A synergetic locating method for abnormal interval of stacker safety maintenance

Ling Ni, Yongchao Wang, Jian Wang, Wenjuan Dong, Hongliang Liu, Yudong Xing, Huang Darong and Ke Lanyan

Xinjiang Electric Power Science Research Institute, Xinjiang, People's Republic of China; Beijing Nanri Technology Co. Ltd., Beijing, People's Republic of China; College of Information Science and Engineering, Chongqing Jiaotong University, Chongqing, People's Republic of China

ABSTRACT

The stacker is an important part of automatic storage. The safety and health of the running track are the primary premise to ensure the stable operation of the stacker. In this paper, a new combinational method to locate abnormal interval for running track of stacker is proposed. First, the interval smoothing method and data interpolation method are used for preprocessing of the original current data sampled from stackers; second, the box plot method for outlier detection is applied to the smoothed data; at the same time, in order to make up for the defect of the box plot method that can only detect the extreme points, failing to detect abrupt change points, the box plot method is combined with the wavelet transformation method to construct a combinational anomaly interval location method; finally, the validity of the algorithm proposed in this paper is verified by the running current data of the stacker in the intelligent operation and maintenance warehouse of the national power grid.

ARTICLE HISTORY

Received 27 June 2018
Accepted 30 October 2018

KEYWORDS

Running current data of the stacker; mean smoothing; outlier detection; wavelet transform; track anomaly interval location

1. Introduction

The automatic stereoscopic warehouse is a highly flexible logistics system where the warehousing, information and management are integrated. Automatic stereoscopic warehouse plays a key role in the daily operation of large- and medium-sized manufacturing enterprises. As the core equipment, the running state of stacker will directly affect the safety and stability of the operation for the whole logistics system (Ting et al., 2014). At present, the research of stacker at home and abroad is widely focussed on operation control. Unfortunately, based on data, fault diagnosis research of stacker is still at the initial period (Hongyan, Jun, & Kewei, 2017; Huang, Lanyan, Bo, Ling, & Guoxi, 2018), which is different from the widespread concern in the control aspect of stacker. In reference (Stuart-Bruges & Srinivasan, 1975) which first studied the fault diagnosis of the stacker, a small monitoring computer was installed on the stacker equipment to automatically diagnose the power and mechanical faults. Wenwei et al. applied FTA technology to intelligent fault diagnosis of the stacker (Wenwei, 2002a, 2002b). Because the stacker has the characteristics of high complexity and strong modularity, the probability that the equipment cannot operate normally caused by various causes has different levels of uncertainty. Therefore, by introducing fuzzy mathematics theory, the fuzzy fault tree analysis for the stacker was made. On this basis, Tao et al. studied the stacker fault diagnosis method based on PLC monitoring technology (Tao, Hua, & Ming, 2005). On the long-term study of fault diagnosis system for stacker, Zhang has designed reference architecture and functional model for intelligent monitoring and fault diagnosis of the large and complex automated logistics system, which managed the monitoring and diagnosis modules in a multi-level and hierarchical way (Zhang, Zhang, Luo, Tang, & Zhuang, 2003). Zhang Caipin used FTA to analyse the stacker and used the production rule as the representation of knowledge to establish a knowledge base prototype of fault diagnostic experts' system (Jide, Ronggang, & Jian, 2005). Xiaoping et al. designed the overall scheme of the remote diagnosis and maintenance expert system for the stacker. In the reference (Xiaoping & Kangkang, 2011), the Web, OPC-XML is proposed as the way of remote information transmission, and FTA technology is proposed as an intelligent diagnosis method for the stacker. The scheme covered all aspects of the stacker’s data acquisition, transmission and the fault diagnosis based on the expert system.

Although methods of fault diagnosis for the whole parts of the stacker are in the primary period, the preliminary research results have been achieved. However, the track is an important part of the stacker, but there are few studies on individual anomaly detection and abnormal
interval location of the track. Stacker track directly affects the stability of the device. When the track is severely strained, the stacker’s vibration signal along the track greatly increases that leads to the tooth surface wears of the guide device and reduced reliability of the brake device. On the other hand, the levelness of track directly affects the stability of horizontal movement and the accuracy of goods extraction on stackers. For the sky rail, the excessive rail deviation will lead to the decrease of the goods extraction accuracy, the increase of the operation resistance of the stacker and the abnormal wear of the top wheel, which will cause the fracture of the rail.

