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A CRITICAL CHANGE POINT DETECTION METHOD IN THREADED STEEL PIPE CONNECTION PROCESSES USING TWO STAGE SEQUENTIAL PIECEWISE LINEAR APPROACH

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ABSTRACT

Leak tightness is one of the key quality characteristics of oil pipelines. In pipe connection processes, this quality characteristic is mainly characterized by two critical interpretable change points in the torque signals collected by sensors mounted on the connection machine. However, because of various noises from the operation and measurement systems, latent process factors, such as mechanical return difference, assembling misalignment, and straightness of pipes, cause various nonlinear patterns to exist in the torque signals. Hence, precisely identifying the change points for automatic quality examination is still challenging. In this paper, a two-stage modeling framework is proposed to utilize sequential change point detection to precisely locate the two critical change points. A two-phase regression model based on the F maximum test is employed to detect all potential change points in the first stage. Subsequently, a two-step backward change point selection algorithm based on mechanical principles is implemented to select the critical change points in the second stage. Finally, the change point selection based on a three-phase regression model is developed. The efficacy of the proposed framework is validated by a case study on a real threaded steel pipe connection process.

1. INTRODUCTION

Threaded steel pipe connection is widely utilized in many applications, such as petroleum well drilling and oil pipeline connection. A nonconforming connection steel pipe will cause a petroleum well to become unusable if the connection fails. As reported in literature, the annual cost accrued by the failure of steel tubular products amounts to half a billion dollars, and two-thirds of all drilling failures are caused by connection failure [1]. Furthermore, the incidence of connection failure tends to increase because of the harsh environment. Many types of failure forms exist in the threaded pipe connection. One of them is galling failure, which is shown in Figure 1 [2]. Thus, the quality examination of the threaded steel pipe connection is quite important for applications in well drilling. Traditional methods, such as fatigue analysis, micro crack analysis [3], and finite element analysis [2], have been developed to analyze the mechanical behaviors of the threaded pipe connection. Aside from mechanical properties, a quality analysis method of the threaded pipe connection is also required. Advancement in sensor technologies and computational capabilities provide us an unprecedented opportunity to acquire efficient information for decision making in various manufacturing processes, including threaded pipe connection processes. Within this data-rich environment constructed by numerous sensors in a production line, automatic process monitoring and fault detection by studying profiles of the sensing signals significantly improve production efficiency and reduce the nonconforming rate of products.

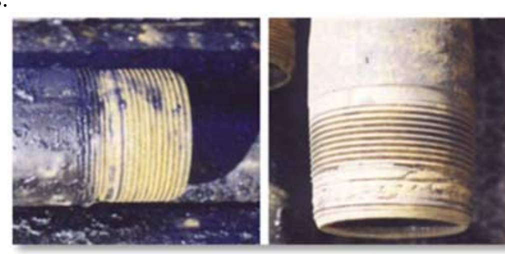


Fig. 1. Threaded galling connection [2]

To illustrate the threaded steel pipe connection process, a schematic of premium threaded connection and a theoretical torque curve are shown in Figures 2(a) and 2(b), respectively. The physical properties of premium threaded connection depends on three major geometrical characteristics, namely, thread, torque shoulder, and metal-to-metal surface, which are marked in Figure 2(a). The pipe and casing are connected by a coupling machine. The entire pipe coupling turns (shown as x-axis), and torque can be recorded by sensors during steel pipe connection. The slight and dramatic shifts in torque occur once the pipe touches the sealing surface and the shoulder of the casing, respectively, as shown in Figure 2(b). Notably, the sealing surface and the shoulder contact points, which are two of the critical change points that characterize the quality of connection, are called sealing and shoulder point. Three segments are defined in the torque signal in terms of these two change points: the signal before the sealing point (which represents the thread engagement process), the signal between the sealing point and the shoulder point (which represents the metal sealing process), and the signal after the shoulder point (which corresponds to the shoulder contact process). In engineering practices, the quality of the steel pipe coupling connection depends on the shoulder and sealing torque values. Therefore, a precise detection of these two critical change points is an essential job in threaded steel pipe connection processes.

