CYCLIC WAVEFORM SIGNAL ANALYSIS FOR ONLINE MONITORING OF VALVE SEAT ASSEMBLY PROCESSES

Yong Lei, Kamran Paynabar, Judy Jin
Department of Industrial and Operations Engineering
University of Michigan
Ann Arbor, MI 48109

John Agapiou*
Manufacturing Systems Research Laboratory
General Motors R&D
Warren, MI, 48090

KEYWORDS

Cyclic Waveform Signal, Wavelet Analysis, Valve Seat Assembly, Process Monitoring, False Rejection

ABSTRACT

High dimensional cyclic waveform sensing signals are commonly used for manufacturing system monitoring. However, the lack of effective analysis methods in current monitoring systems causes major concerns in production in terms of monitoring performance. In this study, a generic methodology for analyzing cyclic waveform signals is proposed, and a false rejection problem in the engine valve seat assembly process was used as a case study to illustrate the proposed methodology. Performance comparison using production data has been conducted and the results have demonstrated the improvement on the false rejection reduction for potential productivity improvement.

INTRODUCTION

In modern manufacturing systems, cyclic waveform sensing signals are online collected from many processes, which conduct repetitive operations to produce products. To monitor the product quality and process condition, online monitoring systems are widely used to monitor the features extracted from the waveform sensing signals [Wang et al. 2008].

In industrial practice, simple statistical features are often used to characterize the signal profiles for process monitoring [ABC,1997; Grogan, 2002; Knussmann and Rose, 1993; Sah and Gao, 2008]. A shortfall of those methods is that a large amount of profile information contained in the waveform signals is not fully utilized. Moreover, the monitoring limits for these features used in production are often based on trial and error. As a result, the monitoring systems often suffer either a high false alarm rate or a relatively low detection rate for various faulty conditions due to variations in material's properties, manufacturing tolerances, etc.

Recent research efforts have been made to extract advanced features from the waveform signals. For example, in [Koh et al., 1995], wavelet features are selected using the Haar transform to detect and isolate faults. In [Zhou and Jin, 2005], PCA features are automatically selected using unsupervised clustering methods for fault diagnosis purposes. In [Mosesova et al., 2006], a mixed-effect model is used to approximate the signal profile and principal component analysis is conducted for data dimension reduction. The aforementioned literatures assume that the alignment index of the signal is available, e.g. signals are aligned based on other physical references, such as press crank angle in [Koh et al,1995; Zhou and Jin, 2005], or the alignment index can be found by using statistical functional registration methods to align the cyclic waveform signals [Mosesova et al., 2006].

The methods found in literature cannot be directly applied to our study for the following reasons. First, the signals in this study do not

* Corresponding author

have available alignment index. Second, when applying functional registration methods to align the waveform signals, important quality measures will no longer be valid and physically interpretable. Therefore, a new method for monitoring and diagnosis of cyclic waveform signals is highly demanded in industrial practice.

In this paper, a general cyclic waveform signal monitoring framework is proposed to improve the assembly process control for valve seat pressing operation in engine cylinder heads. In this framework, wavelets-based signal alignment and feature extraction algorithms are developed to enhance the monitoring and diagnostic capability of the currently used online monitoring system.

The rest of the paper is organized as the follows. Firstly, the engine valve seat assembly process is introduced. Secondly, the proposed cyclic waveform signal monitoring framework is presented. Thirdly, a false rejection problem in the engine valve seat assembly process is investigated as a case study. Next, the proposed waveform signal alignment and feature extraction algorithm will be discussed in detail followed by performance validation. Finally, summary and future work are provided.

