On-line Piercing Process Monitoring Based on Vibration Signals

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Abstract: This paper focuses on developing an in-line monitoring technique to classify the piercing head conditions in the seamless tube piercing process. An advanced in-line imaging system is deployed in real time to capture the vibration of steel bars during the piercing process. The Vibration signal, extracted from in-line images, can be used to analyze the relationship between damping values of the process and piercing head conditions. Specifically, a time series model is built based on the vibration signal to obtain the process damping value, which can be treated as a feature to infer the piercing head condition in real time. Finally, a statistical control chart is established based on the extracted features to distinguish different piercing head conditions. The case study shows that the proposed methodology can satisfy the accuracy requirements for abnormal piercing head condition detection.

Keywords: ***pro***cess monitoring; time series; control chart; in-line

1. Introduction

Seamless steel tubes are widely used in modern industrial processes, such as energy production, petrochemical processes, chemical engineering and industry, gas transmission, automotive manufacturing processes, etc. It is very important to monitor the seamless tube manufacturing processes and improve the tube quality.

Seamless tube manufacturing processes include bar piercing, punching, straightening, trim, inspection and testing. The rotary piercing process contains steel bar, roller, piercing head, mandrel and other accessories. In this process, the steel bar has the largest deformation, which will determine the tube quality. There are many process parameters in bar piercing process, such as the rotary speed, the roller angle, diameter, the bar temperature, the piercing plug location and condition. If the piercing head has problem, it will have large impact on tube quality. Even it may causes serious production accident. So people need to monitor and diagnose the piercing plug condition on-line, and make a decision in real time.

There are some researches on reasons of the piercing head faulty and trying to improve the piercing head performance. Wang (2006) focus on changing the material composition to improve the piercing head performance [1]. Wang (1998) want to improve the plug manufacturing processes to increase the piercing plug service time [2]. Mori (1998) have used the Finite element methods (FEM) to simulate the metal deformation process [3]. But few people do the research of monitoring the piercing head on-line, because of the harsh work environment with the high temperature and complicate deformation. The current way to inspect the piercing head condition is just detect the head off-line.

Many works have been done to do data classification and identification. Robbins (1994) used Shewhart control chart for monitoring single parameter [7]. Li and Shi (2007) used a T^2 control chart to detect the slab surface seam [8]. In this paper, we use t-statistic test to classify different steel bar damping information, then identify the piercing head condition.

In this paper, on-line image-based detection system is used to monitor the piercing head condition. The system utilize two line-scanning cameras to capture the bar edgy images, to record the bar movement. Then the steel bar vibration signal can be extracted based on these images. Two high-speed line scanning cameras are installed on two different directions of the bar to capture the steel bar surface images at a high temperature. When the bar moving forward, the cameras will take images to record the bar surface all time. The two cameras form about 90 degree to detect the both horizontal and vertical vibration signal.

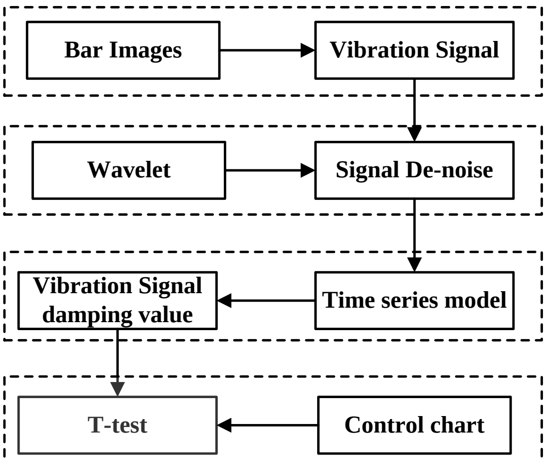

Figure 1. Framework of this paper.

The main work of this paper is finding out the relationship between vibration signal and piercing head condition, then extracting the feature to classify the different piercing head conditions on-line. The outline of this paper is listed as shown Figure 1. First, the original data will be obtained and de-noised by wavelet analysis method. Then the characteristics of the vibration signals are derived by time series analysis. The control chart is conducted on the characteristics to monitoring the conditions of vibration. At last, a real case study is given to demonstrate the proposed method.

