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Identification of Influential Functional Process Variables for Surface Quality Control in Hot Rolling Processes

Nong Jin, Shiyu Zhou, Tzyy-Shuh Chang, and Howard Hsun-Hau Huang

***Abstract*—This paper focuses on surface quality improvement in hot rolling processes. A systematic method based on functional data analysis is developed to identify the key influential process variables. It provides guidelines for hot rolling process control and can also be expanded to generic scenarios of functional variable selection.**

***Note to Practitioners*—Surface defects have been a long-term troubling issue in hot rolling processes. In this paper, functional data analysis and rigorous statistical testing are integrated to identify the process variables that significantly influence the surface quality of the finished products. The results can provide guidelines for root cause identification and surface quality improvement in hot rolling processes.**

***Index Terms*—Functional data analysis (FDA), functional variable, hitting rate, hot rolling process, surface quality control.**

I. Introduction

Modern hot rolling process is highly automated and often monitored by many sensors. The large amount of sensing data (e.g., the billet temperature at a certain rolling stand, billet speed, and the flow rate of the cooling water) provide great opportunities for effective quality control of hot rolling processes [1], [2]. In this paper, we focus on the *surface quality control* issue. Surface defect is a weakness or stress concentration area of the bulk material and, hence, could cause catastrophic failure when the rolled product is in use. Therefore, it is highly desired to detect, reduce, and eventually eliminate the surface defects. Current surface quality control of hot rolling processes is very primitive. Indeed, the surface defects reduction has been identified as a major research thrust by American Iron and Steel Institute [3].

One major obstacle in the surface quality control is the limited knowledge of the root causes of surface defects, and thus even surface defects are detected, people often do not know how to adjust the process to reduce them. This paper presents a technique that can systematically identify the key influential process variables to the occurrence of surface defects by using the process sensing and surface quality data. Clearly, with this technique, useful insights and guidelines can be obtained for surface quality control.

Fig. 1 shows the measurements of a typical process variable, the billet temperature at the 21st rolling stand, for two billets. For each billet, the measurements are made at equally spaced locations (total

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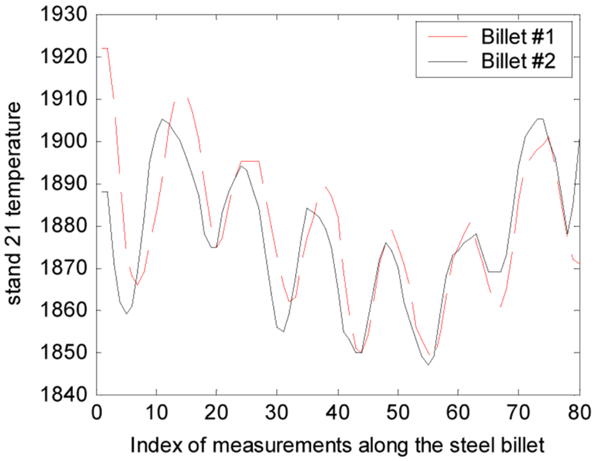

Fig. 1. Stand 21 Temperature signals of two steel billets.

80 locations in this example) along the steel billet. Since the process variable measurement for a billet is a vector as a sample of a functional curve, the process variables are called *functional variables* in this paper. Due to the inevitable process noises and errors, the process variables are always different for different billets, as illustrated in Fig. 1. This difference could be due to random disturbances and tend to be small. This difference could also be due to systematic root causes in the process and tend to be large. Intuitively, if a functional variable (e.g., "stand 21 temperature") is influential to the surface quality, then the samples of this variable from billets *with* and *without* surface defects will tend to have large differences because these two types of billets are usually produced under different working conditions. On the other hand, if a process variable is not influential to the surface quality, then the samples of this variable from the steel billets with and without surface defects will not exhibit significant differences. Thus, by comparing the samples of functional variables from billets with and without surface defects, we can judge if a process variable is influential or not.

