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Frequent Event Pattern Extraction of Drilling Time Series Using Change Point Detection and Event Sequence Generation

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Abstract: In drilling processes, non-stationary phases corresponding to shifts between operating conditions and changes in downhole formations typically lead to false alarms. Extracting these frequent event patterns is critical to build drilling process monitoring and fault diagnosis models. This study aims to extract the frequent event patterns associated with non-stationary phases in drilling time series. In this way, diversified information related to signal changes under normal conditions can be obtained, which is beneficial for suppressing false alarms and improving fault detection performance. The main contributions of this study are twofold: 1) a non-stationary phase detection method is proposed to extract drilling frequent event patterns based on t-distributed stochastic neighbor embedding and relative unconstrained least-squares importance fitting; 2) an event sequence generation method is proposed to express drilling frequent event patterns with a group of symbols. The effectiveness of the proposed method is demonstrated by data from a real drilling project.

Keywords: Drilling processes, pattern extraction, change point detection, event sequence generation, frequent event pattern.

1. INTRODUCTION

Geological drilling plays an essential part in obtaining deeply buried resources, such as minerals, oil, and natural gas (Gan et al., 2020). With the depletion of shallow resources, the complex and harsh downhole environments bring challenges to deep drilling processes. On the one hand, the risk of downhole faults increases with the drilling depth; On the other hand, the drilling operator needs to adjust the operational variable timely to adapt to the varying downhole formations. Statistically, more than 20% of the engineering time was devoted to dealing with downhole faults, such as the lost circulation, kick, and stuck pipe (Willersrud et al., 2015). Therefore, process monitoring and fault detection are significant to ensure drilling safety and reduce maintenance costs.

Traditional downhole fault detection methods are usually based on mechanism models, such as a hydraulic or kinematic model described by differential equations. The main idea is to detect parameter changes that are sensitive to downhole faults in the mechanism model. The hydraulic model is widely used in fault diagnosis of drilling fluid systems. A downhole fault detection method was proposed based on adaptive observers and single phase hydraulic model (Willersrud et al., 2015). Further, a fault classification method was developed using an unscented Kalman filter based on pressure and flow rate responses (Jiang et al., 2020). Considering that the motion characteristics of drillstring were related to downhole faults, differential equation models describing the stick-slip fault were established in (Kamel and Yigit, 2014). However, due to the limitation of measurable variables, establishing mechanism models is rather tricky in geological drilling processes.

Recently, data driven fault detection methods have received plentiful attention with the popularity of data acquisition and storage (Zhao and Zhao, 2020). A notable advantage of this method is that the underlying structure of the drilling process can be learned from historical data without the first principle model. By transforming the fault diagnosis into a binary or multi-classification problem, supervised learning approaches were adopted to diagnose downhole faults based on multi-class SVM and neural networks (Li et al., 2020; Zhang et al., 2018). Besides,

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unsupervised learning algorithms were also introduced to establish fault detection models. The main idea is to analyze drilling time series based on distance metrics, such as the morphological distance (Zhao et al., 2019), local distance (Zhang et al., 2021), and dynamic time warping (Li et al., 2021a). Further, Tang et al. (2019) defined two indicators calculated from time series to predict the probability of the kick incident. Regarding incipient fault detection, distribution-based approaches exhibited good performance in capturing changes in drilling data. The generalized Gaussian distribution was used to describe the drilling data, enabling a detection decision by comparing the Kullback Leibler divergence from the distribution of normal data to that of online data (Li et al., 2021b). The above methods achieved good fault diagnosis performance under the stationary drilling phase by extracting the data features under normal and faulty conditions. However, the false alarms generated during the non-stationary phases are rarely considered.

Due to the changes in formation and shifts between operating conditions, the drilling operation is not always in a stationary phase. This makes it necessary to analyze the characteristics of non-stationary phases that are prone to cause false alarms, so as to suppress the false alarms and enhance the overall performance. According to the above analysis, most methods assume that the templates of all drilling modes are known and well-prepared, while few studies discuss how to obtain these templates. Hence, extracting these non-stationary phases that lead to false alarms from historical drilling data is an essential prerequisite for the design of fault diagnosis and process monitoring methods.