VALVE SEAT ASSEMBLY PROCESS AND THE MONITORING SYSTEM

The valve seat assembly process in cylinder heads production is performed by a pressing assembly operation where a valve seat and guide are pressed into the seat counterbore pocket and guide bore respectively. As shown in Fig. 1, the seat counterbore and guide bore are machined in aluminum cylinder heads with a very narrow diameter tolerance to provide the amount of interference fit that is required to retain seats and guides in the head. The valve seats play a critical role in the longevity of the valves and guides. Once the counterbore in the head has been machined for the desired interference, the seat is installed by the pressing operation. Fig. 2 shows the valve seat pressing machine. The seat has a radius or chamfer side down and is lightly lubricated prior to being pressed to prevent cocking and scraping any metal off the head as it is being driven into position. If metal gets under the seat or if it is not pressed all the way, it will create a gap. A gap forms a heat barrier and/or causes erosion in the aluminum section. This, in turn, could lead to premature valve failure.


(a)
(b)

FIGURE1. VALVE SEAT COUNTER BORE POCKET AND VLAVE GUIDE BORE (A) AND CROSS SECTION VIEW (B)

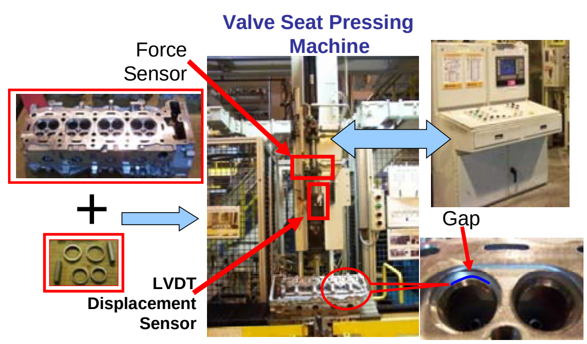

FIGURE 2. VALVE SEAT ASSEMBLY PROCESS AND THE MONITORING SYSTEM.

The product quality measures of this process are: (1) the gap between the seat bottom and the bottom of the pocket, and (2) the proper interference fit. However there is no automatic sensor technology available to online inspect the gap. Therefore, process monitoring is performed by online monitoring the load-displacement sensing signals for indirectly inferring the performance of pressing operation.

At each cycle of the seat pressing process, the force exerted on the ram and the displacement of the seat during pressing are collected using load cell and LVDT sensor respectively; this results in cyclic waveform signals corresponding to each cycle of repetitive pressing operations. In practice, press force (measured by load cell) is plotted against press distance (measured by LVDT); Fig. 3 shows a typical load-displacement profile for the valve seat assembly process after removing the initial load offset reading (to adjust the initial sensor preload to zero). In practice, four predefined features (depth, peak, work and force), as illustrated in Fig. 3, are used in the current online monitoring system:

- o Depth: maximum value of the distance transducer (extractable form distance vs. time signal).
- o Peak Force: maximum extracted value of the force transducer (extractable form force vs. time signal).
- o Work: area under entire extracted force vs. distance signal.
- o Force: maximum value of the force transducer before bottom out (extractable form force vs. time signal).

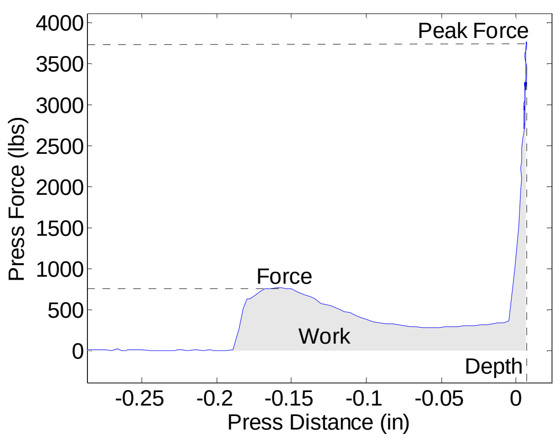

FIGURE 3. A TYPICAL LOAD-DISTANCE PROFILE OF THE VALVE SEAT PRESSING PROCESS.

