Online Monitoring of Manufacturing Process Based on autoCEP

https://doi.org/10.3991/ijoe.v13i06.6812

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Abstract—Complex Event Processing (CEP), which can identify patterns of interest from a large number of continuous data steam, is becoming more and more popular in manufacturing process monitoring. CEP rules are specified manually by domain expert, which is a limiting factor for its application in manufacturing enterprises. How to analysis historical data and automatically generate CEP rules is becoming a challenge research. This paper proposed a model of autoCEP for online monitoring in product manufacturing, which can automatically generate CEP rules based on association rules mining in key processes. First, the key quality factors in manufacturing process were extracted by grey entropy correlation analysis. Then, association rules mining method based on product process constraints was used to find the association rules between key factors and product quality. At last, the extracted rules are algorithmically transformed into CEP rules. The experimental results show the effectiveness and practicability of the proposed method.

Keywords—complex event processing, online monitoring, manufacturing process, association rule

1 Introduction

The emergence and application of cloud computing and Internet of Things (IoT) have been profoundly changing the manufacturing production mode[1-3]. Manufacturing factories record tremendous amounts of production process data with Radio Frequency Identification (RFID) technology in manufacturing line. However, the production process data from manufacturing line is independent with each other in the process of physical collection and too simple to be directly used for business and execution level. To get useful information to monitor and control the quality of products from manufacturing process data, Complex Event Processing (CEP) has been highly concerned in industry recently[4-6].

CEP is a kind of technology that used to discover more meaningful and actionable information from low-level events. Because of the advantages such as expressive rule language and efficient event detection model, CEP has been widely used in manufacturing and enterprise business applications[7-10]. Ahmad et al. Ref. [11] proposed a method to model CEP using Timed Net Condition Event System to analyze and describe discrete-event dynamic systems in a manufacturing line. The author in Ref. [12] provided a Lightweight Stage-based Event-Driven Process based on a layered architectural design, which is a novel CEP engine conceived with each of use. This system is mainly used for sense and responds application. The paper [13] introduced the open-source Esper technique for processing complex event and event stream, and provided a CEP based on Open Service Gateway Initiative platform with the features of reconfigurable, customized and so on. In the work of [14], the author introduced a parallel processing system called PM-CEPs, which can efficiently share the associated event pattern and simultaneously process multiple event sources by defining an extended colored Petri-net. In the paper of Ref. [15], the author proposed a model of uncertain complex event processing system for real-time monitoring in product manufacturing process.

However, most of the CEP systems have to predefine the pattern rules by writing them manually, and little work exists on the learning of CEP pattern rules[16-19]. Moreover, many of predefined pattern rules are based on human beings subjective experience so that it is not necessarily accurate in practice. We deem the ultimate fact that the acquisition of knowledge as a limiting factor for the prosperity and diffusion of CEP. Especially in the manufacturing industries, there has a potential coupling relationship between the manufacturing processes, such as error transfer between processes. So how to extract pattern rules correctly and automatically for CEP according to the data of manufacturing processes is an urgent problem.

In order to solve the problem and monitor the manufacturing process effectively, this paper proposes a model of automatic learning of pattern rules for CEP (autoCEP). First, a framework for online monitoring based on autoCEP is given. Then this paper presents a rule generation method for autoCEP that is able to extract association rules in key manufacturing processes and produce CEP rules automatically. Finally, simulation results validate the effectiveness and practicability of the proposed method.

2 CEP preliminaries

CEP was proposed by David Luckham[20] to detect known patterns of events, correlate them to complex events in real-time, improving situational awareness and enable immediate response to emerging opportunities and threats. It basically consists of data filtering and event detection. Data filtering aims at filtering useless data and correcting errors, providing clean and ordered data streams for event detection[21].

Definition 2.1 Basic event. A basic event is a record of a status value for the observed object. It is atomic, indivisible and occurs at a point in time. The parameters of the activity that caused the event called event attributes, by which, the event of a certain type can be defined as a multi-tuple composed of event attributes. A common event model is a tuple expressed as $Event = <ID, A, T>$. *ID* is the unique identifier of the event. *A* is a set of the event's properties, which represented as $A = \{A_1, A_2, ..., A_n\}$, $n>0$. *T* is the time of occurrence of the event.