With the continuous improvement of mechanized operation level, the track of the stacker needs to be more and more precise. Coupled with uncertain factors such as external environment and human operations, it is difficult to accurately characterize the stacker track failure. Therefore, designing a diagnostic structure that can quickly and accurately locate the anomalous interval of stacker track has become an urgent research topic for industry and scientific researchers. In order to solve this problem, a method for anomaly detection and location based on the running current data for stacker is proposed. First, we establish data preprocessing model for the current data; second, the outlier detection model is set up based on the box plot method to filter out the abnormal point; furthermore, the box plot method cannot detect the abrupt change points, so the wavelet transform is combined with the box plot to construct anomaly detection and positioning model for outlier detection and location of the track; finally, the validity and applicability of the algorithm was verified by the examples of the stacker signals collected from the intelligent operation and maintenance of the warehouse in Beijing Jie Hong Nari Technology Co. Ltd.

2. The data preprocessing model

2.1. Original current data analysis

The data collected from the position in 0 m–24 m on 17th January 2018 is analysed. The distribution of the data is shown in Figure 1.

From the figure, we can know that the original data is messy and unordered, and the sample size is too large. In order to solve the above problems, the current data is equidistantly divided at the interval of 100 mm. The longitudinal axis is the distribution of the sampled data between each interval. In the real working process of the stacker, the amount of operation data in single batch is small, which makes it difficult to reflect the operation of the whole track, so we have to take multiple batches of operation data into consideration. However, when multiple batches of data are considered, due to the unfixed data interval of different batches, the amounts of data are not evenly distributed. Therefore, considering the sampling is beneficial to the smoothing of the data, the monitoring and analysis of the running state of the track. The mean smoothing of the obtained data can not only reduce the size of the data but also enhance its regularity.

2.2. Data smoothing model

In the practical operation process, there are repetitive operation intervals, including initial current and stopping current. At the same time, there are interferences between intermittent faults and hidden faults, so we need to smooth the data by interval mean algorithm. To this end, a data smoothing model is established in this paper, which is divided into two steps that are the interval sampling and the mean smoothing (Biao, Qiao, & Xiaohang, 2017; Xiaoyu, Hanbing, Shuai, & Junjun, 2014; Xinchun & Yue, 2017).

(1) The interval sampling

In order to solve the repeated operation interval problem of sampling data, the running data of the stacker is isometrically divided. The interval sampling parameters are set as follows:

The start point of the interval sampling: start = 0 mm
The space of the interval sampling: space = 100 mm
To sum up, the interval 0 m–24 m will be divided into [0 100], [101 200] and so on by the mean smoothing method.
2. The interval distribution data samples.

\[ S_I(t) = (s_1(t), s_2(t), \ldots, s_N(t)) \]

This smoothed value of the interval is specified as follows:

\[ S'_I(t) = \frac{1}{N} \sum_{i=1}^{N} s_i(t). \]  

As a result, the smoothed signal set is shown as follows:

\[ S = (S'_1, S'_2, \ldots, S'_M), \]

where \( M = \frac{24000}{100} = 240. \)

The whole algorithm flow of data smoothing is shown in Figure 3.

The MATLAB software is used to implement the algorithm above, and the data smoothing result of the stacker’s running state is shown in Figure 4.

2.3. Interpolation processing model

Compared with the original signal, it is found that the signal after the interval mean smoothing is more regular and clearer. The signal after the mean smoothing is more favourable for the location and detection of the abnormal interval. However, there is the absence of data...
in the process of the stacker running at a constant speed. Therefore, the data interpolation is used to make up the absence of data. The comparison between original data and interpolated data is shown in Figure 5.