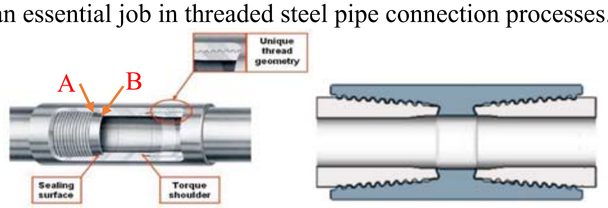


Fig.2. (a) schematic of premium threaded connection [5]

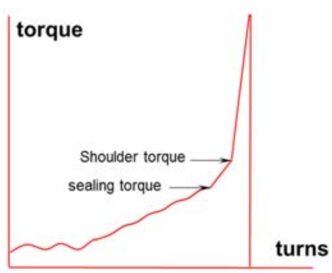


Fig.2. (b) Theoretical torque curve

Owing to the complexity of the threaded steel pipe connection assembling system, many factors such as bended shape of pipes and misalignment of pipe pre-connection may influence sensing torque signals; such an influence may cause practical recording signals to become very different from the theoretical curves. Torque profiles are theoretically regarded as piecewise linear curves in the three segments, according to the ideal physical model [4]. However, because of the large amount of noise caused by the operation and measurement systems and several process factors (e.g., mechanical return difference, assembling misalignment, and straightness of pipes), three challenges exist for developing a precise detection methodology of these two critical change points in threaded steel pipe connection processes. First, the torque signal always contains many types of nonlinear profiles, as shown as Figure 3, leading to multiple change points spreading in practical coupling torque signals, which masks the true critical points. In Figure 3, multiple points can be observed including both true change points and fake change points. Second, owing to mechanical return difference, horizontal oscillations exist in the original signal, as shown in Figure 3(d). Hence, traditional methods, such as functional data analysis methods and spectrum analysis, fail while torque signal is not complete time series data. Last, the torque signals may have different lengths, as shown in Figure 3. Therefore, developing a critical change point detection approach for torque profiles with different signal lengths (turns) in threaded steel pipe connection processes is both interesting and challenging.

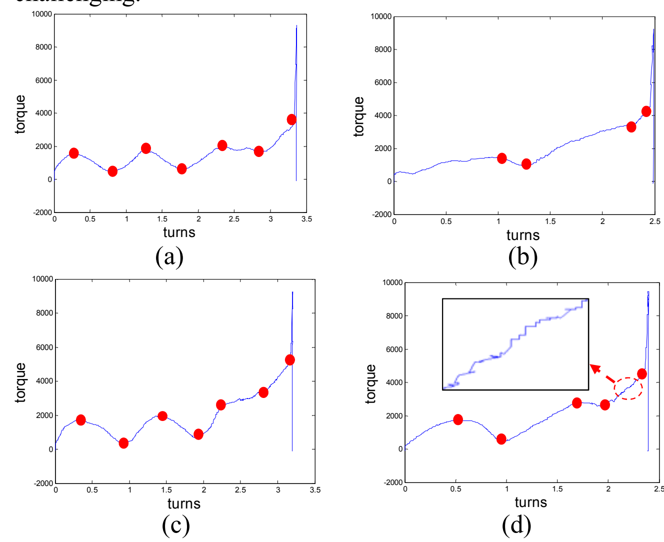


Fig. 3. Practical threaded torque signals with nonlinear profiles

To the best of our knowledge, little work has been done on critical change point detection in the threaded pipe connection process. Some relevant research can be found on change point detection. Control chart-based methods, such as Shewhart control chart [6], $\bar{X}$ chart, individual X chart, and exponential weighted moving average (EWMA) charts [7], have been developed for distribution change detection in quality control. Hypothesis tests, such as generalized likelihood ratio test, are also commonly used to detect change points. For example, Siegmund and Venkatraman proposed a sequential detection of a change point using the generalized likelihood ratio statistics. This method focuses on normal mean detection when the variance is fixed or unknown [8]. Fan et al. proposed a simultaneous penalized likelihood estimation change point detection method to detect changes for subsets given many noisy observables [9]. Nonparametric methods, such as neural network, have also been proposed to detect distribution change. For example, Rao et al. proposed a recurrent predictor neural network model for early surface variation detection using particle filtering [10]. In addition, various methodologies for the detection of distribution change exist in literature. However, these methods mainly focus on detecting distribution changes. For nonlinear and non-stationary processes, these methods fail because the underlying data may follow different distributions. To fill the research gap, a number of point detection approaches to address nonlinear profiles have been developed as summarized by the review paper of Cheng et al. [11]. Meanwhile, similar work to study the process signal with nonlinear profiles can be found in literature. For instance, a hidden Markov model based on wavelet feature extraction has also been proposed to detect the condition of tool wear in the machining process using the vibration signal [12]. However, the vibration signal in their case is quite different from the torque signal in pipe connection processes. Therefore, a general critical change point detection approach for threaded steel pipe connection is desired. The main contributions of this study is that this is the first paper to address the abnormal condition in coupling process by searching the critical points, where we can detect critical points accurately and efficiently via our proposed method.