Definition 2.2 Complex events. Complex events are composed of basic events by connecting those using temporal, spatial or logical relations. A complex event is also expressed as a tuple. The expression is $Complex\ Event = <E, R, Ts>$, where *E* represents the elements that make up the complex event, *R* represents the composition rule, and *Ts* represents the time span of the complex event occurrence.

Event constructors are used to express the relationship among events and correlate events to complex events. Attributes of complex event are composed by the attributes of the basic events. Table 1 shows the event constructors. Event Process Language (EPL) is a SQL-like language which is used to predefined rules and interesting patterns. The processing engine continuously monitors the incoming event stream. Once the events of interest are identified, the listener takes automatic response to be followed. Fig 1 is a CEP pattern diagram. Assuming there has an event pattern "A → (B and C) →D", it means that if event A occurs first, then B and C occurs, and at last D happens, the pattern is matched successfully.

Table 1. Complex event constructors

Constructors	Description
[FROM <input stream>]	Specify the input stream
PATTERN<pattern structure>	Declare the structure of a pattern to be matched
[WHERE <pattern matching condition>]	Constrain the relevant events defined in the pattern
timer:within<sliding window>	The valid time of the complex event occurred
[HAVING <pattern filtering condition>]	Filter each pattern from the constituent events
AND, OR, NOT	Logical operators

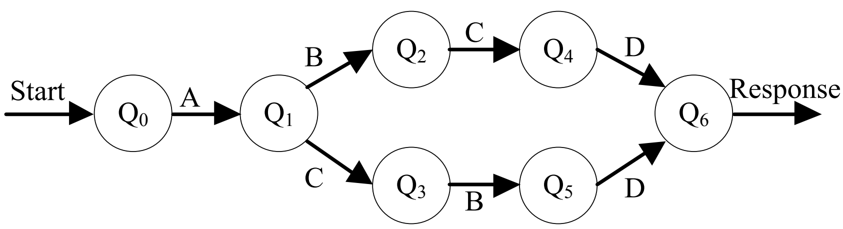

Fig. 1. A CEP pattern diagram

3 Online Monitoring Framework of Production Line Based on autoCEP

As discussed in the introduction section, to monitor the quality in working process and instead of manually define CEP rules, we proposed a framework for online monitoring based on autoCEP to fulfill the need of monitoring in production lines. Fig. 2 shows the architecture of the proposed online monitoring framework based on autoCEP.

The proposed online monitoring framework has four layers, manufacturing workshop layer, event producer layer, complex event management layer and enterprise application layer. Manufacturing workshops provide raw data of physical world using RFID readers, sensors and other devices. Event producers transform raw data to primitive events and submit them to complex event management layer. Complex event management layer, which is the core component of the whole online monitoring framework, integrate all the primitive events into high-level complex events and send notifications to the enterprise applications according to the complex event detection rules generated by autoCEP automatically. The autoCEP includes three phase. In the first phase, recognize key quality operations, then the relevance rules between operations and production quality are extracted from historical trace based on data mining in the second phase. In the last phase, CEP rules are transformed by the association rules and used to monitor manufacturing status. According to the notifications from complex event management, enterprise applications visualize the information and send a response execution command to the workshop layer to control the production quality.

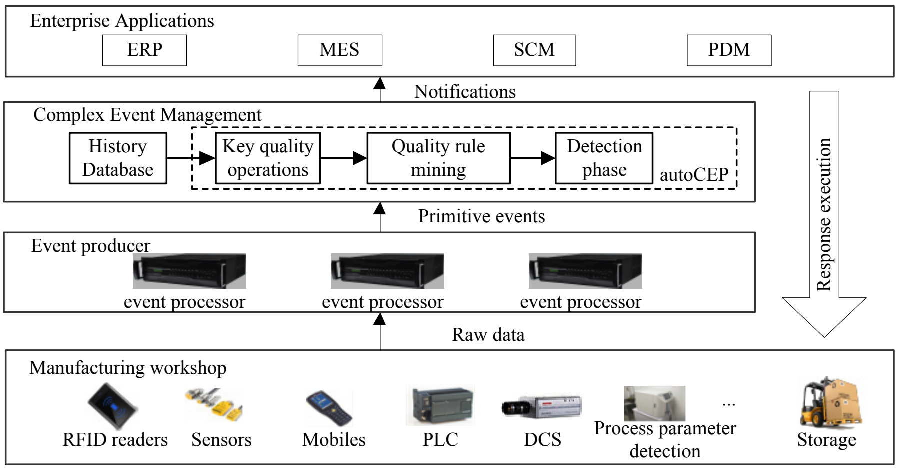

Fig. 2. Online monitoring framework based on autoCEP

4 Rules generation method for autoCEP based on association analysis in key manufacturing processes

The association analysis is a method commonly used in data mining. If there is an association between two or more data items, the value between them will have a high probability of repetition, and through the analysis of these data items may establish the association rules. In manufacturing enterprises, association rule mining can extract the potential correlation between different processes from the manufacturing process quality information, so as to provide rule template for online monitoring of manufacturing process. But in fact the manufacturing processes have a lot of attributes related to product quality which brings great inconvenience to association rules extract in processes.