2. Ease of Use

2.1. Piercing Head Faulty Analysis

The piercing heads have three kinds of failure modes: collapsing nose, sticking steel and cracking [9]. In this research, we only consider two failure modes, 'collapsing nose' and 'sticking steel' case.

'Collapsing nose' means the front part of piercing head have worm. In this case, the forward resistance of steel bar will increase largely, the steel bar horizontal velocity as showed in Figure 1 will reduce. But the roller's rotating speed is fixed and will not change, so the bar's rotating velocity will increase. The gap between and will be large than normal condition. In image signal, the steel tube vibration amplitude will increase and the frequency will change frequently. The signal damping values will increase.

'Sticking steel' means the surface of the kind of piercing head damaged by strong friction at high temperature, the piercing head will stick to steel tube, and the friction between tube and piercing head will increase. So will reduce and will increase. The steel tube vibration amplitude will reduce and the frequency will change frequently. The signal damping will increase due to the large bar friction.

Both piercing head faulty condition have the relationship with the steel bar vibration damping value. So the damping information can be a feature used to classify the piercing head condition.

Figure 2 shows the vibration signal extracted from images. The red color curves represent the camera 1 captured steel bar left and right edge movement. The blue color line represent the camera 2 captured steel bar up and down sides edge movement. It is easy to see that the data series can be divided into three sections, divided by the dashed line. The first section represents the bar begin to piercing, the second section represents the main process of bar piercing process, the third section represents the bar waiting to come out from the piercing area. The second section is more stable, so the data analysis mainly conducts on this data segment.

2.2. Data Pre-process

Wavelet analysis can be used to eliminate noise. Wavelet transform will produce a set of coefficients corresponding to different frequency with the signal behavior in time domain. The data pre-process will conduct based on these coefficients. If $f(x) \in L^2(R)$, then $f(x)$ can be expressed as

$$f(x) = \sum_{h \in Z} c_{l_o,h} \phi_{l_o,h}(x) + \sum_{l=l_o, h \in Z} d_{lh} \Psi_{lh}(x) \quad (1)$$

Where functions $\phi(x)$ and $\Psi(x)$ are the two basic functions, called scaling function and mother wavelet [10]. The $c_{l_o,h}$ and d_{lh} are called approximation coefficients and detail coefficients. If there is a signal $= (x_1, x_2, \mathrm{L}, x_N)$, the signal can be decomposed as $[C_d, D_d, D_{d-1}, \mathrm{L}, D_1]$, where C_d is the approximation coefficients, according to Mallat algorithm [11], D_d is the detail coefficients, d is the decomposition level. If the signal sampling frequency is f_s, the main frequency of the signal is f_0, then the decomposition level $d = \lfloor log_2(f_s/f_0) \rfloor$. It means the coefficients C_d and D_d containing the most part of the signal information. In this work, the signal frequency $f_0 = 1 \sim 50Hz$, the system sampling frequency is $f_s = 16000Hz$, then we can calculate the decomposition level to do wavelet transform on the signal. After obtaining C_d and D_d, the signal can reconstruct based on these coefficients. Thus, it achieve the data de-noise.

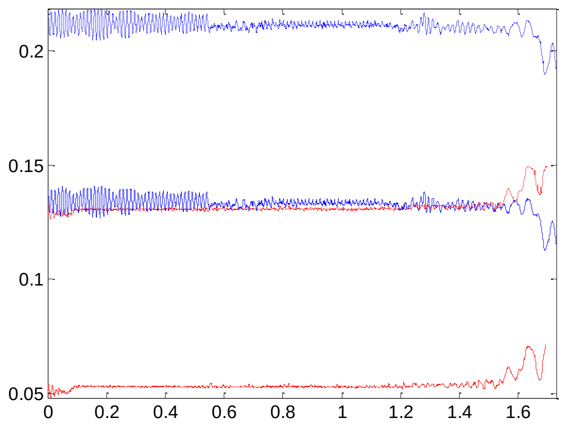

Figure 2. Vibration signal extracted from images.