3. The coordination location method of the track’s anomaly interval

Due to the complexity of the real engineering conditions, the current change is complicated when the track of the stacker is abnormal, so it is necessary to analyse the anomalous point of the current in detail. In combination with theoretical knowledge and engineering experience, we have found that the abrupt change points and the points with large amplitude in the current data can correctly reflect the track anomaly of the stacker. Because there is almost no research on the track diagnosis of the stacker, we can only draw lessons from the traditional anomaly detection methods to detect the outliers of the current data for track abnormal interval location. But the traditional outlier detection methods can only detect the larger amplitude points or the mutational points which cannot meet the actual engineering requirements of detecting the points with large abrupt change and large amplitude at the same time.

3.1. Outlier detection algorithm based on the box plot method

An outlier is a data object that is significantly different from other data objects as if it was produced by different mechanisms. Outlier detection is the process of finding out some points that are greatly different from the expected object.

The box plot method based on the quartiles of statistics theory divides the data into four equal parts in order to obtain three segmentation points namely quartiles (Chao, 2015; Menghui et al., 2016).

For the running state data of stacker is unlabelled, the abnormal data can only be set up as a percentage of the total. The box plot method can automatically set the percentage to screen out the outliers.

The outlier is usually defined as a value which is less than $Q_l - 1.5IQR$ or larger than $Q_U + 1.5IQR$, where $Q_l$ is the lower quartile, which means that 1/4 of the observations values are smaller than the value; $Q_U$ is the upper quartile, which means 1/4 of the total observations are larger than the value; $IQR$ is the distance between the quartiles, which is the difference between $Q_l$ and $Q_U$. It contains half of the total observation values and is shown in Figure 6.

3.2. Singular point detection algorithm based on wavelet transformation

The wavelet analysis can accurately locate the abrupt points of the processed signal. Owing to the lack of spatial locality, Fourier transform can only determine the global nature of a function’s singularity, but it is difficult to determine the location and distribution of singularities in space. The zero-crossing points, breakpoints and signal’s abrupt points are often the most characteristic parts of the signal which are also the focus of the analysis. After the signal transformed by wavelet, the singularity of the signal can be displayed at different scales. These singularities can reflect the transient characteristics and the mutational points, so wavelet transform can be used for the detection of abrupt points.

Suppose that $\phi(t) \in L^2(R)$ satisfies the following formula:

$$\int_R |\Psi(\omega)|^2 |\omega|^{-1} d\omega < +\infty. \quad (3)$$

In the formula, $\psi(\omega)$ is the Fourier transform of $\phi(t)$ and $\phi(t)$ is a wavelet generating function or a basic wavelet. Through the translation and expansion of the wavelet function, we can get the formula which is...
expressed as follows:
\[ \phi_{a,b}(t) = a^{-\frac{1}{2}} \phi \left( \frac{t - b}{a} \right) \quad a > 0, b \in \mathbb{R}. \]  
(4)

In the formula, \( a \) is an expansion factor (or a scale factor) and \( b \) is a translation factor. \( \phi_{a,b}(t) \) is the small wavelet basis function, which is related to \( a \) and \( b \), and can be traced after expansion and translation from the generating function \( \phi(t) \).

Suppose that the signal \( x(t) \in L^2(\mathbb{R}) \), the inner product of the signal and the wavelet basis function can be calculated, and then the expression of the wavelet transform can be obtained as follows:
\[ W_x(a,b) = \langle x, \phi_{a,b}(t) \rangle = a^{-\frac{1}{2}} \int_{\mathbb{R}} x(t) \phi_{a,b} \left( \frac{t - b}{a} \right) dt, \]  
(5)
where \( W_x(a,b) \) is the continuous wavelet transform (CWT) of \( x(t) \).

And its inverse transform is expressed as follows:
\[ x(t) = \frac{1}{C_{\phi}} \int_{\mathbb{R}} \int_{\mathbb{R}} W_x(a,b) \phi_{a,b} \left( \frac{t - b}{a} \right) dadb. \]  
(6)

The wavelet transform can reflect the low-frequency and high-frequency components of the signal adaptively. Based on this characteristic, we can use the wavelet transform to detect the local singularity of the signal.

The singularity of the signal features can be characterized by the modulus maxima of the signal’s wavelet transform \( W^J_xf(x) \), which can guarantee the completeness of the wavelet transform (Mallat & Sifen, 1992). The modulus maximum corresponds to a sharp change in the signal waveform. The amplitude of the modulus maximum points, which changes with \( 2^J \), reflect the change characteristics of the neighbourhood.