To compare functional variables, the critical features of the function variable need to be extracted and compared. In this paper, this challenging problem is tackled using functional data analysis (FDA) approach. For each functional variable, a critical feature is extracted using a unified FDA approach. Then, the steel billets are grouped into two classes: the billets without surface defect, denoted as class A and the billets with surface defects, denoted as class B. The features of the functional variable extracted from those two classes are compared and the significance of the difference is determined through a rigorous statistical testing. A functional variable is said to be influential to the surface defects when its difference between these two classes is significant.

This paper is organized as follows. The procedure of influential process variable identification is presented in Section II. A case study of a real industrial dataset is presented in Section III to demonstrate the effectiveness of the developed procedures. Conclusion remarks and future works are discussed in Section IV.

II. Methods for Identifying Influential Process Variables

Our goal is to find out the key functional variables that are influential to the surface quality using the historical production data. Previous study [4] has shown that the surface quality in the hot rolling process varies significantly for different billet diameter and material grade. These two factors are usually specified by the customers and, thus, cannot be changed. Thus, the material grade and the billet diameter will be assumed to be fixed in this study. Section II-A provides a brief review of FDA techniques. The critical feature selection and the significance testing of the differences of the features are presented in Sections II-B and II-C, respectively.

A. Functional Data Analysis (FDA) of Process Variables

A straightforward method to analyze functional variables is to treat each element of a functional variable as an independent variable and use traditional linear regression techniques to model the relationship between each element of the functional variable and the surface quality. However, the dimension of the problem increases dramatically as the dimension of functional variable increases. One might think that the huge dimensional problem can be resolved by applying principal component analysis (PCA) for dimension reduction, and then choosing the first few principal components for further analysis. Unfortunately, our studies show that none of the first few principal components of those functional variables are significant to the surface quality. Obviously, the first few principal components fail to capture the critical information in the hot rolling data relevant to the surface quality. In PCA, the intrinsic smoothness of the variables is not considered: PCA assumes that all the measurements along the same steel billet are not linked together in any particular order. This assumption does not hold for the hot rolling data because all the functional variables are physical variables whose elements are bonded by their adjacent elements and cannot be arbitrary.

To solve this issue, FDA methodology can be applied. FDA method assumes that the measurements of a functional variable for each steel billet are sampled from an unknown smooth curve that can be estimated by nonparametric regression techniques. FDA is currently an active research area [5], [6]. The basic framework of FDA can be summarized as follows.

Equation (1) is a general model for the typical functional data. Y_{ij} is the jth component of the ith functional curve observation. The independent variable t_{ij} can be used to model either temporal or spatial measurements. There are n curves (e.g., a single curve for each billet) in total. Each observation is longitudinally (equally spaced) sampled at m locations

$$\begin{aligned} Y_{ij} &= f_i(t_{ij}) + \varepsilon_{ij} \\ i &= 1, \dots, n; \\ j &= 1, \dots, m, t_{ij} \in [0, 1] \end{aligned} \tag{1}$$

where f_i is an unknown smooth function that will be estimated by nonparametric regression, ε_{ij} are independent errors with mean $\mathrm{E}(\varepsilon_{ij}) = 0$ and finite variance $\mathrm{var}(\varepsilon_{ij}) = \sigma_i^2 > 0$. Compared with traditional least square model assumption $\mathrm{var}(\varepsilon_{ij}) = \sigma^2$, our model assumes that the variance of each individual curve can be different from each other, and thus is more flexible. The value of t_{ij} is scaled to be within the interval [0, 1] for the sake of easy interpretation. Any features that are identified by the functional curves can be directly interpreted as being located at its t_{ij} percentage along the steel billet length. An optimal estimator (denoted as $\hat{f}_i$) of function f_i can be obtained by minimizing

$$\frac{1}{m}\sum_{j=1}^{m}(Y_{ij} - f_i(t_{ij}))^2 + \lambda \int_0^1 f_i^{(r)}(u)^2 du, \quad \lambda > 0 \tag{2}$$

where

$$\hat{f}_i = \sum_{k=1}^{(r+2)/2} c_k x_k + \sum_{k=(r+2)/2}^{m} \frac{c_k}{1 + \lambda\gamma_{k-q}} x_k. \tag{3}$$