The monitoring system monitors each individual feature separately by using multiple charts. If any of the features exceeds the inspection limits pre-set by the experts, the engine cylinder head will be rejected from the production line and be subjected to manual inspection before the cylinder head is scrapped. However, the high false rejection rate is a major concern in production since good quality cylinder heads are rejected from the production line from time to time, which causes considerable inspection cost and production loss. With the help of plant engineers, some of the rejected engine heads were manually inspected and the quality reports were recorded along with the rejection reports from online monitoring systems. The quality inspection records showed that 35% of the inspected rejections were falsely rejected. Therefore, there is a need to investigate this problem and improve the current process monitoring practice.

PROPOSED METHDOLOGY

As illustrated in Fig. 4, the valve seat pressing operation can be divided into three phases, which are (1) initial insertion; (2) slide insertion and (3) final insertion, according to their different pressing force characteristics involved. Therefore, the collected sensing data are high-dimensional non-stationary signals.

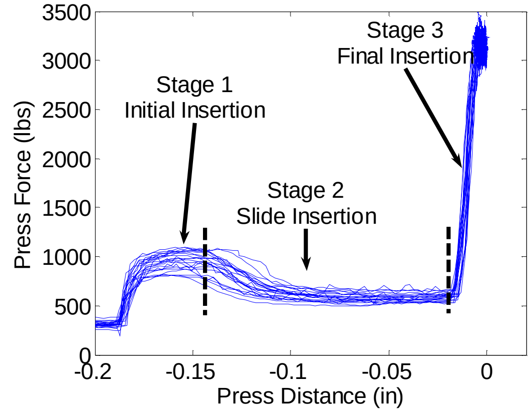

FIGURE 4. SIGNAL PROFILE AND THE PROCESS CHARACTERSTICS.

In this study, a new monitoring system framework is proposed to effectively extract the process information to improve the valve seat assembly process monitoring. As the flowchart diagram in Fig. 5, the cyclic waveform signal analyzer is the core component of the proposed monitoring system, which extracts low dimensional and physically interpretable features from the raw sensing signals, and uses these features for process monitoring and diagnosis purposes. The proposed cyclic waveform signal analyzer consists of the following major algorithms:

- o signal alignment algorithm,
- o signal segmentation algorithm,
- o feature extraction algorithm,
- o online process monitoring algorithm, and
- o fault classification algorithm.

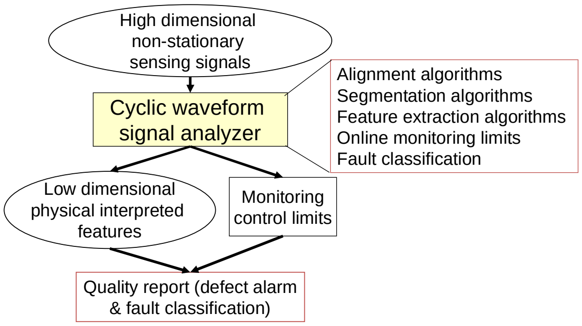

FIGURE 5. THE PROPOSED MONITORING SYSTEM FOR CYCLIC WAVEFORM SIGNALS.

The decision flow chart of the proposed waveform signal analyzer is shown in Fig. 6. At the first step, the sensor fault is identified and isolated before further signal analysis. At the second step, the monitoring features are extracted and the monitoring limits are constructed to detect possible defects.

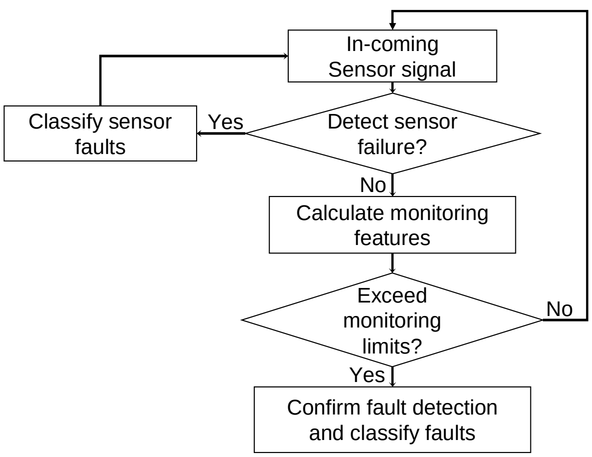

FIGURE 6. THE FLOWCHART OF THE DECISION PROCESS OF THE PROPOSED MONITORING SYSTEM.