In this study, through the sensing torque signal, plenty of information regarding the conditions of the threaded pipe connection process can be extracted. Fast Fourier transform (FFT) is performed to filter the high-frequency noise which could not be physically interpreted. After that, the potential change points are obtained by sequential forward change point detection based on a two-phase regression model under the F maximum test. A two-step backward selection algorithm based on engineering knowledge is proposed after the potential change points have been determined. Finally, two significant change points can be found by solving an optimization problem. The general framework of the proposed methodology is shown in Figure 4 as below.

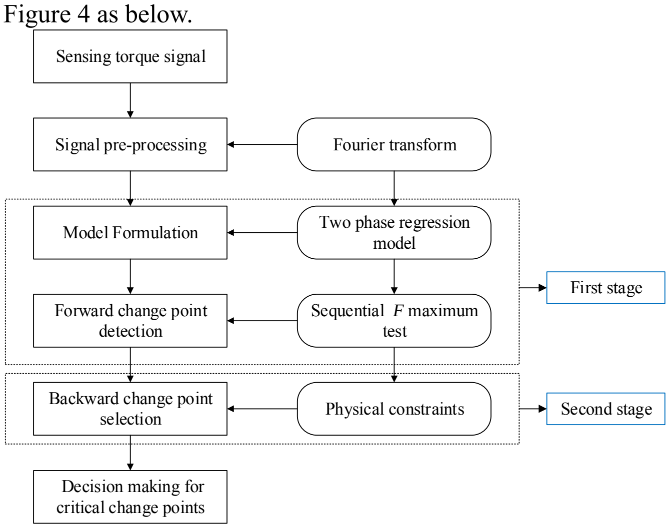


Fig. 4. Framework of the proposed methodology

The rest of this paper is organized as follows. Section 2 introduces the first-stage forward sequential change-point detection. It includes model assumptions and formulation of critical change point detection by a two-phase regression model. Signal preprocessing is performed through FFT to denoise a high-frequency component. Moreover, sequential model selection based on the F maximum test is also proposed. Section 3 presents an analysis of the second-stage two-step backward selection algorithm involving engineering domain knowledge for critical change-point selection. In Section 4, case studies based on the threaded steel pipe connection process are presented. The conclusions and discussions are provided in Section 5.

2. FIRST-STAGE SEQUENTIAL FORWARD CHANGE POINT DETECTION

2.1. Two-phase regression model

(1) Physical interpretation and model assumptions

The threaded pipe connection can be viewed as pushing a block up or down an inclined surface with inclined angle φ. Figure 5 shows that a thread touches the mating thread in the plate [4]. From mechanical equilibrium, the required force can be obtained via

$$F_u = \frac{\mu\cos\varphi + \sin\varphi}{\cos\varphi - \mu\sin\varphi} F, \quad (1)$$

where F_u is the required force that tends to push the screw thread uphill and must be applied to prevent loosening, μ is the coefficient of friction, and F is the applied force. The required torque is proportional to the required force according to physics.