For the detailed definitions of each parameter, please refer to [7]. The parameter λ is called the smoothing parameter of the curve, which governs the balance between the smoothness of the curve and the goodness-of-fit on the data. When λ is large, the smoothness of the curve is emphasized, while for λ close to zero, the curve will be similar to the curve estimated by ordinary least square method. Rice and Silverman [8] proposed a systematic way to calculate an optimal λ by using a cross-validation score. However, in most cases, a subjective selection of λ is sufficient for analysis.

B. Latent Feature Extraction

An individual functional curve can vary in many forms (the variation of amplitude, phase, shape, etc.,). In general, it is not practical to compare two individual curves directly. By assuming that all the individual curves from the same working condition will be similar to each other and thus share a similar latent feature, the latent feature for that particular working condition can be estimated as the average (mean) curve of those individual curves [6]. For the steel billets without surface defects (class A), the average of the curves is called the mean curve of class A and can be calculated as follows:

$$\mathrm{MC}_A(t) = \frac{1}{n_A}\sum_{i\in A}\hat{f}_i(t). \tag{4}$$

The derivative of a mean curve can be defined as

$$\mathrm{DC}_A(t) = \frac{1}{n_A}\sum_{i\in A}\hat{f}_i^{(d)}(t) \tag{5}$$

where d is an integer number and n_A is the number of observations in class A. In this paper, only $d = 1$ is discussed. However, higher order derivative curves (especially for $d = 2$) might also be of interest in practice (e.g., accelerations of moving subjects). Similarly, $\mathrm{MC}_B(t)$ and $\mathrm{DC}_B(t)$ can be obtained for the billets with surface defects (class B). To study the functional variables in the hot rolling process, the *derivative of the mean curve* will be treated as the latent feature of the functional variable. The major reason to adopt the derivatives of the mean curve instead of the original mean curve is that based on the physical characteristics of the hot rolling processes, we know that the change speed of the values of a process variable, instead of the values themselves, impacts on the product quality significantly. Thus, the first derivative of the mean curve is a better choice. This method can be generalized to other manufacturing processes, where the change speed of the functional variable is of our primary interest. For a given functional variable and a historical dataset, a visual plot can be used to compare $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ by plotting them in the same figure. If $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ are very similar to each other, it is sufficient to conclude that the given functional variable has very little influence on the surface quality and, thus, should be ruled out as an influential variable.

The visual plot is very efficient to quickly rule out those noninfluential process variables if $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ almost coincide with each other. However, for those variables with visually different derivative curves, it will be subjective to conclude whether such difference is caused by the random sampling errors or actual systematic errors. A quantitative method is proposed in Section II-C to solve this issue.

C. Quantification of the Significance of the Difference

To compare the difference between $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ for a given functional variable, the difference between these two curves should be quantified. It is well known that the severity of unevenness in the steel structure tends to cause surface defects in the hot rolling process and one major cause of the unevenness is the fast change of the functional variables during the production. To utilize this important information, the *fastest* changing point of the process variables can be used to quantify the difference. Mathematically, the fastest changing point is corresponding to the largest point of the derivative curve of the functional variable. Thus, the difference between $\max(\mathrm{DC}_A(t))$ and $\max(\mathrm{DC}_B(t))$ could be used as a quantitative measure of the difference between $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$. The function $\max(\cdot)$ is to search for the largest peak *within* the curve. In general, the two ends of the functional curve will have very large variation due to the estimation error and, thus, should not be considered as a peak of the curve. An immediate question is: How large the difference is large enough to conclude that the functional variable is *systematically* different for two classes? To answer this question, we propose the following method.