The expected outputs from the proposed signal analyzer are defect alarm report and fault classification results if the same type of the fault had occurred before and recorded in the database. In this study, we focused on development of signal alignment and feature extraction algorithms.

INVESTIGATION AND IMPROVEMENT ON FALSE REJECTION PROBLEM

In order to identify the root causes of the false rejections, a careful evaluation of the rejected engine cylinder heads and the corresponding signals was performed. In addition, the sensitivities of the monitoring features that caused the rejections were analyzed.

Fig. 7 shows the contributions of different monitoring features on part rejections, where symbol DP denotes the rejects are caused by depth and peak force features. Symbol DF denotes the rejects are caused by depth and force features. As can be seen, 88.2% of the rejections are related to depth features. Therefore, our major effort is focused on the depth feature and its contribution to false rejections.

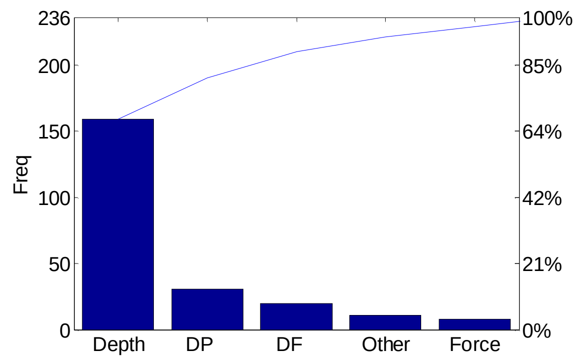

FIGURE 7. THE PARETO CHART OF REJECTIONS CAUSED BY THE MONITORING FEATURES.

In the current monitoring system, the depth feature is calculated using the maximum reading of the displacement transducer during the seat pressing process. However, this measure does not reflect the actual moving range of the seat inside the seat pocket. As a result, when a shift occurs at the relative position of the seat pocket to the reference position due to LVDT movement, the corresponding depth feature may exceed the inspection limits. Fig. 8 shows an example of two valve seat pressing data at the same seat pocket position. The inspection limits shown in the figure are lower and upper limits for "Depth" feature. Both engine cylinder heads satisfy quality requirements. However due to the misalignments of displacement signals, the depth feature of the rejected cylinder head exceeds the inspection limits, which resulted in the false rejection.

In order to extract effective features that measure the actual travel range of the seat inside the seat pocket, a new feature, "aligned depth", is proposed as shown in Fig. 9. The "aligned depth" is defined as the distance from the contact point, where the seat begins to contact the seat pocket, to the position that the seat stops. Therefore, the aligned depth is the true measure of the seat travel range inside the seat pocket. As can be seen, identifying the contact point is critical to the "aligned depth" feature extraction. Instead of using a predefined force threshold to find the contact point, which introduces additional variance due to manufacturing tolerances of the components for interference fit, a wavelet transform based contact point detection algorithm is proposed.

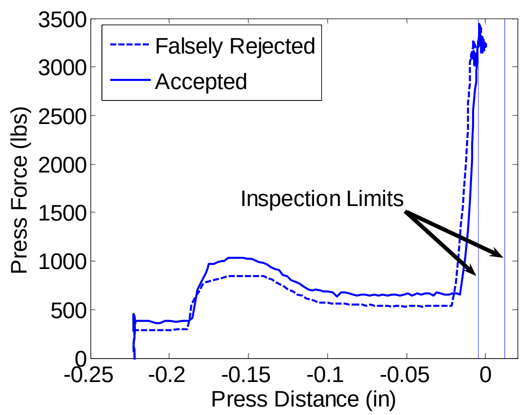

FIGURE 8. ILLUSTRATION OF THE MISALIGNMENT EFFECT OF DEPTH FEATURE ON FALSE REJECTION. IN THIS PLOT, BOTH SEAT PRESSING PRODUCED GOOD QUALITY ENGINE HEADS.