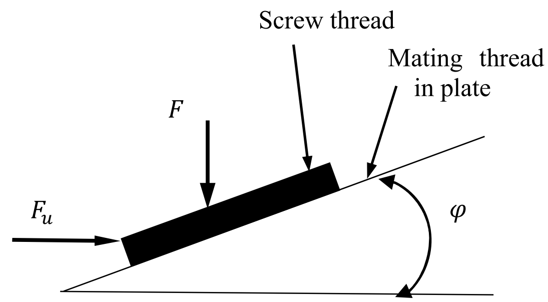


Fig. 5. Forces on a thread

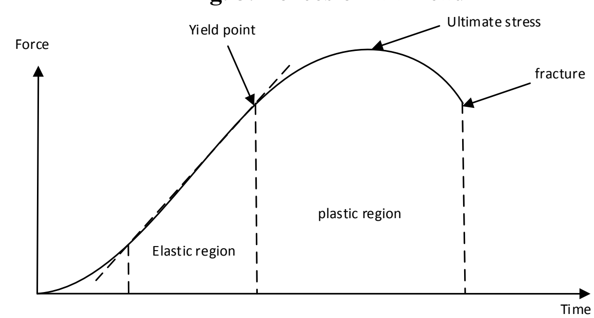


Fig. 6. Mechanical property of a ductile material

The threaded pipe connection process gradually enters into the thread engagement process, then the metal sealing process, and finally, the shoulder contact process. In each of these three processes, the material remains in the elastic state. Otherwise, the material would fail because of strain and stress. Figure 6 shows the mechanical property of a ductile material. This type of material is under normal condition if and only if the stress of the material is less than the yield stress. Thus, the corresponding force would have linear dependence on deformation, that is, torque is proportional to force. Meanwhile, these three processes have different values of Young's modulus; hence, the corresponding linear incremental change is different for the same deformation. In the threaded steel pipe connection process, the Young's modulus of the shoulder contact process is the maximum, followed by the metal sealing and the thread engagement. Therefore, in the torque-sensing signal corresponding to the same unit of turns, the magnitude of linear incremental change represents the process condition, which provides an insight to detect critical change points. Based on the aforementioned mechanical analysis, the following model assumptions are established.

a) The three segments have piecewise linear curves;
b) Two critical change points can capture the condition of the threaded pipe connection; and
c) A significant incremental change in slope in each segment exists.

A popular model for slope change detection is the two-phase regression model that is based on a hypothesis test. This model is quite powerful if the regression structure and Gaussian noise are satisfied [13]. Two-phase regression for the sensing torque signal can be formulated as

$$y_k = \begin{cases} a_1 + b_1 x_k + \varepsilon_k & 0 \le x_k \le c_c \\ a_2 + b_2 x_k + \varepsilon_k & c_c < x_k \le x_n \end{cases}, \quad (2)$$

where k denotes time; x_k and y_k are turns and torque at time k, respectively; c_c is the change point where the slope experiences an incremental change at time c; ε_k follows an independent identical distribution (i.i.d.), which is Gaussian noise; (a_i, b_i) is the coefficient of regression $i = 1,2$; and x_n is the turn that corresponds to the maximum torque of the torque sensing signal. The null hypothesis is $H_0 : b_1 = b_2$, and the alternative hypothesis is $H_1 : b_1 \neq b_2$. For the continuous case where the response values in the two-phase regression are similar at the change point position, the F statistic for change time $c \in \{2, \ldots, n-1\}$ is

$$F_c = \frac{(SSE_0 - SSE_1)/3}{SSE_1/(n-4)}, \quad (3)$$

where SSE_1 is the sum of squared residuals under the alternative hypothesis and SSE_0 is the sum of squared residuals under the null hypothesis. Therefore,

$$SSE_0 = \sum_{k=1}^{n} (y_k - a_0 - b_0 x_k)^2,$$
$$a_1 = a_2 = a_0,\ b_1 = b_2 = b_0, \quad (4)$$
$$SSE_1 = \sum_{k=1}^{c} (y_k - a_1 - b_1 x_k)^2 + \sum_{k=c+1}^{n} (y_k - a_2 - b_2 x_k)^2. \quad (5)$$

The inference of c is provided by

$$F_{max} = \max_{1 \le c \le n} F_c. \quad (6)$$

The above equations are optimization and hypothesis test problems, respectively. Lund and Reeves provided the F_{max} percentile [14]. Thus, a search for all feasible solutions is usually performed to determine the optimal change point that maximizes F_c. Then, F_{max} is compared with the critical value of the given significant level to decide whether to accept or reject the null hypothesis.

As previously mentioned, this model is effective when the piecewise linear structure holds. However, many nonlinear patterns are included in torque-sensing signals because of noise and process factors. The two-phase regression model fails under this circumstance. A sequential forward change point detection method is proposed to address this issue.

2.2. Sequential forward change point detection

The physical structure indicates that the critical change points do not exist in the front part of the sensing signal. Thus, prior turns and torque data can be obtained from historical data. From the beginning of the connection process to the prior turns, the slope and intercept can be estimated from least squares. After the prior turns, a new (future) data point is included. Two-phase regression based on the F_{max} test is performed from the initial data up to this new data point to test whether a change point exists at a given significant level. If the null hypothesis is rejected, a potential change point exists in this segmentation. This change point detection will be performed again on the new segmentation data (from the current change point to next new data point). This process is repeated until the last data point is included. The flowchart of sequential forward change point detection is shown in Figure 7.