The whole dataset is separated into two portions: the training dataset and the test dataset. The training dataset will be used to estimate the derivative curves, while the test dataset will be used to quantify the difference between the derivative curves. The derivative curves of two mean curves $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ can be estimated from the training dataset by the methods in Section II-B. For any observation U in the test dataset, an association index (κ) is proposed to quantify the likelihood of U having surface defects. The association index is defined as follows:

$$\begin{aligned}\kappa(U) = {}& \mathrm{abs}(\max(\mathrm{DC}_A) - \max(\mathrm{DC}_{A+U})) \\ & -\mathrm{abs}(\max(\mathrm{DC}_B) - \max(\mathrm{DC}_{B+U}))\end{aligned} \tag{6}$$

where for any given class C (either class A or class B), $C + U$ refers to a class that includes all the observations in class C and the new observation U. The expression $\mathrm{abs}(\max(\mathrm{DC}_C) - \max(\mathrm{DC}_{C+U}))$ actually measures how the maximum point of the DC_C curve will be affected by admitting the new observation U into the class. This quantity will tend to be small if the new observation U is very similar to the observations in class C. The function $\mathrm{abs}(\cdot)$ is to take the absolute value. The $\mathrm{abs}(\cdot)$ function is applied by assuming that the fastest increase and the fastest decrease of the process variables have approximately the same effect to the unevenness of physical properties of steel billets. Different weights can be assigned to improve this model if more industrial knowledge is available. Clearly, the association index given in (6) represents the similarity between the new observation U and class A versus the similarity between the new observation U and class B. The more the new observation U is different from class A, the larger the κ value.

For a functional variable that is influential to the surface quality, the difference between its $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ should be large. Thus, for a billet U with surface defects, the first term in (6) tends to be large and the second term in (6) tends to be small. This leads to a large κ value for this billet. Consequently, for an influential functional variable, the associated κ value is helpful in identifying the steel billets with surface defects. In other words, if the functional variable is influential, the selection of n billets based on the first n largest κ values should have larger probability to have surface defects than the n steel billets randomly picked from the dataset. On the other hand, if a function variable is not influential, then the corresponding κ values will tend to be random and not helpful in identifying the billets with surface defects.

A consequential question is: how helpful the κ value of a functional variable is enough to conclude that the functional variable is influential to the surface quality? To answer this question, the effectiveness of κ values can be quantified by comparing the following two billet selection schemes. Assuming there are N steel billets in the test set, the goal is to pick $n(n < N)$ steel billets that are more likely to have surface defects. Scheme I randomly picks n steel billets and scheme II chooses n steel billets with the first n largest κ values. We denote p_1 and p_2 as the proportion of steel billets with surface defects among n steel billets chosen by the two schemes. p_1 and p_2 are also called "hitting rate" of these two schemes. If a process variable is influential to the surface quality, its κ values will be informative to ensure that $p_2 > p_1$ is statistically significant. In summary, the comparison of these two schemes is equivalent to the following hypothesis test:

$$\mathbf{H}_0 : p_2 = p_1 \quad \text{vs.} \quad \mathbf{H}_1 : p_2 > p_1.$$

Fig. 2. An example of the image for the "checking" defect.

Scheme II is claimed to be superior to Scheme I if the test dataset tends to reject the null hypothesis. A Pearson χ^2 test can be used for this purpose. The χ^2 statistic can be calculated as follows:

$$\chi^2 = \frac{(p_2 n - p_1 n)^2}{p_1 n} + \frac{((1-p_2)n - (1-p_1)n)^2}{1 - p_1 n} = \frac{n(p_2 - p_1)^2}{p_1(1-p_1)}. \quad (7)$$