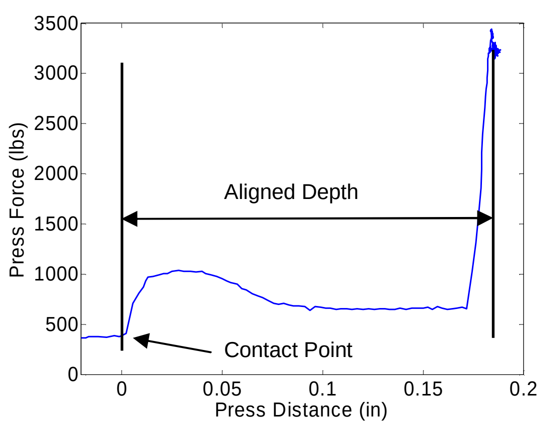

FIGURE 9. DEFINITION OF THE PROPOSED "ALIGNED DEPTH" FEATURE, WHICH IS THE DISTANCE BETWEEN THE CONTACT POINT AND THE MAXIMUM READING OF LVDT.

In the following sections, the detailed development of the contact point detection algorithm will be introduced. First, a wavelet transform is performed using the Haar transform [Coswami and Chan, 1999]. Second, the signals are aligned according to their contact points and the "aligned depth" feature is calculated according to the above definition.

.

Wavelet Analysis for Signal Alignment

In this research, the wavelet transform is used to help determine the contact points. In practice, the discrete wavelet transform (DWT) is used since the signal is discrete-time sampled in finite time span. For a square-integrable function $f(t)$, it can be approximated by the sampled signal vector $\mathbf{Y} \in \Re^{p}$. As shown in Eq. (1), the DWT is a linear transform of the signal using wavelet transform matrix $\mathbf{W} \in \Re^{m \times p}$:

$$\mathbf{C} = \mathbf{W}\mathbf{Y}, \tag{1}$$

where $\mathbf{C} \in \Re^{m}$ denotes the wavelet coefficients vector using j_0 level decomposition in DWT. $\mathbf{C} = [\mathbf{cA}_{j_0}, \mathbf{cD}_{j_0}, ..., \mathbf{cD}_2, \mathbf{cD}_1]'$, where $\mathbf{cA}_{j_0}$ denotes the approximate coefficients for decomposition level j_0, $\mathbf{cD}_k, k = 1,2,..., j_0$ denotes the detail coefficients for decomposition level k.

In this research, the Haar transform is used to detect the contact point of the valve seat pressing process because it has the following merits [Koh et al., 1999] to make it particularly attractive. Firstly, the Haar transform is an efficient transformation algorithm that can satisfy the computing speed requirement for the on-line monitoring purpose. Secondly, the Haar transform has the shortest support length among all wavelet basis functions, which provides the highest resolution in the time domain to get the accurate position of contact point. Thirdly, the Haar transform is effective on detecting the signal change points, which are closely related to the contact points of valve seat pressing operation.

Contact Point Detection

An automatic contact point detection algorithm has been developed to detect the contact point and align the signals according to its contact point for "aligned depth" feature extraction. The flowchart of the algorithm is shown in Fig. 10. Firstly, at j-th level ($j = 1,..., j_0$), the local maximums of the detail coefficients d_k^j are calculated within the given data window which depends on the application (k denotes the index of the detail local maximum coefficient). Secondly, at each decomposition level j , the time region support $[a_k^j, b_k^j]$ of each local maximum coefficient is obtained by using the algorithm introduced in [Jin and Shi, 1999], where a_k^j denotes the beginning time index that support the coefficient d_k^j , while b_k^j denotes the ending time index that supports the same coefficient. Thirdly, candidate contact points C_k can be found by calculating the overlapped time support region across the consecutive decomposition levels.

$$C_k \in \bigcap_{j=1}^{j_0} [a_k^j, b_k^j]. \qquad (2)$$

In this study, normally there will be two local candidate contact points in a force signal, which correspond to the points where the seat begins to contact the seat pocket and the seat reaches the bottom of the seat pocket respectively.