In order to improve the efficiency of the association rules mining and produce CEP rules automatically, this section proposed a CEP rules automatic generation method based on association rules mining in key manufacturing processes. At first, gray entropy correlation analysis was used to extract key quality factors in manufacturing processes. Then with the constraint of process sequence, the association analysis was applied to mine association patterns. At last, the CEP rules generation module transforms them into CEP rules automatically.

4.1 Key Quality Factors Extraction Based on Gray Entropy Correlation Analysis

In order to reduce the complexity of the event patterns for manufacturing process monitoring and improve the exercise speed of CEP system, the gray entropy correlation analysis algorithm was used to extract the key attributes from a large number of attributes related to product quality.

(1) Data preprocessing. The various factors that affect product quality have different meanings, often with different dimensions and data levels. After the original data are processed by means of the averaging method, not only the effect of the index dimension and data's quantity is eliminated, but also the variation degree and mutual influence degree of each index in the original data can be more comprehensively reflected.

(2) Gray correlation coefficient calculation. Establish a reference sequence by collecting *n* sets of production quality parameters.

$$X_0=(x_0(1),x_0(2),\cdots,x_0(n)) \tag{1}$$

Collect *m* groups of quality parameters to establish the comparison sequences.

$$\begin{cases} X_1 = (x_1(1), x_1(2), \cdots, x_1(n)) \\ \vdots \\ X_i = (x_i(1), x_i(2), \cdots, x_i(n)) \\ \vdots \\ X_m = (x_m(1), x_m(2), \cdots, x_m(n)) \end{cases} \tag{2}$$

The correlation coefficient of the reference sequence X_0 with the comparison sequence X_i (i=1,…,m) at the k-th (k=1,…,n) point is

$$\gamma(x_0(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \delta \max_i \max_k x_0(k) - x_i(k)}{|x_0(k) - x_i(k)| + \delta \max_i \max_k x_0(k) - x_i(k)} \tag{3}$$

(3) Calculate the state probability of the gray correlation coefficient

$$P_t = \frac{\gamma(x_0(k), x_t(k))}{\sum_{t=1}^{n} \gamma(x_0(k), x_t(k))} \tag{4}$$

(4) Calculate the gray correlation entropy

$$L(\gamma(X_0, X_i)) = -\sum_{t=1}^{n} P_t \ln P_t \tag{5}$$

(5) Calculate the gray entropy correlation

$$E(X_i) = \frac{L(\gamma(X_0, X_i))}{\ln n} \tag{6}$$

The gray entropy correlation degree reflects the influence relation of the comparison sequences to the reference sequence. To arrange the sequences and select factors with high gray entropy correlations as the key quality attributes of product.

4.2 Association Rules Mining Based on Process Sequence Constraints

Apriori algorithm is a classical algorithm of association rules mining. It is an effective method to mine association rules from large scale data. The minimum support and minimum confidence must be determined firstly in mining association rules. The purpose of association analysis is to find all the rules that meet minimum support and minimum confidence. It consists of two processes, find all the frequent item sets whose support is not less than minimum support and generate the association rules from the frequent item sets with the confidence of not less than minimum confidence. Aprior algorithm is an unsupervised learning algorithm, and each variable in the algorithm has the same value. If the algorithm is used in manufacturing field directly, not only the calculation quantity is very grate, but also some of the rules be extracted are inconsistent with the actual production process.

Drawing on the idea of supervised learning, the process quality information is a set as the input variable of association rules, and the product quality information is a set as output variable. The rules extracted by the association rule algorithm are expressed in a pattern that is easy for the user to understand. An association rule is represented as a tuple ***r***=<*conditions*, *result*>, where *conditions* are the process quality information, *result* is the product quality information.

The calculation flow of association rules based on process sequence constraints is shown in figure 3.