Under the null hypothesis (p_1 and p_2 are similar to each other), the χ^2 statistic should follow a χ^2 distribution with one degree-of-freedom. For a given p_1 and p_2 with $p_2 > p_1$, Scheme II is said to be significantly better than Scheme I if

$$p_2 > p_1 + \sqrt{\frac{\chi^2_{1,\alpha} p_1(1-p_1)}{n}} \quad (8)$$

where $\chi^2_{1,\alpha}$ is the critical value of χ^2 distribution with one degree-of-freedom. At the level of $\alpha = 0.05$, its value is approximately 3.84. If the fastest change of a process variable is critical to the surface quality, its corresponding hitting rate p_2 should be large enough to reject the null hypothesis and, thus, Scheme II will prevail. A functional variable is said to be influential to the surface quality if Scheme II prevails in the comparison.

This section proposes a general procedure to identify the process variables that are influential to the surface quality in the hot rolling process. The procedure will be applied to a real dataset from industry to demonstrate its effectiveness in the next section.

III. Case Study

In this case study, the surface defect of interest is called "checking" [3], as illustrated in Fig. 2.

A steel billet group with "Material Grade H1214" and "Billet Diameter 0.75" where many checkings have been historically detected has been chosen for the study. There are 754 steel billets with complete surface quality and functional variable measurements. The whole dataset will be separated into two portions: The training and test datasets include the first quarter (188 billets in total) and the other three quarters (566 billets in total), respectively. Among the training dataset, there are 163 steel billets that have no checkings (class A). The other 25 steel billets have checkings (class B). From the training dataset, for a given functional variable, $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ can be estimated by using FDA. These two curves can be plotted in the same figure to identify the process variables that do not have much influence on the surface quality. Fig. 3 shows such a figure for four functional variables. The horizontal axis of Fig. 3 is the relative location along the steel billet normalized by the billet length. Clearly, the derivatives of the mean curves for some functional variables (e.g., "NTM Entry Speed," "NTM Entry Temperature," etc.,) appear to be very similar to each other and these variables should be identified as noninfluential. The functional variables "flow rate of waterbox1" [Fig. 3(c)] and "stand 16 flow" [Fig. 3(d)] show noticeable differences between $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$.

Are both differences shown in Fig. 3 between the derivatives of mean curves related to the surface quality? To answer this, Pearson χ^2 tests is used to verify whether this difference between $\mathrm{DC}_A(t)$ and $\mathrm{DC}_B(t)$ of "flow rate of waterbox1" is significant or not. For this particular material grade and bar size, historical data show that the percentage of the billets with at least one surface defects is 15%, which means that if billets are randomly picked from a population, then with 15% probability a picked billet will have surface defects. Thus, we take 15% as the hitting rate of the random pick scheme. Association index is computed for each steel billet in the test dataset by using (6). In this example, we will choose $n = 150$ steel billets with the largest κ values. By checking with the surface quality measurements, there are 37 billets with surface defects. Thus, the hitting rate of Scheme II is $37/150 \cong 25\%$, which is a large improvement from the hitting rate (15%) of random pick scheme. Given $\alpha = 0.05$, the χ^2 statistic calculated by (7) is $10.065 > 3.84$, indicating that Scheme II is significantly better than Scheme I. Therefore, we may conclude that "flow rate of waterbox1" is influential to the surface quality. From (8), we can also calculate the minimal significant hitting rate ($p_2 = 20\%$) in order to claim Scheme II is significantly better than Scheme I when $\alpha = 0.05$ and $n = 150$. Similarly, we can apply the procedure to "stand 16 flow," where p_2, the hitting rate of Scheme II, is around 16%, which is less than 20% and, therefore, is not large enough to conclude that the functional variable "stand 16 flow" is influential to the surface quality.

From this case study, we have the following observations.