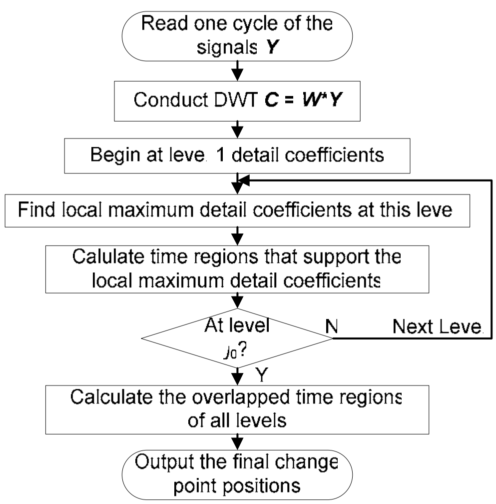

FIGURE 10. FLOWCHART OF THE CONTACT POINT DETECTION ALGORITHM.

Fig. 11 illustrates an exemplary analysis result of the contact point detection algorithm. For illustration purpose, two levels of the signal decomposition are used. Subplot (a) of Fig. 11 shows the one sample of the force signal vector, Subplot (b) shows the magnitude of the detail coefficients at different levels. As can be seen from subplot (b) in Fig. 11, at the first level, the time region that supports the first local maximum point is [4832, 4833]. At the second level, the region that supports the first local maximum point is [4832, 4835]. Therefore, the initial contact point is located at time index 4832. The advantage of this analysis is that it is robust to process noise and force variation under different parts since the proposed method is used to identify the signal change points that are truly reflect the contact point of starting the valve seat pressing operation.

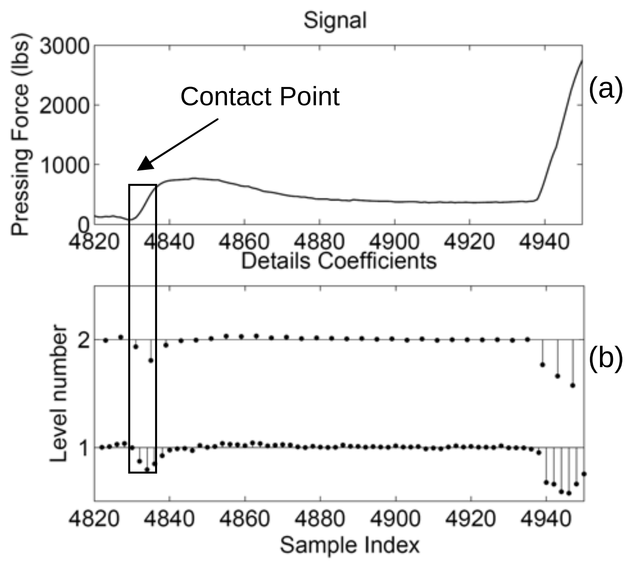

FIGURE 11. ILLUSTRATION OF WAVELET ANALYSIS OF A TYPICAL FORCE PRESSING SIGNAL.

PERFORMANCE COMPARISON OF THE PROPOSED "ALIGNED DEPTH" AND THE "DEPTH" FEATURES IN CURRENT ALGORITHM

Performance comparison has been conducted to demonstrate the effectiveness of the proposed feature on false rejection reduction. Fig. 12 shows the box plot of the "depth" feature of the falsely rejected and accepted engine cylinder head groups. From subplot (b) of the figure, it can be seen that the rejected "depth" samples on the right exceed the production inspection limits (UL and LL denote the upper and lower inspection limits for depth feature, respectively). However, these rejected parts, which are 35% of the total rejects, were false rejection because they all satisfy the manual quality inspection requirements.