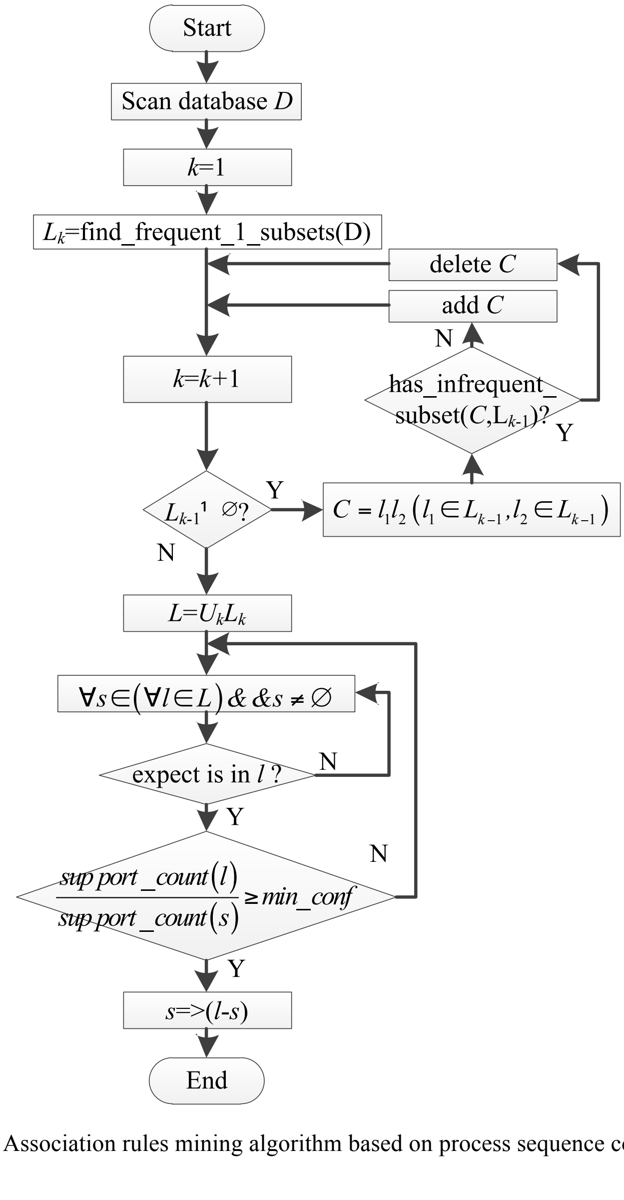

Fig. 3. Association rules mining algorithm based on process sequence constraints

4.3 CEP Rules Generation

At this stage, the extracted association rules sever as inputs, where they will be automatically transformed into CEP rules to be used later for online monitoring.

The proposed algorithm extracts the event type and condition block from association rules and their parameters. For each association rule a CEP rule is created. This process is list in the following algorithm. Given an association rule ***r***=<*conditions*, *result*>, the *result* of ***r*** is extracted as the event type, then the *conditions* of ***r*** are transformed to the CEP pattern.

Algorithm 1 CEP Rules Generation Algorithm

Input: A set of association rules ***R***
Output: A set of CEP Rules *rules*
rules $\leftarrow \emptyset$
for each association rule *r* in *R* do
    /* create an empty CEP rule *cep*
    cep.setWindowBlock();
    E $\leftarrow$ Extract event types from ***r***;
    cep.setEventTypes(*E*);
    cep.setConditionBlock(***r***.*conditions*);
    cep.setListener(this stream is predicted to belong to ***r***.*result*);
    rules.add(*cep*);
end
return *rules*;

5 Experiment and analysis

In this section, we implement the proposed approach to verify its effectiveness. The experiment is run on Microsoft windows 10 operating systems, Intel i7-4510U CPU processor, 8GB memory, all algorithms are implemented in Eclipse 4.5.2 with Java (JDK version 1.8), and the CEP engine is Esper 5.0 version.

The data set selects the yarn production data from an enterprise. The yarn quality is measured by the value of the yarn strength δ, which represents the maximum tensile external force that the yarn can withstand. The unit is cN. To ensure the yarn strength δ, seven related parameters are selected to analysis, the fiber strength C_1 , Yarn length C_2, elongation rate C_3, impurity rate C_4, length unevenness rate C_5, micronaire value C_6, yellowness value C_7.