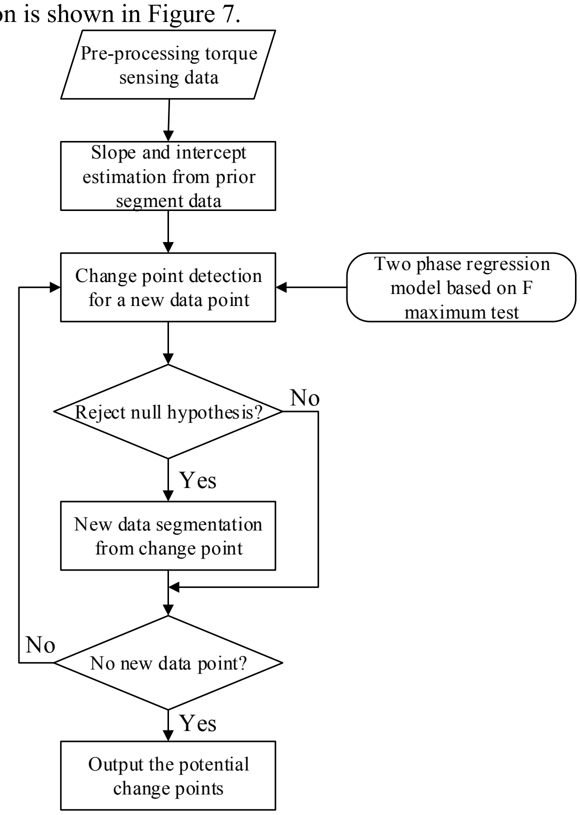


Fig. 7. The flowchart of sequential forward change point detection

3. SECOND-STAGE SEQUENTIAL BACKWARD CHANGE POINT SELECTION

Multiple potential change points might be picked up because of nonlinear patterns and measurement noises existing in the torque signal. Thus, a backward change point selection is necessary to help establish the decisions on the two critical change points.

3.1. The physical constraints for threaded pipe connection

The structure of the threaded pipe connection is shown in Figure 2(a). As shown in the figure, the apparent turn distance from the thread contact with the sealing metal to the casing is connected by the sealing metal. In other words, the physical distance exists between marked points A and B, which is also shown in the same figure. Meanwhile, a slight deformation that can hardly be seen by naked eyes occurred on the shoulder.

According to these two physical features, a sequential backward change point selection can be performed. Corresponding to the first physical constraint, the location difference between two adjacent change points must be larger than the given threshold, as denoted by h_1, which can be estimated from historical data. The change point with a larger F_{max} is retained and the other is culled. The first step in the backward change point selection is to eliminate the pseudo change points. The second property indicates that the last change point is the second critical change point in the feasible solution set constrained by first step selection. Moreover, another turn constraint estimated from historical data can be added to select the first critical change point (sealing point) after the second critical change point (shoulder point) is fixed.

3.2. Sequential backward change point selection

Multiple potential change points have been obtained in Section 2. Let χ include all these potential change points, and the number of potential change points is M, and only two of them are the critical change points of interest. Thus, we proposed a point screening approach to select the two critical change points. The following three-phase (piecewise linear) regression model is built based on the process assumptions in Section 2.1.

$$y_k = \begin{cases} a_1 + b_1 x_k + \varepsilon_k & 0 \le x_k \le c_{c_1} \\ a_2 + b_2 x_k + \varepsilon_k & c_{c_1} < x_k \le c_{c_2} \\ a_3 + b_3 x_k + \varepsilon_k & c_{c_2} < x_k \le x_n \end{cases}, \qquad (7)$$

where k denotes time; x_k and y_k are turns and torque at time k, respectively; c_{c_1} is the first critical change point where the connection process evolves to the sealing process at time c_1; c_{c_2} is the second critical change point where the connection process evolves to the shoulder contact process at time c_2; ε_k follows i.i.d., which is Gaussian noise; (a_i, b_i) is a coefficient of regression $i = 1,2,3$; and x_n is denoted as the number of turns that corresponds to the maximum torque of the signal. The two critical change point detection problem can be transformed as an identification problem of the two points in the potential change point set:

$$\min_{c_1, c_2} SSE, \qquad (8)$$

$$\text{s.t. } c_1, c_2 \in \chi$$

$$\chi = \{c_j | c_j - c_i \ge h_1, i < j, j = 1,2, \dots, M\}, \qquad (9)$$

$$SSE = \sum_{k=1}^{c_1} (y_k - a_1 - b_1 x_k)^2 + \sum_{k=c_1+1}^{c_2} (y_k - a_2 - b_2 x_k)^2 + \sum_{k=c_2+1}^{n} (y_k - a_3 - b_3 x_k)^2. \qquad (10)$$