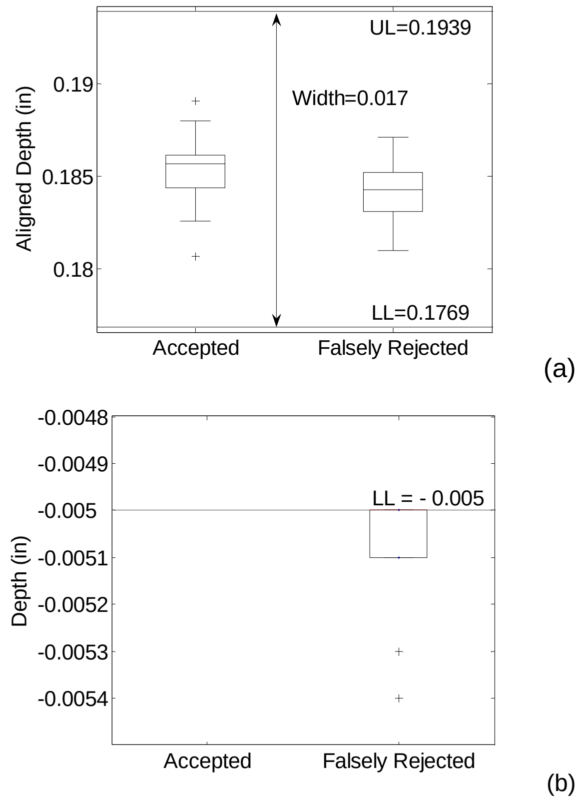

FIGURE 12. THE BOX PLOT OF ACCEPTED AND FALSELY REJECTED "DEPTH" FEATURE SAMPLES. SUBPLOT (B) IS THE LOCAL ENLARGED PLOT OF THE REJECTED SAMPLES

Statistical testing is also conducted for the "depth" feature between the falsely rejected samples and the accepted samples by using the following hypothesis test:

$$H_0 : \mu_{reject} = \mu_{accept}$$

$$H_1 : \mu_{reject} \neq \mu_{accept}$$

where μ_{reject} and μ_{accept} denote the mean values of the depth feature based on the falsely rejected samples and accepted samples respectively. The p-value of this hypothesis test is smaller than 0.05, which indicates that the distributions of the tested depth features are significantly different between the falsely rejected group and the accepted group although cylinder heads in both groups are all in good quality.

For comparison, the box plot of the "aligned depth" features of the two groups is also shown in Fig. 13. Noted that the "aligned depth" features in the falsely rejected group are all within the equivalent inspection limits. A similar statistical test is also conducted, which does not show the significant difference on the mean values of the aligned depth between these two groups. It can be seen that no false reject occurs since all the "aligned depth" features are within the equivalent inspection limits. By further considering other three features used in the current monitoring system, there are still 5% samples exceed other inspection limits although the aligned depth feature of these samples are all within the equivalent inspection limits. Therefore, it is concluded in this case study that 35% false rejects was reduced to 5% through the improvement of the monitored depth feature.

Moreover, as shown in Fig. 13, the current inspection limits are much wider than the sample range of the "aligned depth" features. Therefore, these limits can be set more effectively (for example, reduce the width of the inspection limits to more sensitively identify parts with a smaller gap than the current inspection limits, which can also further improve the detection performance of the current process monitoring system.

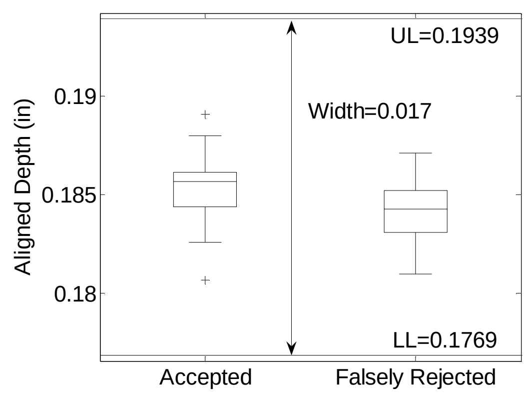

FIGURE 13. THE BOX PLOT OF THE ALIGNED DEPTH FEATURES. NOTED THAT NO FALSE REJECT OCCURS USING THE PROPOSED "ALIGNED DEPTH" FEATURE.