First, FDA provides a new technique in the modeling of the process variables in hot rolling processes. In this study, we successfully identified "flow rate of waterbox1" as an influential factor to the occurrence of checkings. This result has been validated by the plant engineers. The difference between the DC curves may provide intuitive guidance to the industrial practice. For example, "flow rate of waterbox1" is the first waterbox after the no-twist mill. This variable can be viewed as an indicator of how the steel billet is cooled down after it comes out of the no-twist mill. Obviously, the steel property will be greatly affected by how fast and where the water flows to cool down the steel billet and, thus, is deemed to be an important process variable. Fig. 3 also shows that under abnormal conditions (Class B), no-twist mill waterbox flow changes more dramatically than that of the normal conditions (Class A). It is highly likely that the physical property of the steel surface is weakened by the abrupt change of "flow rate of waterbox1" and, thus, causes the generation of checkings in the later phase of the hot rolling process. An immediate remedy is to investigate the no-twist waterbox and stabilize the waterbox flow to improve the surface quality of the steel billets.

Second, the hitting rate of Scheme II for "flow rate of waterbox1" is 25%, which improves the hitting rate from Scheme I by more than 60%. It is well known that multiple factors will contribute to the surface defects in the hot rolling process. It is very unlikely to reach an extremely high hitting rate by considering only one process variable. Due to the low hitting rate, this scheme cannot be used for quality prediction or classification purpose. However, this is not a limitation of our method. To a rolling steel company, it is much more valuable to identify the influential process variables than to predict the actual surface quality of the steel billets. With the existing industrial knowledge, a process variable can be quickly adjusted after it has been identified to be influential to the surface quality, and the visual plot obtained from our analysis may also provide the guidance for the process adjustments.

Third, in this paper, we only differentiate the steel billets into two classes: the class without surface defects and the class with surface defects. The class with surface defects could be further classified into multiple classes if the information for the severity of surface defects of each steel billet is available, which will definitely improve the accuracy of the method.