After data cleansing, the partial data are shown in Table 2. Use the gray entropy correlation analysis algorithm to extract the main factors which affect the product quality. The attribute values are used as the comparison sequence X_i (i = 1, 2,..., 7). The yarn quality is represented by the value of the yarn strength δ, so take it as the reference sequence X_0.

Table 2. Manufacturing and quality parameters of yarn production line

Parameter	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7
C_1/cN	27.27	20.87	30.74	24.26	27.02	26.66	21.14
C_2/cm	1.541	1.724	1.926	1.28	1.776	1.173	1.561
C_3/%	5.59	6.36	5.16	6.62	6.68	5.37	5.4
C_4/%	4.2	4.9	3.8	7	3.8	5.9	6.3
C_5/%	43	50	48	54	49	44	46
C_6	4.09	4.81	4.53	4.74	4.15	4.58	4.58
C_7	11.1	11.1	8.7	10.7	9.9	10.2	10.5
δ/cN	13.2	14.4	14.5	13.9	11.4	11.7	13

According to the calculation result, the gray entropy correlation degree rank of the manufacturing parameters which influence the yarn quality is shown in Table 3.

Table 3. Grey entropy correlation degree

Parameter	Value
C_1/cN	0.997881
C_3/%	0.997145
C_5/%	0.997012
C_6	0.986897
C_4/%	0.985901
C_2/cm	0.985675
C_7	0.985552

Chose the parameters, whose grey entropy correlation degree greater than 0.99, as the key quality factors. The association rule algorithm does not accept continuous attributes because it is a counting engine that counts the dependencies of the discrete attribute states and must use the discretization of successive attributes in the mining model. Taking the three extracted key factors as input, and the yarn strength as the output, analyze the historical data, setting the yarn strength less than 12.5 as the split point. Setting the minimum support threshold is not less than 6% of the total amount of data, and the minimum confidence is 80%. The result of mining process association rules is shown in table 4. The results show that the input and output of association rules can meet the requirements of processing sequence after adopt the supervised learning mechanism, and avoid the generation of nonsensical rules.

Table 4. The result of mining process association rules

Association rule	Support	Confidence
$21.2<C_1<26.2$ and $C_3>5.85 \Rightarrow \delta<12.5$	0.078	87.95%
$C_1<21.2 \Rightarrow \delta<12.5$	0.075	87.5%
$21.2<C_1<26.2$ and $C_3<5.85$ and $C_5<43 \Rightarrow \delta<12.5$	0.074	86.97%

According to the data in Table 4, the following 3 association rules are obtained. (1) When the fiber strength $C1$ is between 21.2 and 26.2 and the elongation rate $C3>$ 5.85%, the yarn quality is unqualified. The proportion of this rule occur in the sample was 7.8%, a confidence level of 87.95%. (2) When the fiber strength $C1$ is less than 21.2, the yarn strength is less than 12.5 and the yarn quality is unqualified. The proportion of this rule occur in the sample was 7.5%, a confidence level of 87.5%. (3) When the fiber strength *C*1 is between 21.2 and 26.2, the elongation *C*3 is less than 5.85% and the length irregularity *C*5 is less than 43%, the yarn quality is not up to standard. The proportion of this rule occur in the sample was 7.4%, a confidence level of 86.97%.

These association rules are algorithmically transformed into CEP rules by using of proposed CEP rules generation algorithm. Setting the valid time of the complex event occurred is 10 minutes. The converted CEP rules are as follows.

Rule 1. SELECT COUNT (*) FROM pattern [every (*C*1 < 21.2)] -> timer: interval (10 min).

Rule 2. SELECT COUNT (*) FROM pattern [every (21.2 <*C*1 <26.2 and *C*3 <5.85 and *C*5 <43)> -> timer: interval (10 min)

Rule 3. SELECT COUNT (*) FROM Pattern [every (21.2 <*C*1 <26.2 and *C*3> 5.85)] -> timer: interval (10 min)