The characteristic signal is distinguished from the noise by the Lipschitz index. The singularity of the characteristic signal is usually expressed as the positive Lipschitz index, while the singularity of the noise signal is negative Lipschitz index. It is known mathematically that the infinite differentiable function is smooth or non-singular. If a point in a function is a discontinuous point or its \( N \)-th-order derivative is discontinuous (\( N \) is an arbitrary positive integer), then this point is considered to be a singularity. The local singularity of a function is mathematically described by Lipschitz.

Definition 1: Suppose that \( n \) is a non-negative integer, \( n \leq \alpha < n + 1, m > 0 \) and \( h \) is an infinitesimal positive number, and then in the vicinity of \( t_0 \), the following formula can be obtained as
\[ |f(t_0 + h) - p_n(t_0)| \leq m|h|^\alpha. \]  
(7)

The Lipschitz index of \( f(t) \) at \( t_0 \) is \( \alpha \). At the \( t_0 \) point, the \( f(t) \) is expanded by Taylor series and \( p_n(t_0) \) is the former \( n \) term.

The Lipschitz index \( \alpha \) represents the singular size of the function \( f(t) \) at \( t_0 \). The bigger the \( \alpha \) is, the smoother the \( f(t) \) is at \( t_0 \); the smaller the \( \alpha \) is, the greater change occurred in the \( f(t) \) is at \( t_0 \). If \( f(t) \) can find derivative at \( t_0 \), \( \alpha = 1 \); if \( f(t) \) is not continuous but bounded at \( t_0 \), \( \alpha = 0 \).

Definition 2: If there is \( |WT_f(s,t)| \leq |WT_f(s,t_0)| \) for \( t \in \delta t_0 \), then \( t_0 \) is the local extreme point of the wavelet transform under the scale \( s \).

Definition 3: There is the following relationship between the wavelet value of the maximum value line and the Lipschitz index at \( t_0 \).
\[ |WT_f(s,t)| \leq Ks^\alpha (K \in \mathbb{N}^*), \]  
(8)
\[ \alpha = \lg \left( \frac{|WT_{f^2}(x)|}{|WT_{f^2}(x)|} \right), \]  
(9)
where \( \alpha \) is the singularity index at \( t_0 \), that is, the Lipschitz index.

### 3.3. New location algorithm for abnormal interval of combined track

In practical engineering, the abnormal points that are made up of the larger current amplitude and also the abrupt points of the stacker track should be taken into account. Unfortunately, abnormal points detection based on wavelet transform and the box plot method can only detect abrupt points or extreme points, failing to accurately locate abnormal intervals. Therefore, considering the combination of two algorithms, a new algorithm for detecting track abnormal interval and locating is proposed.

The steps are given as follows:

Step1: By using the constructed data preprocessing model, the data is smoothed and interpolated to supplement the missing data.

Step2: The box plot method is used to screen out the outlier points of the preprocessed data, and the location of the singularity is stored in the vector \( V \).

Step3: Using the Lipschitz index of wavelet transform to locate the singularity points, the specific steps are described as follows:

(1) Select the wavelet generating function \( \varphi \) and the number of decomposition layers \( J \).
(2) The current signal of the stacker is decomposed by wavelet transform, and then the wavelet transform coefficients of each layer are obtained namely \( W_1T_f(c) \ldots W_JT_f(c) \).
(3) Detect the modulus maximum point of \( W_jT_f(c), j = 1, \ldots, J \). The Lipschitz index \( \alpha \) is calculated and the modulus maximum of \( \alpha \leq 0 \) is removed; only the modulus maximum of \( \alpha > 0 \) is retained.
(4) Check the points obtained from step (3) to determine whether it is the extreme point on every scale to get the mutation locations $l(0), \ldots, l(s)$, and then these locations are stored in vector $V_1$.

(5) Comparing the position information in the vector $V$ and $V_1$, complete the combination of the two-singularity location.

The flowchart of the algorithm proposed in this paper is shown in Figure 7.