The physical constraints in Section 3.1 show that c_2 is the last point in set χ, that is, $c_2 = c_M$. Then, the above formulation can be simplified to

$$\min_{c_1} SSE, \qquad (11)$$

$$\text{s.t. } c_1 \in \Omega \quad \Omega = \{c_i | c_M - c_i \le h_2, i = 1,2, \dots, M\}, \qquad (12)$$

where h_2 is another threshold that is also estimated from historical data. The physical meanings of h_1 and h_2 are the maximum distance and minimum distance between point A and point B estimated from historical data, respectively. Actually, the sensitivity of h_1 and h_2 do not impact the detection of critical points significantly. The optimal value of c_1 is determined to minimize SSE, and it is the first critical change point. The two-step sequential backward change point selection is performed. The selection criterion is mainly based on the physical constraints of the connection and the objective function. The flowchart of sequential backward change point selection is shown in Figure 8.

4. CASE STUDY

In this section, the proposed method is validated based on the torque sensing signal dataset in a real threaded pipe connection process. The dataset was collected in a real production line by force and grating sensors. The resolution of the turn sensor is 0.002 and sampling time is 50ms. The real torque signals are with different lengths, various nonlinear profiles and horizontal oscillations. The true torque signal involves many high-frequency noisy signals because of horizontal oscillations and noises; thus, the first step is to filter out the high-frequency components through Fourier transform. The cutoff frequency, which is 125 Hz, can be estimated from the historical torque sensing data. An example of the original and pre-processing signals filtered with 125 Hz using FFT are shown in Figure 9, and another example of the torque turn signal is also shown in Figure 10.

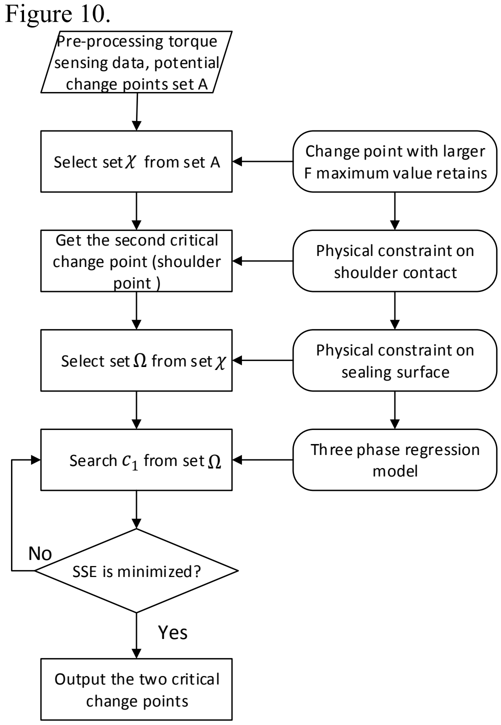


Fig. 8. The flowchart of sequential backward change point selection

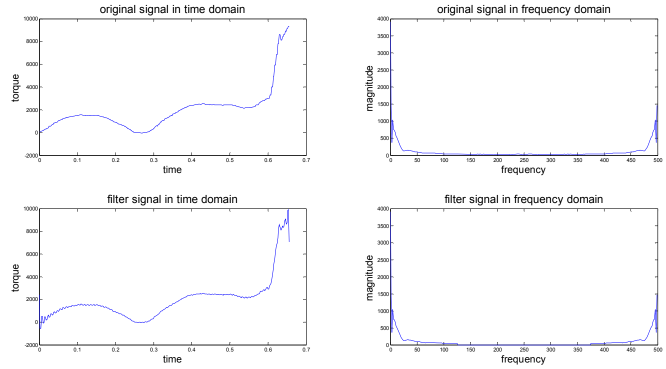


Fig. 9. Original signal and pre-processing signal in time and frequency domains

Sequential forward change point detection is performed to obtain the potential change points. The significance level is 0.99, and the corresponding F_{max} percentile is 22.38 [14]. The result of sequential forward change point detection on the above sample is shown in Table 1 and Figure 11. The red marked points are potential change points detected through forward sequential change point detection. Figure 11 shows that multiple pseudo change points are detected because of existed nonlinear abnormal patterns. Moreover, several change points are very close to one another because of return difference (horizontal oscillations). Thus, a two-step backward selection algorithm based on physical constraints were used here.