3. Condition Monitoring AL Gorithm

As mentioned before, the vibration signal damping value can be a feature to classify the piercing head conditions. In this chapter, first, establish the time series model of vibration signal, then calculate the damping value based on this model. The 'Cumulative quantity' of each steel bar damping value will be the feature.

3.1. Modeling the Vibration Signal

If we consider the pixel coordinate as the time index, the gray value as the amplitude, the steel bar vibration signal will like a time series. Then the time series analysis can conduct on the vibration signal. But there are some challenges.

Challenge 1: Generally, we use $ARMA(n, m)$ model to model the vibration signal. But every steel bar vibration signal consists of about 90,000 pixel points. This means the vibration signal will have 90,000 points in time domain. So how to decide the m and n? How to check the model adequacy?

Challenge 2: The piercing process have many factors, the piercing head condition is only one of these factors. So damping result will have large error, and may hard to distinguish in some case.

For challenge 1, in time series theory, people usually use an $ARMA\ (n, n-1)$ model to model the vibration signal and check the model adequacy. If the model can't satisfy the adequacy condition, we need to change n to $n+1$ or $n-1$. We must do the work until the model can satisfy all adequacy conditions. But in some case, $ARMA\ (n, n-1)$ can't work well. George's work shows that $ARMA\ (n, n-1)$ will cause local optimization solution and $ARMA\ (2n, 2n-1)$ will be better [12]. In their research, represents the system degree of freedom. The bar piercing process can consider as a three degrees of freedom system, here $= 3$, so we choose $ARMA$ (6,5) model.

Some measures can take to avoid large error: 1) Choose the same length of data to analyze. The selected data segment will have the same data points, the analysis result will have less difference during different bars. 2) Divide the selected data segment into small segment to do analysis. Use $ARMA$ (6,5) model to analyze the signal in a 'window' and then moving the window along the vibration signal to do the same work in every new window. In this case, it can get a sequence of more accurate signal damping values. So we need to decide the selected data segment length L_o , the time window length L_w and moving average length L_m. 3) Use *F-test* to check the model adequacy in every window. If the model has r parameters and we want to test whether s of these are restricted to zero based on N observations, then the *F-test* can be represented as:

$$F = \frac{A_1 - A_0}{s} \div \frac{A_0}{N-r} : \ F(s, N-r) \qquad (2)$$

Where A_0 is the residual sum of square (RSS) of the unrestricted model, A_1 is the RSS of restricted model, $F(s, N-r)$ and denotes F *-distribution* with s and $N-r$ degrees of freedom.

3.2. Extracting Damping Information

After get the vibration signal model, we can calculate the signal damping. The following formula can used to calculate the signal damping [13]:

$$\zeta = \sqrt{\frac{[\ln(-X_2)]^2}{[ln(-\phi X_2)]^2 + 4[cos^{-1}(\frac{X_1}{2\sqrt{-X_2}})]^2}} \qquad (3)$$

Here, $X_1 = \lambda_1 + \lambda_2$, $X_2 = -\lambda_1\lambda_2$, and λ_1, λ_2 are the two conjugate complex characteristic roots. But in the time series model, it can gets 6 characteristic roots, $\lambda_i, i = 1,2,3,4,5,6$. Two pairs of them are conjugate complex roots and one pair of the roots are $|\lambda_i| \approx 1$. This means the vibration signal has seasonal or periodic patter. One of the constant characteristic root is $|\lambda_i| \approx 1$, it means the vibration signal has a trend. After we remove the seasonality and trend from the vibration signal, we can get only one pair of conjugate complex characteristic roots. Define these conjugate roots are λ_1, λ_2, we can use the formula (3) to calculate the vibration signal damping.

From the chapter third (A), the vibration signal divided into small 'windows'. If set the data segment length L_o, the 'window' length L_w, the moving average length L_m, then for one vibration signal, it has $n = \frac{L_o - L_w}{L_m}$ 'windows', this means there are n sub-models in single steel bar piercing process. Every sub-model can obtains one damping value, so it can gets damping values for each bar's vibration signal. If use a curve to combine all damping values, it can gets the 'damping curve' for every steel bar.