This work aims to extract the frequent event patterns associated with non-stationary phases in drilling time series. Motivated by the above discussions, a frequent pattern extraction method is proposed for drilling processes based the change point detection and event sequence generation. The main contributions are two folds:

(1) A non-stationary phase detection method is proposed to extract drilling frequent event patterns based on t-distributed stochastic neighbor embedding and relative unconstrained least-squares importance fitting;
(2) An event sequence generation method is proposed to express drilling frequent event patterns with a group of symbols.

Historical data from real drilling processes is used to demonstrate the effectiveness of the proposed method.

The remainder of this paper is organized as follows: Section 2 briefly describes the drilling process and the problem. The frequent pattern extraction method is introduced in Section 3, including the dominant feature extraction, non-stationary phase detection, and event sequence generation. Section 4 shows the industrial case study, followed by conclusions in the final section.

2. PRELIMINARIES

This section describes the background of the drilling process, introduces the key variables involving the drilling process, and points out the frequent pattern extraction problem.

2.1 Description of drilling systems

A typical drilling system is composed of two subsystems, namely, the drilling rig subsystem and the circulation subsystem. The drilling rig subsystem mainly provides drilling power. On the one hand, the drilling rig provides torque to drive the drillstring, so as to rotate the drill bit to break the downhole rock. On the other hand, a hook carries part of the weight of the drillstring, and the rest is applied to the drill bit to provide weight on bit. Fault-related variables in the drilling rig subsystem are the Weight On Bit (WOB), hook load, Torque (TRQ), Rotary Per Minute (RPM), and Armature Current (AC) of a rotary motor. As for the circulation subsystem, it is designed to transport downhole cuttings and ensure the stability of the wellbore. The drilling fluid stored in a mud pit is pumped down to the drill bit by a mud pump, and then returns to the surface with cuttings. Critical variables in the circulation subsystem include Stand Pipe Pressure (SPP), mud flow in, and mud pit volume.

However, there is a strong correlation between variables in the same subsystem. For example, the WOB is directly converted from the hook load. In addition, a downhole fault can hardly cause abnormal changes in signals such as mud flow in, so they are not considered for process monitoring. To avoid redundant information, only part of the variables are kept for pattern extraction. Table 1 summarizes the full names, abbreviations, and units of the above variables.

Table 1. List of drilling process variables.

Method	Full name	Abbreviation	Unit
1	Weight on bit	WOB	kN
2	Torque	TRQ	N.m
3	Rotary per minutes	RPM	r/min
4	Armature Current	AC	A
5	Stand pipe pressure	SPP	MPa

2.2 Problem description

Frequent event pattern refers to drilling conditions or operations that trigger alarms. Among them, the alarm caused by the non-stationary phase of the drilling process is known as a false alarm. The main goal is to extract those non-stationary phases caused by the shifts between operating conditions and changes in downhole formations. Given the historical data under the normal condition, the first step is to obtain a dominant feature sensitive to the drilling operation state, which is reflected by changes in multivariate drilling signals. Then, non-stationary phases can be identified by monitoring the variation of the dominant feature signal. It is necessary to extract the common features of non-stationary phases and transform them into knowledge representations. Considering the noise and disturbance, the corresponding signals of these non-stationary phases are concluded and converted into symbols. This can be helpful in exploring the common features of the frequent event patterns compared with the original drilling data.

3. THE PROPOSED METHOD

This section presents the pattern extraction method for drilling time series. First, the dominant feature of the multivariate drilling time series is extracted based on the t-distributed stochastic neighbor embedding (t-SNE); then, the non-stationary phase that may cause false alarms is detected using a change point detection algorithm; last, event sequences that correspond to the non-stationary pattern are generated with a group of event symbols.

3.1 Dominant feature extraction based on t-SNE

The drilling process is a typical multivariate process, including WOB, TRQ, RPM, AC, and SPP. As different variables show different characteristics, using only one variable to determine whether the drilling process is stable is challenging. Hence, a dominant feature describing the drilling operation needs to be extracted. The t-SNE method is a non-linear algorithm for dimensionality reduction and data visualization based on manifold learning. The main idea of t-SNE is to transform the high-dimensional data into a low-dimensional space using similarity probabilities. The t-SNE is utilized to obtain the single dominant feature of drilling signals to handle multiple drilling variables.