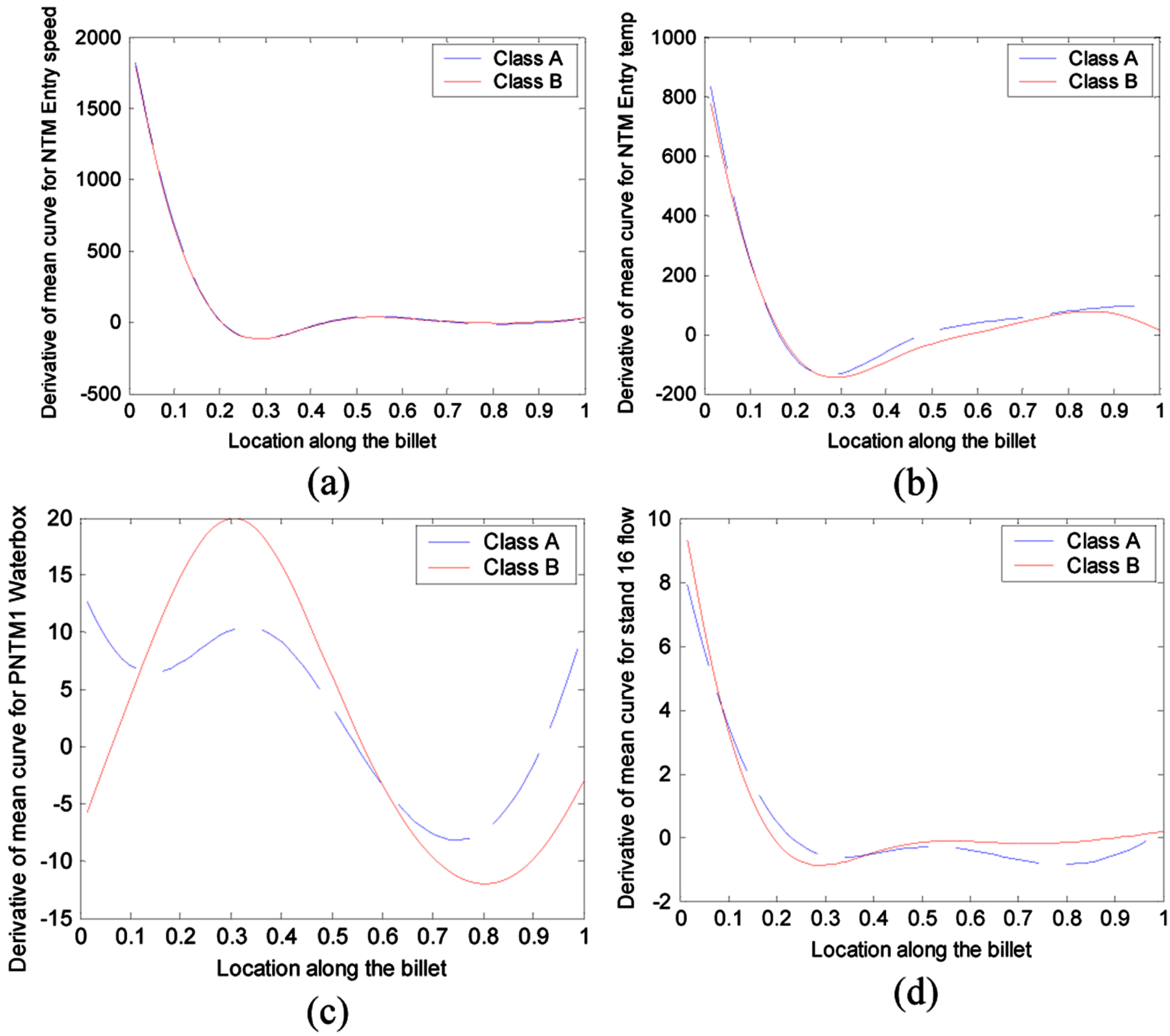

Fig. 3. Visual plots for four process variables. (a) NTM entry speed. (b) NTM entry temperature. (c) Flow rate of waterbox 1. (d) Stand 16 flow rate.

IV. Concluding Remarks

The goal of this paper is to identify the key influential functional process variables in hot rolling processes. Due to the high dimensionality and complexity of the functional variables, the traditional regression analysis and dimensional reduction techniques such as principal components analysis are ineffective. In this paper, we apply the FDA method to model these process variables. By integrating the rigorous statistical testing and an important piece of engineering knowledge that the fast change of a process variable tends to cause the surface defects in the hot rolling process, we propose a new quantitative method to identify the influential process variables to the occurrences of the surface defects. With the recently available surface quality measurements, this method provides a link between the surface defect and the influential functional process variables. A case study is implemented to demonstrate its effectiveness in practice. The developed method can provide guidelines for surface quality improvement of the hot rolling processes. This method can also be used for the identification of influential functional variables in other processes.

In this paper, we assume that the same number of measurements at the same locations along the billet for each steel billet. This is not a limitation to the proposed procedure. A simple translation method or a systematic curve registration method [5] can be used to "standardize" the observations before using our developed procedure if different numbers of measurements or unevenly spaced measurements are obtained for each steel billet. The choice of the sample size n for the test datasets will slightly affect the performance of the proposed procedure. Extremely small or extremely large sample size will make the procedure less effective. Although it is quite easy to choose a satisfactory sample size manually after a few screenings, it might be interesting to study the impact of sample size in a systematical way. This is our future research.

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Toward Autonomous Excavation of Fragmented Rock: Full-Scale Experiments

Joshua A. Marshall, Patrick F. Murphy, and Laeeque K. Daneshmend

***Abstract*—This paper presents the results and subsequent analysis of full-scale excavation experiments aimed at developing a practical understanding of how actuator forces evolve during excavation and how they relate to the interactions that occur between an excavator's end-effector and its environment. Our focus is on the excavation problem for fragmented rock, as is common in mining and construction applications. Based on an analysis of the experimental data, an example admittance-type autonomous excavation controller is postulated.**