SUMMARY

A generic monitoring system framework is proposed in the paper, which aims to use online sensing waveform signals to effectively monitor the engine valve seat assembly processes. By investigating the current monitoring system, a severe high false rejection problem was found. A statistical hypothesis testing was conducted, which proved that the currently defined "depth" feature could not truly reflect the actual assembly operation condition due to the inevitable misalignments of sensing signals. For improving the monitoring performance and reducing the false rejects, a new “aligned depth” monitoring feature is first time proposed in the paper. For the purpose of extracting aligned depth features, a new signal alignment algorithm is proposed in the paper by aligning the signals using wavelet analysis of signal change points. The new algorithms have been validated through the real world production data. The results show that the proposed new algorithms can significantly reduce the false rejects of the total rejected parts. Moreover, the new algorithms also show the potential benefit to improve system detection power by reducing the variability of new monitoring features under the normal working condition. Some future work will be further investigated, for example, the development of fault classification algorithms to identify the root causes of the detected faults and conducting design of experiments tests to identify the diagnostic features for gap failures.

ACKNOWLEDGMENTS

The authors would like to gratefully acknowledge the financial support of the Engineering Research Center for Reconfigurable Manufacturing Systems (NSF Grant EEC-9529125) at the University of Michigan; General Motors Corp; and the NSF Grant: NSF DMI F0541750.

REFERENCES

ABC, (1997). “Total Tonnage Signature Decomposition for a Transfer/Progressive Die Process Analysis of Station-by-Station Test at A. J. Rose250 Ton Press,” NIST Advanced Manufacturing Program: NZS Technical Report, NZS-204.

Chui C.K. (1992), An Itroduction to Wavelets, Academic Press, Inc.

Coswami, J.C. and A.K. Chan, (1999). *Fundamentals of Wavelets*. Wiley.

Grogan, R., (2002), “High Speed Stamping Process Improvement Through Force and Displacement Monitoring.” Technical Report, Helm Instrument Company, Ohio.

Knussmann, K.D., and C. Rose, (1993). “Signature-Based Process Control (SbPCTM),” Signature Technologies Technical Reports, pp. 311-325.

Jin, J. and J. Shi, (1999), “Feature-Preserving Data Compression of Stamping Tonnage Information Using Wavelets,” *Technometrics,* Vol. 41, No. 4, pp. 327-339

Koh, C.K.H., J. Shi, and W. Williams, (1995). ‘‘Tonnage Signature Analysis Using the Orthogonal Haar Transforms,’’ *NAMRI/SME Trans.*, 23, pp. 229–234.

Koh, C.K.H., J. Shi, W. Williams, and J. Ni, (1999), “Multiple Fault Detection and Isolation Using the Haar Transformation, Part 1: Theory,” Journal of Manufacturing Science and Engineering., Vol. 121, pp 290-294.

Mosesova S.A., H.A. Chipman, R.J. MacKay and S.H. Stainer, (2006). “Profile Monitoring Using Mixed-Effects Models.” BISRG report RR-06-06, University of Waterloo.

Sah S. and R.X. Gao (2008), “Process Monitoring in Stamping Operations Through Tooling Integrated Sensing,” Trans. of NAMRI/SME Vol. 36, pp. 161-168.

Wang H., H. kababji, and Q. Huang (2008), “Monitoring Global and Local Variations in Multichannel Functional data for Manufacturing Processes,” Trans. of NAMRI/SME Vol. 36, pp. 469-476.

Zhou, S., and J. Jin, (2005), “Automatic Feature Selection for Unsupervised Clustering of Cycle-based Signals in Manufacturing Processes.” *IIE Transactions on Quality and Reliability*, Vol. 37, pp. 569-584.