Figure 3 shows the two damping curves under different piercing head condition. The red curves represent the piercing head under 'collapsing nose' conditions. The blue curve represents the piercing head under normal condition.

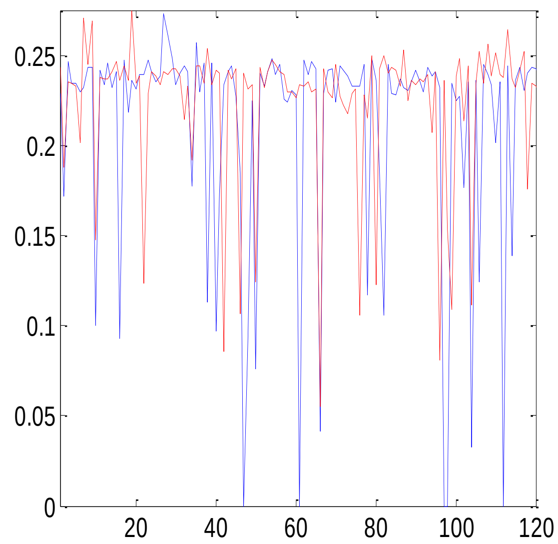

Figure 3. Vibration signal damping curve.

3.3. Abnormal Condition Identification

In this chapter, we will use *t-test* to identify the wear-out and normal piercing head. We define A_i as the i-th steel bar's 'damping curve' covered area, the 'cumulative quantity' is A_1, A_2, L, A_M , it represents the m-th bar's damping information in t-test. We can write the t-test as:

$$t = \frac{y_1 - y_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \qquad (4)$$

Where y_1 and y_2 are the sum of 'cumulative quantity' group values, s_1 and s_2 represents the standard derivation of 'cumulative quantity' group values, n_1 and n_2 represents the elements numbers of each 'cumulative quantity', here $n_1 = n_2 = m$. The *t-test* degree of freedom is:

$$v = \frac{(\frac{s_i^2}{n_i} + \frac{s_{good}^2}{n_{good}})^2}{\frac{1}{(n_i - 1)}(\frac{s_i^2}{n_i})^2 + \frac{1}{n_{good} - 1}(\frac{s_{good}^2}{n_{good}})^2} \qquad (5)$$

If the significant of *t-test* is α, the confidence interval is:

$$y_i \geq y_{good} - t_{v,\frac{\alpha}{2}}\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}} \qquad (6)$$

$$y_i \le y_{good} + t_{v,\frac{\alpha}{2}}\sqrt{\frac{s_i^2}{n_i} + \frac{s_{good}^2}{n_{good}}} \qquad (7)$$

We can calculate every steel bar's damping information and cumulative damping value. If this damping value is located in the confidence interval, it means this bar produced by the normal piercing head. If this damping value is out of the confidence interval, it means this bar produced by the wear-out piercing head.

4. Case Study

In this section, a real case of seamless tube manufacturing processes is studied to demonstrate the process monitoring algorithm. The description of the dataset will be introduced firstly, and the de-noise method and time series modeling method are conducted to analyze the vibration data. The statistical control is built to identify the abnormal condition.

4.1. Dataset Description

In this case, 60 bars of data obtained for the normal production condition and five different faulty conditions. For each bar, it can takes about 190 images. Each steel bar vibration signal can extracts from the steel bar edge images. The run order and the corresponding piercing head conditions are recorded. At the beginning of the experiment, 15 bars are pierced with new piercing heads. After these bars, five wear-out piercing heads are installed in turns, and 6 bars are pierced for each faulty condition. In total, there are 30 bars are pierced with faulty conditions. Finally, another 15 bars are pierced with new piercing heads. But the last 4 steel bars data are invalid, we have 56 bars data. We take the 1th to 30th bars as the training data, the 31th to 56th bars as the testing data.