As the magnitude varies by variable, the original multivariate drilling signals x^o are normalized to 0 to 1 as

$$x(k) = \frac{x^o(k) - x^o_{min}}{x^o_{max} - x^o_{min}}, \tag{1}$$

where x^o_{min} and x^o_{max} represent the minimum and maximum values of x^o, respectively.

Suppose $X = \{x_1, x_2, ..., x_M\}$ and $Y = \{y_1, y_2, ..., y_m\}$ denote the normalized drilling signals and the low-dimensional dataset, respectively, where M represents the number of original drilling variables, and m indicates the data space after t-SNE.

The conditional probability distribution $p_{j|i}$ is used to calculate the similarity of x_i and x_j as

$$p_{j|i} = \frac{\exp(-\|x_i - x_j\|/2\sigma_i^2)}{\sum_{k\neq i}\exp(-\|x_i - x_k\|/2\sigma_i^2)}, \tag{2}$$

where σ_i denotes the variance of the Gaussian distribution centered on x_i. In the same way, a similar conditional probability representing the similarity between y_i and y_j in the low-dimensional space is denoted as $q_{j|i}$. Further, the joint probability distribution p_{ij} of x_i and x_j in the high-dimensional space is given by

$$p_{ij} = \frac{p_{j|i} + q_{j|i}}{2M}, \tag{3}$$

where $p_{ii} = 0$ and $p_{j|i} = q_{j|i}$.

The t-SNE method aims to find low-dimensional data as close as possible to high-dimensional data points, ideally, $p_{j|i} = q_{j|i}$. It measures the similarity from the distribution P_i given all datapoint x_i to the distribution Q_i given all datapoint y_i using Kullback-Leibler divergence (KLD). Hence, the goal is to minimize the difference between $p_{j|i}$ and $q_{j|i}$ and the cost function E is designed to minimize the sum of KLDs as:

$$E = \sum_i \mathrm{KL}(P_i\|Q_i) = \sum_i\sum_j p_{ij}\log\frac{p_{ij}}{q_{ij}}. \tag{4}$$

Using the gradient descent algorithm, the gradient of eq. (4) is denoted as

$$\frac{\partial E}{\partial y_i} = 4\sum_j (p_{ij} - q_{ij})(y_i - y_j)\left(1 + \|y_i - y_j\|^2\right)^{-1}. \tag{5}$$

Using eqs. (4-5), the low-dimensional signal Y is obtained and prepared for extracting the non-stationary phase in the drilling process.

3.2 Non-stationary phase detection using change point detection

In drilling processes, the situation in which the signal changes drastically under normal conditions is often referred to as the non-stationary phase. This can be caused by set-point adjustments, mode switching, formation changes, etc. As non-stationary phases usually cause dynamic changes in the time series, the change point detection method is introduced here to detect the change point in the drilling time series, so as to extract all non-stationary phases in historical data.

Change point detection methods are typically divided into two classes, namely amplitude change detection and distribution change detection Truong et al. (2020). Some pioneering studies demonstrated that distribution change detection is more sensitive to changes in the signal. The main idea is to detect changes by the difference between the corresponding distributions of two signals. This study exploits the Pearson (PE) divergence to calculate the distance from distributions $P(A)$ to $P(B)$, where $P(A)$ is a stable template signal, and $P(B)$ denotes the new collected signal. Because it is difficult to find a typical distribution that accurately describes drilling data, the density-ratio function $\frac{P(A)}{P(B)}$ is estimated directly instead of separately estimating $P(A)$ and $P(B)$.

Suppose that $P(y)$ denotes the distribution of the low-dimensional signal Y, and $P_r(y)$ denotes the distribution of a stable reference signal. The PE divergence $\mathrm{PE}(P\|P_r)$ between $P(y)$ and $P_r(y)$ is given as:

$$\mathrm{PE}(P\|P_r) = \frac{1}{2}\int P_r(y)\left(\frac{P(y)}{P_r(y)} - 1\right)^2 dy, \tag{6}$$

where the $\mathrm{PE}(P\|P_r) \leq 0$.