4. Experimental verification

As one of the core technologies of modern logistics, Automatic Storage & Retrieval System (ASRS) has received widespread attention from various enterprises and is widely used in various fields. As the most critical equipment in automated warehouse technology, with the continuous improvement of operation speed, it brings more and more abnormal problems of the stacker. Therefore, the detection of the running state of the stacker is the key to the anomaly detection of the whole automation logistics system. This paper takes the current signal of the intelligent operation and maintenance of the warehouse stacker in Beijing Jie Hong Nari Technology Co. Ltd as the data source which contains the weld seam, track irregularities and other abnormal track.

Figures 8–10 represent abnormality of the sky rail, such as welding joint and wear. Similarly, Figure 9 represents the abnormality of the ground rail. Whether abnormalities of the sky rail or the ground track are easy to cause instability of the operation for the stacker, resulting in the drop of goods when pick-up or inventory goods and affecting production efficiency.

According to the actual survey of the stacker operation field in Anhui Electric Power Research Institute of the State Grid, there are track welds at 20, 18, 13, 7 and 10 m in the stacker running track.
Table 1. The description of simulation data.

| Test time | Serial number | Direction | Load | Data size |
|-----------|---------------|-----------|------|-----------|
| 2018-01-17 | No.1 stacker | Forward | Yes  | 306       |
|           | Back         |          |      | 308       |

Figure 11. Analysis of current data on 17 January 2018 based on the box plot.

Figure 12. Abnormal detection result by the box diagram. The result is obtained by the current on 17 January 2018.

In order to verify the effectiveness and rationality of the above synergetic methods, the data collected from the operation site of Anhui Electric Power Research Institute of the State Grid on 17 January 2018, will be taken as verification data source, and the data specific situation is shown in Table 1.

First, we use interval sampling theorem to complete interval sampling. Second, we use the mean smooth model to get the smoothed and sampled data. Finally, we use the box plot to filter out the abnormal points after smoothing the data. The simulation results are shown in Figure 11. In the actual production environment, too many misjudgments can be made if only select the abnormal points. At the same time, there is a delay in the acquisition of the signal, which leads to the error of the recording position. In order to solve the above problems, the interval of the detected outliers is expanded. The simulation results are shown in Figure 12.

According to the interval location of the box plot, the abnormal interval can be preliminarily determined in Table 2.

To a certain extent, the above model can be used to judge abnormal interval of running stacker track. In order to further locate the abnormal interval, the wavelet transform algorithm is used to locate the abnormal interval, and the simulation results are shown in Figure 13.

According to the results of the wavelet transformation, the abnormal fault interval of the running track of the stacker is shown in Table 3. Considering that the box plot can only detect extreme points, it is impossible to monitor the abrupt change points. Therefore, combined with the above two methods and engineering experience, the results of Table 2 and Table 3 are combined to get the

Table 2. Abnormal interval detection results of the box plot.

| Abnormal interval | Abnormal position | Abnormal interval | Abnormal position |
|-------------------|-------------------|-------------------|-------------------|
| 78–84             | 7.8–8.4 m         | 132–138           | 13.2–13.8 m       |
| 158–169           | 15.8–16.9 m       | 207–211           | 20.7–21.1 m       |
| 226–228           | 22.6–22.8 m       |                   |                   |

Figure 13. Abnormal detection result by wavelet transformation. The result is obtained by the current on 17 January 2018.

Table 3. Abnormal interval detection results of wavelet transformation.

| Abnormal interval | Abnormal position |
|-------------------|-------------------|
| 132–135           | 13.2–13.5 m       |
| 144–147           | 14.4–14.7 m       |
| 158–161           | 15.8–16.1 m       |

Table 4. Final result.

| Abnormal interval | Abnormal position |
|-------------------|-------------------|
| 78–92             | 7.8–9.2 m         |
| 132–135           | 13.2–13.5 m       |
| 144–147           | 14.4–14.7 m       |
| 158–165           | 15.8–16.5 m       |
| 225–229           | 22.5–22.9 m       |
final abnormal interval of the track of the stacker, and the results are shown in Table 4.

From the results above, the results of the two algorithms are more accurate and the interval range is smaller.