4.2. De-noise

Wavelet transform is used to de-noise the signal. In this experiment, the camera scans 16000 lines in one second, it means it can obtains 16000 pixels along the bar forward direction in one second. So the sampling frequency is $f_s = 16000Hz$, the vibration signal frequency range is $f_0 = 1{\sim}50Hz$, the wavelet decomposition level $d = min\lfloor log_2(f_s/f_0)\rfloor$, then $d = 8$. Thus wavelet transform coefficients vector is composed by $[C_8, D_8, D_7, \mathrm{L}, D_1$. The 8-th level approximation coefficients C_8 and detail coefficients D_8 can represent most of the vibration signal information, so the vibration signal can reconstruct based on C_8 and D_8. Figure 4 and Figure 5 show the result. It proves that the wavelet transform can de-noise the vibration signal and remove redundancy information with little loss.

4.3. Modeling the Vibration Signal

The time series model is used to analyze the vibration signal. In this experiment, it sets $L_o = 60000$, $L_w = 2000$, $L_m = 500$, $n = \frac{L_o - L_w}{L_m} = 116$. For each bar vibration signal, it has $n = 116$ $ARMA(6,5)$ models. The *F -test* is used to check every model's adequacy. Here, we should know that in most cases, the $ARMA(6,5)$ model can fits vibration signal 'windows' well, but in some 'windows', it is not the best one, even it performs bad. Every vibration signal 'window' can calculate its damping value, so each bar has damping values.

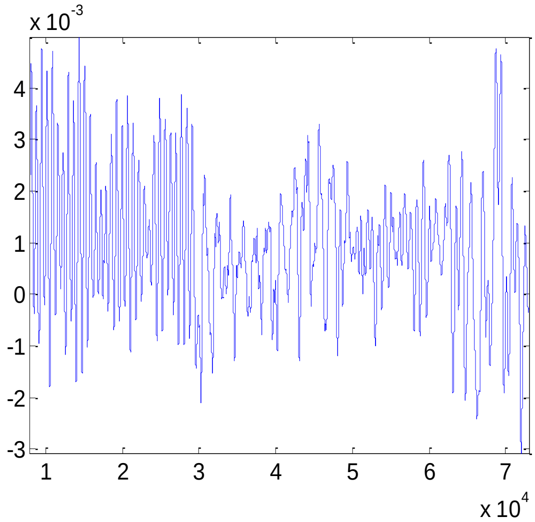

Figure 4. Original vibration data.

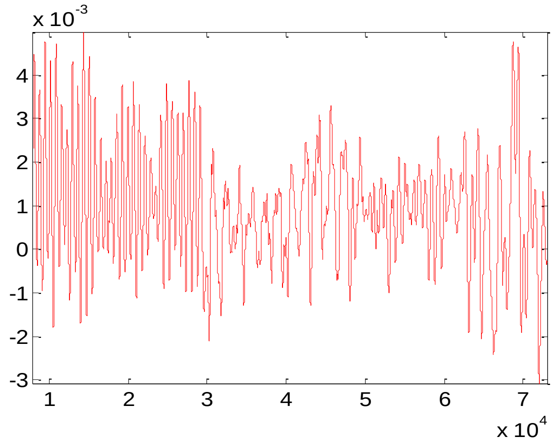

Figure 5. Data after de-noise.

4.4. T-test Result

'Cumulative quantity' mentioned before is used for *t-test*. Each vibration signal can obtain a group of damping values to consist 'cumulative quantity'. The expected identifying rate is about 90%, so the significant level sets as $\alpha = 10\%$.

Figure 6 shows the *t-test* result. The steel bars pierced with faulty piercing head only have 5 points located in the interval. Figure 7 shows the classified result using $\bar{X}$ control chart and steel bar vibration signal's own damping value. It interprets that the using of *t-test* and 'cumulative quantity' perform much better.

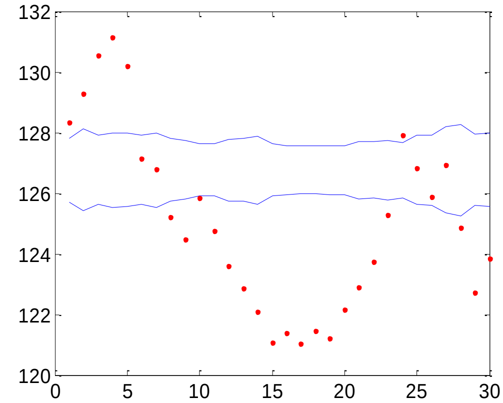

Figure 6. T-test of signal damping with faulty piercing head.