Considering that the analytic forms of $P(y)$ and $P_r(y)$ are unknown, the density ratio $\frac{P(A)}{P(B)}$ is estimated analytically based on the Relative unconstrained Least-Squares Importance Fitting (RuLSIF) algorithm. The α-relative PE divergence is given as (Yamada et al., 2013)

$$\begin{aligned}\mathrm{PE}_\alpha(P\|P_r) &= \mathrm{PE}(P\|g_\alpha) \\ &= \frac{1}{2}\int P_r(y)\left(\frac{P(y)}{g_\alpha(y)} - 1\right)^2 g_\alpha(y)dy,\end{aligned} \tag{7}$$

$$g_\alpha(y) = \alpha P(y) + (1-\alpha)P_r(y) \tag{8}$$

where $\alpha \in (0, 1)$. Then, the α-relative density ratio is given by

$$r_\alpha(y) = \frac{P(y)}{g_\alpha(y)}, \tag{9}$$

which is bounded by α^{-1} (Liu et al., 2013). To solve eq. (9), $r_\alpha(y)$ is estimated based on the sum of kernel models as:

$$\hat{r}_\alpha(y) = h(y) = \sum_{i=1}^{n} \phi_i \mathcal{K}(y, y_i), \tag{10}$$

where n denotes the length of a sliding window, $\phi = (\phi_1, ..., \phi_n)$ can be trained based on historical data, and $\mathcal{K}$ represents the Gaussian kernel function as:

$$\mathcal{K}(y, y_i) = \exp\left(-\frac{\|y - y_i\|^2}{2\sigma^2}\right), \tag{11}$$

where the width of the kernel σ is determined empirically (Li et al., 2021b).

Further, the α-relative PE divergence in eq. (7) is estimated using the two adjacent online segments $Y_1 = [y(1), y(2), ..., y(m)]$ and $Y_2 = [y^r(L+1), y^r(L+2), ..., y^r(L+m)]$ as (Yamada et al., 2013)

$$\begin{aligned} \hat{\mathrm{PE}}_\alpha(P\|P_r) =& \frac{1}{2m}\sum_{j=1}^{m}\left(2\hat{h}(y_j) - \alpha\hat{h}(y_j)^2\right) \\ &- \sum_{i=1}^{m}\frac{(1-\alpha)}{2\tilde{n}}\hat{h}(y_i^r)^2 - \frac{1}{2}. \end{aligned} \tag{12}$$

where m denotes the length of the segment. As the original PE-divergence is asymmetric, the symmetrized form of PE_α is defined as

$$\mathrm{PE}_\alpha^s = \mathrm{PE}_\alpha(P\|P_r) + \mathrm{PE}_\alpha(P_r\|P). \tag{13}$$

Using the symmetrized PE divergence, the change point detection can be conducted by determining if PE_α calculated based on Y_1 and Y_2 exceeds a normal threshold, which is determined by the historical data. Specifically, the threshold PE_{th}^s is calculated using the cumulative distribution as

$$P(s \leq \mathrm{PE}_{th}^s) = \int_0^{\mathrm{PE}_{th}^s} \Gamma(s) ds = \beta. \tag{14}$$

where β is the confidence level, and $\Gamma(s)$ represents the distribution of PE_α^s. By comparing the target PE_α^s and a corresponding threshold PE_{th}^s, the change point is extracted using the following hypothesis testing, i.e.,

$$\begin{cases} \mathrm{PE}_\alpha^s \leq \mathrm{PE}_{th}^s : y(k) \text{ is not a change point,} \\ \mathrm{PE}_\alpha^s > \mathrm{PE}_{th}^s : y(k) \text{ is a change point.} \end{cases} \tag{15}$$

Once a point is identified as a change point, it is regarded as a frequent event pattern.

3.3 Event sequence generation

As the change point is related to the non-stationary phase, signal segments under the non-stationary phase can be found with change points. Then, the multi-signal features of the non-stationary phase need to be extracted and represented. It is well known that event sequences are more robust to noises and disturbances, favoring pattern formation over time. Thus, the drilling signals are transformed into event sequences to express non-stationary patterns that may lead to alarms.