5. Conclusion

In this paper, first, we have divided the running track of the stacker into equal intervals by using equal interval sampling. Second, we have used the mean smoothing method to process each interval data to obtain smoothed data. Compared the smoothed mean signal and the original signal, it is found that the size of the mean smoothed signal is smaller and the regularity is stronger. Furthermore, the box plot method combined with the wavelet transform has been used to screen the abnormal points of the smoothed signal out. The screening results coincide with the field anomalies of the stacker track, which proves the effectiveness and reliability of the proposed synergetic anomaly detection method.

Acknowledgment

The authors gratefully acknowledge two anonymous reviewers for their scientific suggestions and constructive comments.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the National Natural Science Foundation of China P.R. under Grants 61703063, 61663008 and 61573076; the Science and Technology Research Project of Chongqing Municipal Education Commission of China P.R. under Grants KJ1605002, KJ1705121 and KJ1705139; the Program of Chongqing Innovation and Entrepreneurship for Returned Overseas Scholars of China P.R. under Grants cx2018110.

ORCID

Huang Darong @ http://orcid.org/0000-0002-5068-5162

References

Biao, Z., Qiao, L., & Xiaohang, Z. (2017). A data processing method for bridge modal parameter identification based on exploratory data analysis. Sichuan Building Science, 43(02), 33–37.
Chao, Z. (2015). Analysis of functions of skewed robust boxplot. Engineering Journal of Wuhan University, 48(06), 778–781.
Hongyan, F., Jun, L., & Kewei, Z. (2017). Research and progress of stacker status monitoring and fault diagnosis. Logistics Technology, 36(02), 33–37.
Huang, D., Lanyan, K., Bo, M., Ling, Z., & Guoxi, S. (2018). A new incipient fault diagnosis method combining improved RLS and LMD algorithm for rolling bearing with strong background noise. IEEE Access, 6, 26001–26010.
Jide, J., Ronggang, C., & Jian, C. (2005). Internal combustion engine condition monitoring research based on extract time interval sampling. Chinese Internal Combustion Engine Engineering, 06, 72–75.
Mallat, S., & Sifen, Z. (1992). Characerization of signals from multiscale edges. IEEE Transactions on Pattern Analysis and Machine Intelligence, 14(7), 710–732.
Menghui, L., Xiaotian, S., Zhenchuan, T., et al. (2016). Application of box plot in the outlier test of the cotton trash content in the Yangtze river cotton areas. Hubei Agricultural Sciences, 55(11), 2895–2898+i:2954.
Stuart-Bruges, W. P., & Srinivasan, V. (1975). Self-diagnostic control of a stacker crane. Electronics & Power, 21(2), 108–111.
Tao, L., Hua, X., & Ming, Z. (2005). The PLC control and fault detection of the stacking machine in a large high-rise parking system. Lifting the Transport Machinery, 9, 43–45.
Ting, L. V., Tao, Y., Bin, H., et al. (2014). Reliability analysis of stacker system based on fuzzy Bayesian network. Application Research of Computers, 31(12), 3632–3636.
Wenwei, G. (2002a). The application of qualitative analysis of fault tree in fault diagnosis of high-rise warehouses. Lifting the Transport Machinery, 07, 22–26.
Wenwei, G. (2002b). The application of quantitative analysis of fault tree in fault diagnosis of high-rise warehouses. Lifting the Transport Machinery, 12, 24–26.
Xiaoping, L., & Kangkang, Y. (2011). Research on Key technology in remote fault diagnosis of the stacker. Journal of Lanzhou Jiaotong University, 30(4), 21–26.
Xiaoyu, S., Hanbing, G., Shuai, Y., & Junjun, M. A. (2014). An algorithm ofough transform line detection based on the adaptive threshold interval halves sample. Journal of Shenyang Jianzhu University(Social Science), 30(05), 945–952.
Xinchun, L., & Yue, H. (2017). Indoor positioning technology based on improved access point selection and K nearest neighbor algorithm. Journal of Computer Applications, 37(11), 3276–3280+i:3287.
Zhang, D. H., Zhang, J. B., Luo, M., Tang, Y., & Zhuang, L. Q. (2003). A reference architecture and functional model for monitoring and diagnosis of large automated systems. Proceedings of IEEE Conference on Emerging Technologies and Factory Automation, 2, 516–523.