***Note to Practitioners*—This paper was motivated by the problem of autonomously excavating a pile of fragmented rock using a load-haul-dump (LHD) machine, as is common in underground hard-rock mining. In this case, automation serves to remove human operators from hazardous environments underground, as well as to increase productivity by improving utilization and reducing wear on the excavator. In this paper, we take a first step toward the development of a system for autonomous excavation by performing experiments using a ten-tonne capacity machine to excavate fragmented rock taken from an underground mine in Canada. By measuring the status of various vehicle parameters during the excavation process, we reveal a useful characterization of this process based on hydraulic cylinder pressures.**

***Index Terms*—Admittance control, hazardous environments, mining automation, robotic excavation.**

I. Introduction

The invention of robotic excavation machines is of interest in the mining and construction industries, where the aim is remove operators from hazardous environments, improve machine utilization and productivity, and reduce maintenance costs [1], [2]. Autonomous (or robotic) excavation is also of interest in planetary exploration missions (e.g., on Mars), where excavation cannot be carried out by remote control [3], [4]. The research presented in this paper attempts to establish an engineering basis for autonomous excavation by studying the operational parameters of a full-scale excavator driven by experienced operators. Our focus is on excavation in fragmented rock, as is common in mining and construction, using a load-haul-dump (LHD) excavation machine (see Fig. 1).

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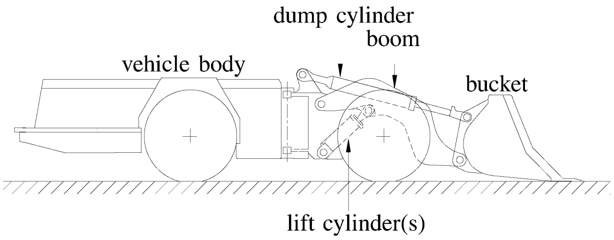

Fig. 1. A LHD machine.

What makes robotic excavation challenging is the nature of the bucket-rock interactions. Performance is strongly influenced by the conditions of interaction between the machine and its environment. For example, the resistance faced by a bucket as it attempts to penetrate a rock pile may vary significantly depending upon the properties of the media (e.g., density and hardness), the rock pile geometry, and the distribution of particle sizes and shapes. Indeed, it would be very difficult to predetermine the exact nature of future bucket-rock interactions prior to the execution of any particular excavation operation.

A. Studies in Autonomous Excavation

The autonomous excavation problem has received attention from several robotics researchers during the past two decades. For example, in [5], it was suggested that the trajectory of an excavator's bucket through the rock pile should not have priority in a devised control scheme, since the objective is to effectively fill the bucket, not to follow a predetermined path.

A number of researchers have proposed the use of machine vision as an enabling technology for autonomous excavation. In the work of Ji and Sanford [6], a laboratory-scale excavation system was developed that utilizes camera data for control and navigation. Petty *et al.* [7] constructed a scale-model system to mimic the motions of an LHD machine and developed different loading strategies depending on sensed information about the rock pile. Similar work by Takahashi *et al.*[8] employed a vision system to obtain images of the rock pile. In their approach, these images are used to plan the excavation task based on an estimated contour of the rock pile.

Under a pioneering Russian project, Mikhirev [9] formulated a set of ideas relating to force, motion, and trajectory control for various excavator mechanisms. Mikhirev advocated that measurement of the resistive forces to excavation could be used as a signal for automatic activation of the mechanism used of bucket rotation in the vertical plane (i.e., motions of the dump cylinder for the LHD in Fig. 1).

More recently, researchers from the University of Arizona [3], [10] have proposed an autonomous excavation system for front-end-loader style machines that uses bucket force/torque feedback, fuzzy logic, and neural networks for control. In their approach, a set of basic bucket action sequences, typically used by human operators, was compiled for use by the controller. A reactive approach, using fuzzy behaviors, was designed to act on force/torque data in order to assess the excavation status and determine an appropriate control input. Experimental results, using a PUMA 560 arm, were reported.