Assuming L represents the length of the sliding window, and a change point is detected at in $t \in (k-L+1, k)$. Let $X(k) = \{x_1(k), x_2(k), ..., x_M(k)\}^{\mathrm{T}}$ denotes an instant of the multivariate time series at k, while the corresponding event sequence is $E(k) = \{e_1(k), e_2(k), ..., e_M(k)\}$, where $e_i = \{a, b, c\}$, $i \in \{1, 2, ..., M\}$; $\mathcal{X}(k) = \{X(k-L+1); X(k-L+2); ...; X(k)\}$ represents M time series of length L, while a corresponding event sequence matrix is $\mathcal{E}(k) = \{E(k-L+1); E(k-L+2); ..., E(k)\}$.

The main idea is to assign an event symbol for each sample to represent the current trend information. Here, symbolic aggregate approximation (SAX) is used to convert the multivariate time series $\mathcal{X}(k)$ into the event sequence matrix $\mathcal{E}(k)$ as

$$\mathcal{E} = \{E_i(k) | \forall i \leq k, E_i(k) = f_i(\mathcal{X}_i(k), \eta_i)\}, \tag{16}$$

where $\mathcal{E}_i(k)$ denotes the i column of $\mathcal{E}(k)$, $\mathcal{X}_i(k)$ represents the ith column of $\mathcal{X}(k)$, f_i indicates the SAX model for $\mathcal{X}_i$, and η_i^u and η_i^l are parameters in f_i.

With the help of f_i, every element $x_i(j)$ of $\mathcal{X}_i(k)$ is mapped to one of the discrete intervals with a certain event symbol as

$$e_i(j) = \begin{cases} a \ \eta_i^l \leq x_i(j) \leq \eta_i^u \\ b \ x_i(j) < \eta_i^l \\ c \ \eta_i^u < x_i(j) \end{cases} \tag{17}$$

where $j \in [1, L]$, η_i^l and η_i^u denote the lower and upper bounds for the ith variable, respectively. The bounds are calculated based on three-sigma limits for the estimated Gaussian distribution of normal historical data (Wheeler and Chambers, 1992).

4. INDUSTRIAL CASE STUDY

The industrial data from a real drilling project located in Shandong province, China, is provided to illustrate the effectiveness and practicality of the proposed method. The five involved drilling variables, namely, WOB, RPM, AC, TRQ, and SPP, are selected to extract the frequent event patterns. As an industrial application case, the proposed method was applied to analyze a historical segment, including multiple frequent event patterns.

First, the segment of 5,000 historical samples of the 5 variables was normalized to 0 to 1. Fig. 1 shows the time series plots of the normalized drilling process signals under a normal condition. During the period, there were several non-stationary phases, such as $t \in [200, 400]$, $t \in [2000, 2200]$, and $t \in [3600, 3800]$, which can lead to alarms. Since all 5 signals exhibited significant changes serval times, it is rather difficult to extract non-stationary phases using only a single signal.

Then, the multiple signals were reduced to a one-dimensional dominant feature. Fig. 2 shows the time series plot of the extracted one-dimensional feature based on t-SNE. According to Figs. 1 and 2, the difference between non-stationary and stationary phases is insignificant. Even if a perfect detection threshold is applied, only a few non-stationary phases can be found from the time series plot of the feature. For example, non-stationary phases such as $t \in [1400, 1500]$ and $t \in [4500, 4600]$ were hard to capture.

The presence of non-stationary phases is usually associated with dramatic changes in the one-dimensional feature. Hence, the PE divergence from a normal stable signal to the current signal is calculated to detect change points. As shown in Fig. 3, segments of time series corresponding

