_1, b_1) \notin R_2 \quad or \quad (a_3, b_3) \notin R_3\} \quad and \quad \{(a_1, b_1) \notin R_3 \quad or \quad (a_3, b_3) \notin R_2\} \tag{12}$$

The scaling procedure is shown in Fig.4. Significant sudden peaks can be extracted by *specified interval scaling* (Fujiwara and Nishitani 1994) before the selective scaling is performed.

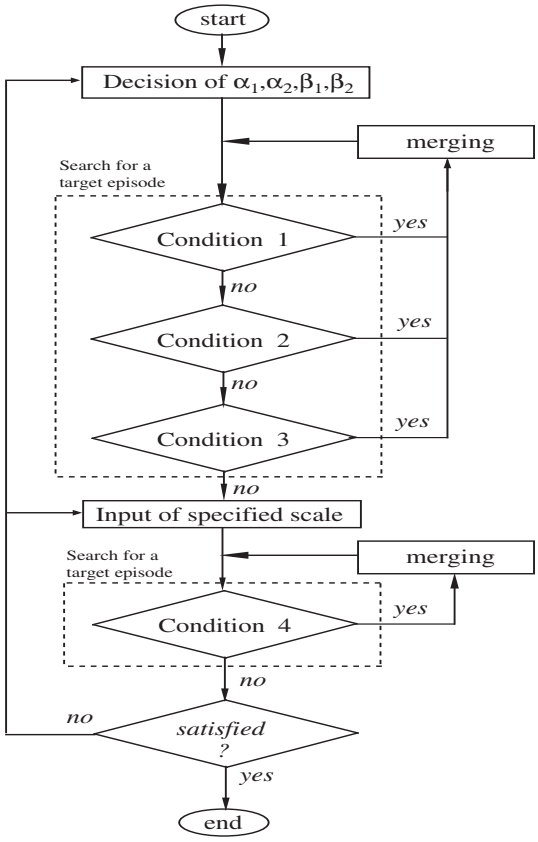

Fig. 4. Procedure of selective scaling

5. ILLUSTRATIVE EXAMPLE

Figure 5 shows an example of the selective scaling for liquid flow rate data. Horizontal axis shows sampling time (steps) and the total number of data is 1440. The flow rate is controlled by a flow controller. But the operator sometimes must change the set-point of the control loop manually from economical reason. The episode map constants are tuned by the trial and error method as $(\alpha_1, \alpha_2, \beta_1, \beta_2) =$ (60, 100, 0.02, 0.04) , and the specified scale is chosen as 10 steps.

As a result, 1104 inflection points initially existed were merged iteratively into only 56 inflection points finally. The significant points, where the effect of set-point changes appeared, such as at 210 steps and 465 steps, are preserved. The initial series of episodes are shown as a chain of points in Fig.6, the resultant series of episodes in this scaling are shown in Fig.7, and the resultant episode map of full size is shown in Fig.8. Although initial points are close to the origin, the points are apart from the origin as the episode merging is repeated. The small episodes near the origin shown in Fig.7 are not merged because of extracting local features. These episodes can be merged properly after scaling. The resultant series of points on the episode map can show the operator the historical features of the process variable. The resultant series of episodes can be easily translated into a verbal expression, e.g. flat, +flat, -flat, up, down, where +flat and -flat denote the degree of flatness. The above verbal expression is also represented by the series of slope values, i.e., 0, 0.005, -0.005, 0.05, -0.05. This expression is also shown in Fig.5.