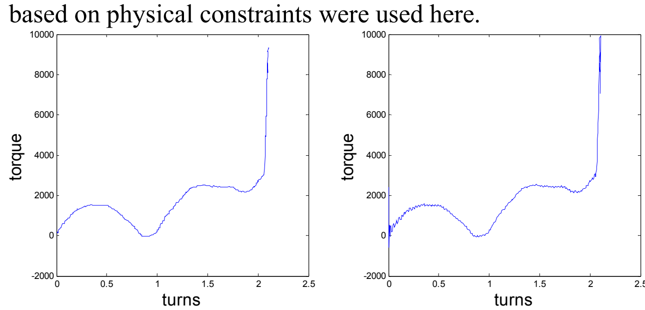


Fig. 10. Original signal (left) and filter signal (right) in the physical (turns) domain

Table 1. Information on the potential change points of the above sample

Turns of change	Torque of change	F_{max} value of change
0.004	115.040	95.236
0.184	1218.680	24.108
0.356	1544.390	22.738
0.516	1459.010	22.491
0.810	190.930	27.014
0.834	29.650	23.654
0.946	29.650	28.463
1.064	753.820	22.974
1.318	2262.230	29.385
1.464	2524.700	23.425
1.708	2429.830	24.072
1.800	2262.230	23.085
1.888	2198.990	26.753
2.060	3008.530	39.981

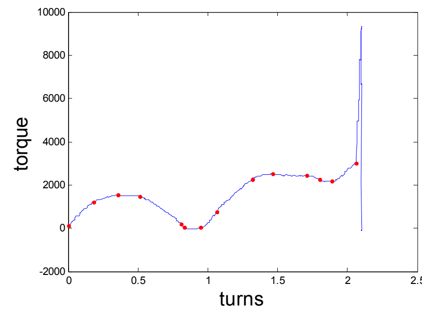


Fig. 11. An example of the potential change points detected through sequential forward change point detection

The first step in backward selection is to eliminate the pseudo change points that are extremely close. Thresholds h_1 and h_2 are estimated from historical data and are equal to 0.126 and 0.762, respectively. The remaining change points after first step selection are listed in Table 2. As shown in the table, the number of potential change points is reduced from 14 to 11. Moreover, the last change point in the potential change set is the second critical change point (shoulder point). Thus, c_{c_2} is equal to 2.06. Second step selection can be performed after the second critical change point is fixed. The remaining change points after second step selection are listed in Table 3. As shown in this table, the number of potential change points is reduced from 11 to 5. The last change point is the second critical change point; hence, only four potential change points are left to select. A three-phase regression model is then built based on these four potential first critical change points. The optimal first critical change point should minimize SSE. Figure 12 shows the final result of the decision making on the two critical change points. The two red marked points are critical change points, and the corresponding value is marked over the points. The proposed method works very fast thanks to the reasonable constraints added by mechanical analysis. For example, the entire computation time of the above sample is 3.695 seconds in MATLAB 2013a of a computer with an i5 CPU and 4 GB RAM, which is eligible for streamline production in steel pipe plant.

Table 2. Information on the remaining potential change points after first step selection

Turns of change	Torque of change	F_{max} value of change
0.004	115.040	95.236
0.184	1218.680	24.108
0.356	1544.390	22.738
0.516	1459.010	22.491
0.810	190.930	27.014
0.946	29.650	28.463
1.318	2262.230	29.385
1.464	2524.700	23.425
1.708	2429.830	24.072
1.888	2198.990	26.753
2.060	3008.530	39.981

Table 3. Information on the remaining potential change points after second step selection

Turns of change	Torque of change	F_{max} value of change
1.318	2262.230	29.385
1.464	2524.700	23.425
1.708	2429.830	24.072
1.888	2198.990	26.753
2.060	3008.530	39.981