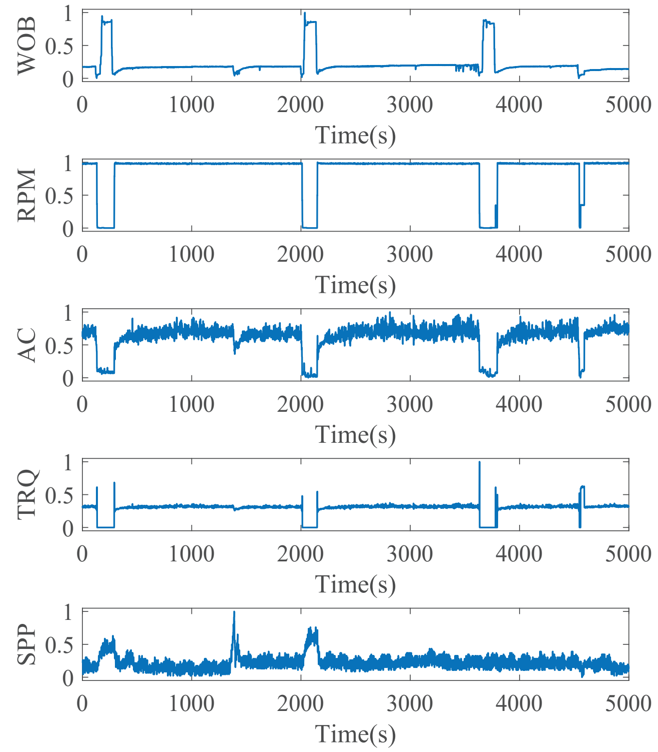

Fig. 1. Time series plots of drilling process signals.

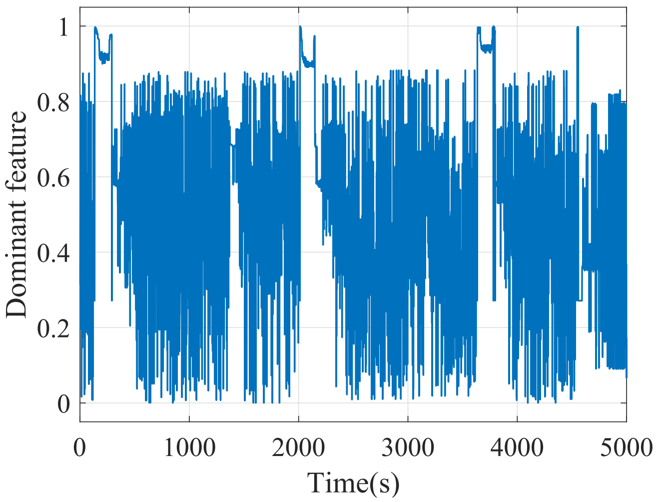

Fig. 2. Time series plot of the extracted dominant feature based on t-SNE.

to non-stationary phases were determined by assessing whether the PE divergence changes significantly, where the red dashed line representing the threshold (PE_{th}^{s}=0.19) is determined by the mean of a stationary historical signal.

Further, drilling process signals corresponding to non-stationary phases were expressed by a group of Event Sequences (ES). Fig. 4 shows time series plots of WOB_{ES}, RPM_{ES}, AC_{ES}, TRQ_{ES}, and SPP_{ES}, where the symbol 'a' denotes high, 'b' indicates normal, 'c' represents low, and 'nul' correspond to stationary phases. The five non-stationary phases were detected successfully and expressed with symbols 'a', 'b', and 'c'. Fig. 5 concludes frequent event patterns correspond to non-stationary phases by a

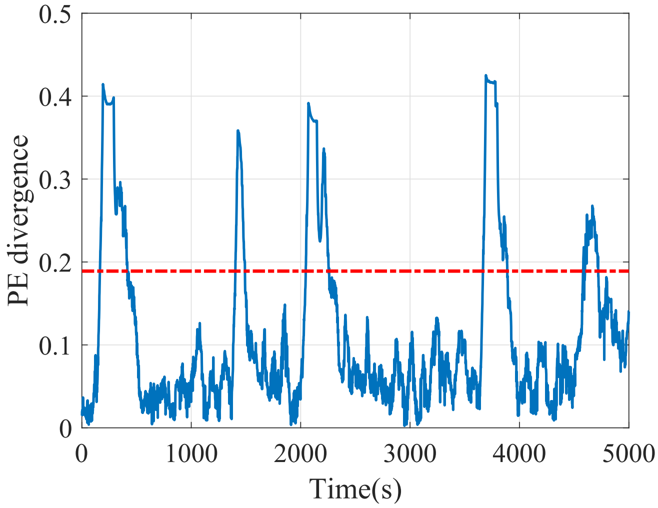

Fig. 3. Change point detection result for the one-dimensional feature based on PE divergence, where the red dashed line represents the alarm threshold.