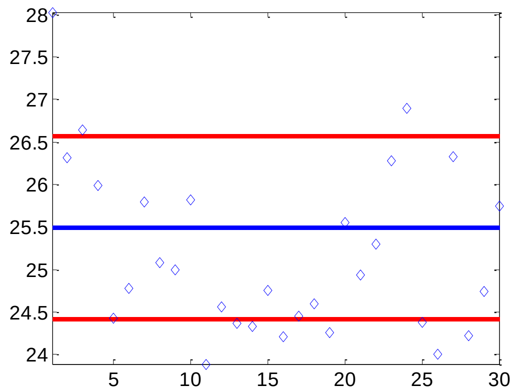

Figure 7. The result of $\overline{X}$ control chart.

5. Conclusion

This paper works on monitoring seamless tube piercing process and identifying the work condition of the piercing head. The seamless steel bar edge images had been captured by a special on-line detection system. The bar vibration signal can extracts from these images. The time series analysis had conducted to model the vibration signal and extract vibration signal damping values, the *t-test* and 'cumulative quantity' had been used to classify the normal conditional piercing head and faulty conditional piercing head.

In this project, there are some limitations. First, the data is not enough. It only takes the steel bar edge vibration images. The piercing head condition has compact relationship with process parameters, but there is no information about the piercing process parameters. The experiment only takes 60 steel bars vibration signal, the data size is too small. Second, the vibration signal damping value is just one feature of the piercing process. Other feature also can be developed to classify the piercing head condition. This work is the original research in monitoring the piercing head condition, and it still needs more future work.

References

[1] F. Hanguang; W. Jianzhong. Development and research on service life increasement of seamless steel tube piercing plug. *Research on iron & steel* 1996, 4(91), 56-60.

[2] B. Wang; D. Yi; W. Botao; L. Huiqun. Failure type analysis and studies on prolonging service life of piercer plug for seamless steel tube. *Materials Review* 2006, 20(6), 82-84.

[3] K. Mori; H. Yoshimura; K. Osakada. Simplified three-dimensional simulation of rotary piercing of seamless pipe by rigid-plastic finite-element method. *Journal of materials of processing technology* 1998, 80-81, 700-706.

[4] J. Jin; J. Shi. Feature-preserving data compression of stamping tonnage information using wavelets. *Technometrics* 1999, 41, 327-339.

[5] J. Jin; J. Shi. Diagnostic feature extraction from stamping tonnage signals based on design of experiments. *ASME Transactions, Journal of Manufacturing Science and Engineering* 2000, 122, 360-369.

[6] L.H. Yam; Y.J. Yan; J.S. Jiang. Vibration-based damage detection for composite structures using wavelet transform and neural network identification. *Composite Structure* 2003, 60, 403-412.

[7] T. Robbions. Signature-based process control & SPC trending evaluation press performance. *Metal forming* 1995, 44-50.

[8] J. Li; J. Shi. On-line seam detection in rolling processes using snake projection and discrete wavelet transform. *ASME transaction, Journal of Manufacturing Science and Engineering* 2007, 129, 926-933.

[9] S. Yuan-hua; L. Guo-zhen. Cross process theory and numerical simulation of production process for steel tubes. Metallurgical Industry Press of China, Beijing, 2001.

[10] I. Daubechies. Ten lectures on wavelets. Philadelphia: Society for Industrial and Applied Mathematics, 1992.

[11] S.G. Mallat. A theory for multiresolution signal decomposition: The wavelet representation. *IEEE Trans. Pattern Anal. March.Intell.* 1989, 11, 674-693.

[12] B. George; J. Gwilym; R. Gregory. Time series analysis: Forecasting and control (Fourth edition). John Wiley & Sons, Inc., Hoboken, New Jersey, 2008.

[13] M. Pandit; W. Shien-ming. Time series and system analysis with application. Krieger Pub Co, Malabar, FL, 1983.