According to the CEP rules, the Esper engine is used to implement the complex event definition, and verified by simulated data sets. Some of the online monitoring results are shown in Fig 4. The experiment result shows that the method proposed can track product quality trends in the process sequence, accurate identification the anomalies of manufacturing process, on-site assessment of the manufacturing status and to guide on-site processing.

```
Transfer data:C1: 27.78C3: 6.8C5: 43.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 28.29C3: 6.63C5: 48.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 24.3C3: 6.13C5: 47.0 time: Tue Dec 06 14:46:41 CST 2016
Parameter exception alert: C1: 24.3C3: 6.13C5: 47.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 24.11C3: 5.76C5: 42.0 time: Tue Dec 06 14:46:41 CST 2016
Parameter exception alert: C1: 24.11C3: 5.76C5: 42.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 29.33C3: 5.3C5: 47.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 23.53C3: 6.63C5: 47.0 time: Tue Dec 06 14:46:41 CST 2016
Parameter exception alert: C1: 23.53C3: 6.63C5: 47.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 28.03C3: 5.95C5: 43.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 22.42C3: 6.42C5: 50.0 time: Tue Dec 06 14:46:41 CST 2016
Parameter exception alert: C1: 22.42C3: 6.42C5: 50.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 21.18C3: 6.36C5: 46.0 time: Tue Dec 06 14:46:41 CST 2016
Parameter exception alert: C1: 21.18C3: 6.36C5: 46.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 22.92C3: 5.3C5: 44.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 29.95C3: 5.45C5: 45.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 30.84C3: 5.6C5: 44.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 21.59C3: 5.24C5: 49.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 28.13C3: 5.78C5: 54.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 26.46C3: 5.75C5: 46.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 29.78C3: 6.8C5: 40.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 27.04C3: 6.76C5: 54.0 time: Tue Dec 06 14:46:41 CST 2016
Transfer data:C1: 22.93C3: 6.06C5: 49.0 time: Tue Dec 06 14:46:41 CST 2016
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Fig. 4. The online monitoring results

From the results, it can be seen that the complex event monitoring system realized by autoCEP can accurately identify the abnormal production parameters and give the alarm timely. In order to validate the efficiency of the model proposed, we compare the proposed model in this paper with the traditional CEP which is not used to extract the key factors, and the results are shown in Fig 5.

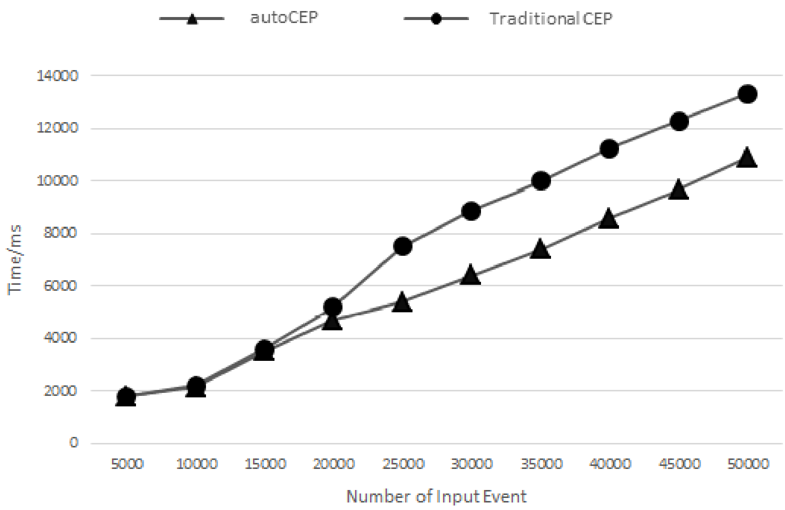

Fig. 5. Time consumption over different size of input event streams

It can be seen from the comparison chart that the traditional CEP is significantly more time consumption than autoCEP when a large number of event inputs are encountered, which is indicates that the model proposed in this paper has higher processing efficiency.

6 Conclusions

The effective analysis of the real-time monitoring data from the production line is an important way to improve the product quality and the efficiency of enterprises. This paper focuses on the problems of intelligent monitoring in manufacturing process and proposed a model of autoCEP for online monitoring in product manufacturing. We design the online monitoring framework of production line and describe the rules generation method for autoCEP based on association rules mining in key processes. The experimental results show that our proposed method is efficient to find out the relationship between the manufacturing processes and automatically transformed into CEP rules to be used for online monitoring, which paves the way for non-expert users to easily exploit the predictive capabilities of CEP engines and provides a new solution for the digital intelligent analysis and control of discrete manufacturing process.

In the near future, with the development of a new generation of information technology and its wide application in manufacturing industry, we project to adopt our algorithms to favor parallelized and exact rule mining in complex manufacturing processes.

7 Acknowledgment

This work was supported by the national natural science foundation of china (51475097), and the Science and Technology of Guizhou ([2014]2001). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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Article submitted 27 February 2017. Published as resubmitted by the authors 14 April 2017.