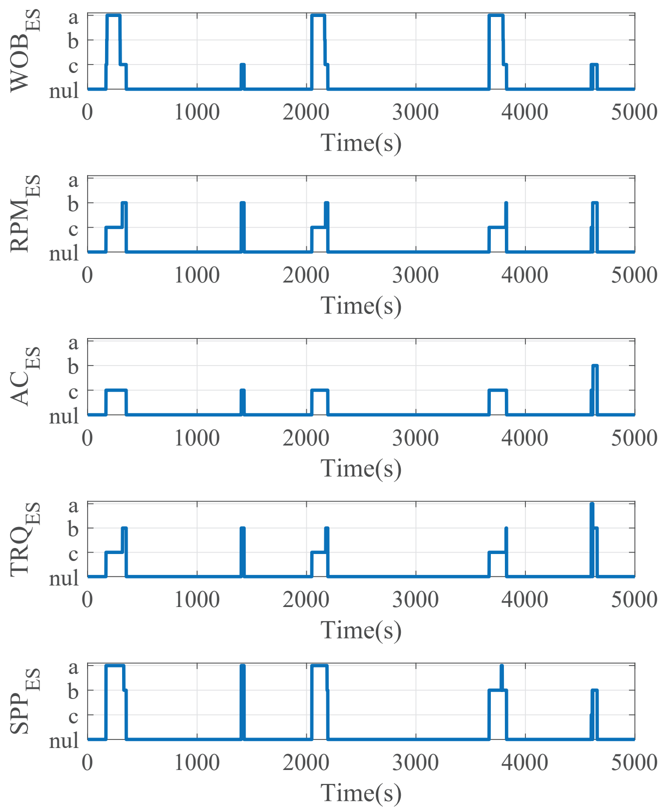

Fig. 4. Time series plots of the generated event sequences for drilling signals.

group of event sequences. The five frequent event patterns correspond to non-stationary intervals [168, 198], [1380, 1410], [2050, 2080], [3670, 3700], and [4600, 4630] in Fig. 4 respectively. It can be found that the first and third non-stationary phases share identical sequences, and thus they are grouped into the same pattern.

For example, the first pattern is characterized by a high WOB value, low RPM value, low AC value, low TRQ value, and high TRQ value. If an alarm is generated with

	Pattern_1				Pattern_2				Pattern_1				Pattern_3				Pattern_4			
WOB_{ES}	a	a	…	a	c	c	…	c	a	a	…	a	a	a	…	a	c	c	…	c
RPM_{ES}	c	c	…	c	b	b	…	b	c	c	…	c	c	c	…	c	c	c	…	b
AC_{ES}	c	c	…	c	c	c	…	c	c	c	…	c	c	c	…	c	c	c	…	b
TRQ_{ES}	c	c	…	c	b	b	…	b	c	c	…	c	c	c	…	c	a	a	…	b
SPP_{ES}	a	a	…	a	a	a	…	a	a	a	…	a	b	b	…	b	c	c	…	b

Fig. 5. Frequent event patterns correspond to non-stationary phases extracted from the above signals.

drilling signals exhibiting the above characteristics, it can be judged as a false alarm. Fig. 5 shows only part of frequent event patterns extracted in historical data. By extracting frequent sequences that occur multiple times, the frequent sequences corresponding to false alarms can be obtained, which provides a path to improve the safety monitoring performance by reducing false alarms.

5. CONCLUSION

This paper proposes an original framework for extracting frequent event patterns based on change point detection and event sequence generation in the drilling process. As multiple drilling variables exhibit different variation characteristics, the dominant feature of various variables is extracted based on t-SNE to describe the drilling operation. Further, the non-stationary phase is identified from the dominant feature based on change point detection. The RuLSIF algorithm is exploited to detect the change point by calculating the relative PE divergence. After that, the frequent pattern associated with the non-stationary phase is determined; the corresponding drilling signals are transformed into event sequences as frequent event patterns that may lead to alarms. Industrial case studies involving the data collected from a drilling project demonstrated the effectiveness of the proposed method.

In conclusion, this study is designed to increase the diversity of training samples by extracting more drilling patterns from historical data. Based on the extracted frequent event patterns, it is helpful to develop novel condition identification, alarm system design, and process monitoring methods for drilling processes. An obvious benefit is the promise of a lower false alarm rate.

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