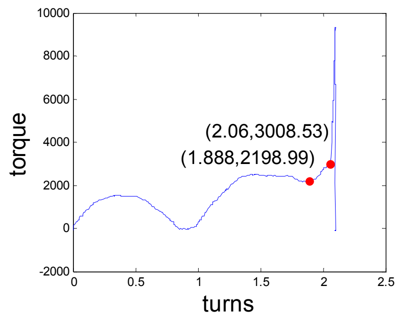
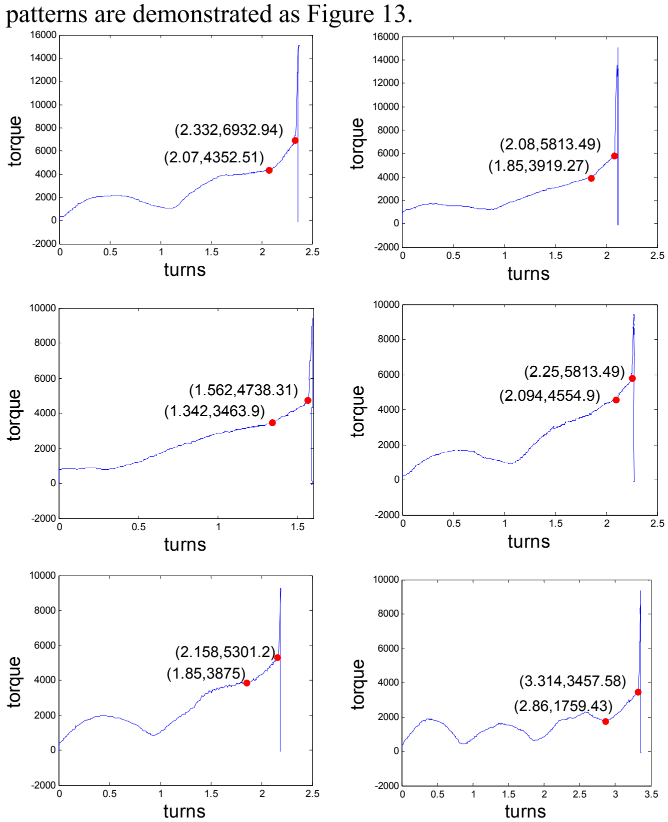


Fig. 12. Final result based on the backward selection algorithm

The proposed method is also tested by a large amount of samples with different nonlinear patterns. Due to limited page of this article, only reprehensive signals with frequently seen patterns are demonstrated as Figure 13.



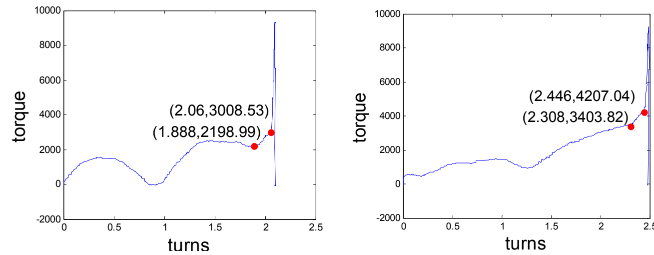


Fig. 13. Critical change point detection results of selected samples

The test results show that the proposed methodology can effectively deal with sealing and shoulder point detection problems in the threaded pipe connection process.

5. CONCLUSION AND DISCUSSION

In this paper, we proposed a critical change point detection approach in threaded steel pipe connection processes by using torque signals. Considered the uncertainties and noises generated from operation and measurement systems, we developed a two stage sequential piecewise linear method by combining a change point selection procedure. Specifically, an FFT was performed to preprocess the signals to eliminate the unnecessary high-frequency components. Based on a two-phase regression model via the F_{max} test, a sequential forward change point detection algorithm was developed to obtain a pool of potential change points. A two-step sequential backward change point selection algorithm based on physical constraints was then developed to reduce the size of the pseudo point set. A three-phase regression model was finally established to obtain the underlying two critical change points.

Generally, the quality of the threaded steel pipe connection depends on the sealing and shoulder torque values. The developed two-stage sequential forward change point detection based the backward change point selection is efficient through a real case validation. The precise point detection procedure may provide a guidance to steel pipe plants for quality examination of the threaded steel pipe connection. It worth pointing out that the proposed method can also be extended to other change point detection jobs of signature signals by combining appropriate engineering knowledge.

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