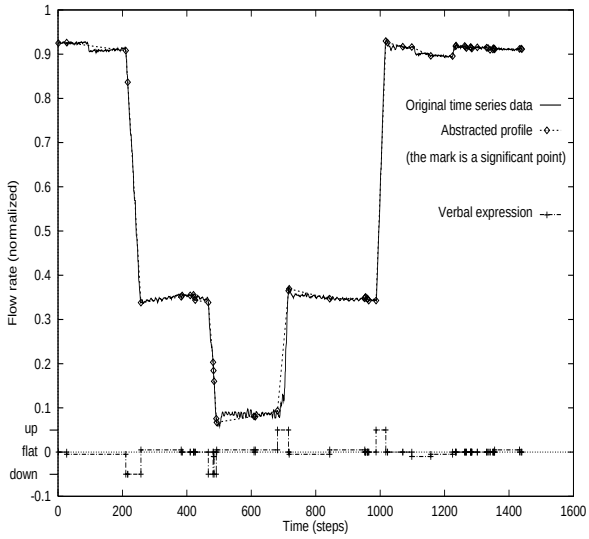

Fig. 5. Abstracted profile

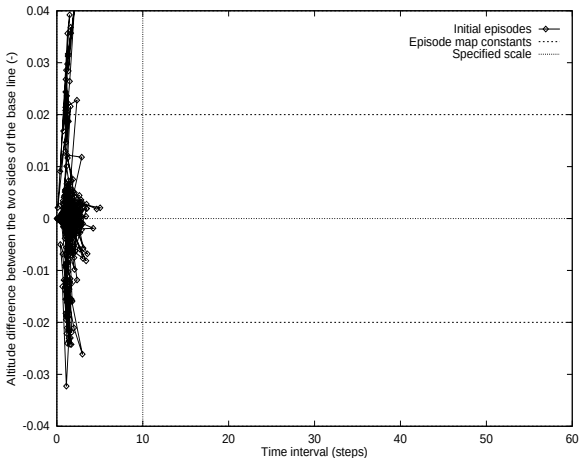

Fig. 6. Initial episodes on the episode map

6. REMARKS AND FUTURE DEVELOPMENT

We provided selective scaling of time series data to extract features of flatness, rapid changes and process trend. The method includes the tuning process by examining abstracted data on the episode map. The required memory size of the resultant abstracted data is relatively smaller than that of the original time series data. By using the abstracted profile as an index of historical data, the operator can search for desired subset from past data for his reference in a shorter time. Moreover, the abstracted profile can be utilized to acquire operator's knowledge and to develop an expert system which supports operator's tasks such as monitoring and decision making.

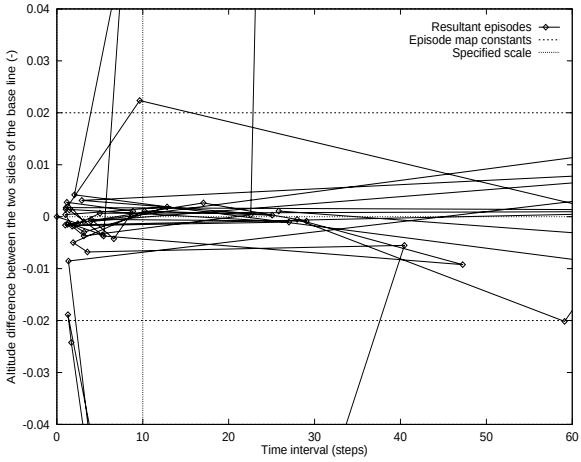

Fig. 7. Resultant episodes near the origin

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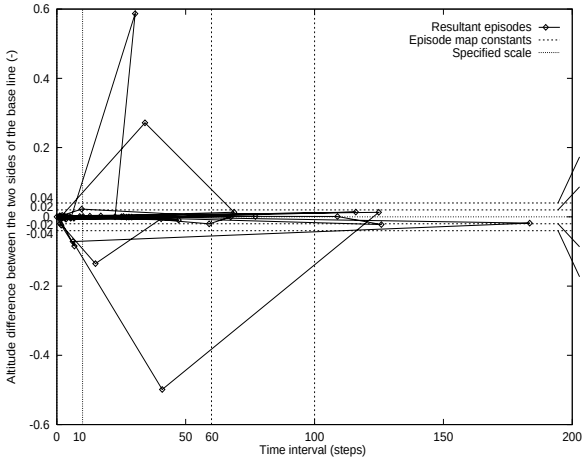

Fig. 8. Resultant episodes of full size