Other assignable causes in Jin and Shi (1999) resulted in oscillation of the tonnage signature that amounted to highly structured changes in $\gamma(x, x')$. Again, an algorithm that incorporates knowledge of the specific structure of the change can result in much more powerful detection. With limited, incomplete knowledge of the structure of the change, monitoring coefficients of a Fourier or wavelet representation of the profiles can sometimes be useful (see Chicken, Pignatiello, and Simpson 2009, and the references therein).

In general, premodeling potential assignable causes and their effects on the profiles may be quite difficult for many applications, requiring advanced engineering knowledge and resources. It will be useful to have better "Phase I" exploratory data analysis tools for discovering and empirically modeling the effects of typical assignable causes based on large historical sets of profiles, over which various assignable causes occurred. It will also be useful to have an approach that looks specifically for a small set of patterns that might be easily premodeled, while simultaneously monitoring for more general profile changes via a $T_{t,h,\lambda}$-like statistic. Apley and Lee (2010) developed a related approach for multivariate process data, but this will be difficult to extend to profile data.

I will close by thanking the authors for a thought-provoking article and a useful approach that I hope will find its way into SPC practitioners' toolboxes. I would also like to thank the editor, David Steinberg, for recognizing the merit of their work and inviting these discussions.

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Comment

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We thank the editor for the opportunity to be discussants and congratulate the authors on a stimulating article.

Profile monitoring is an area of growing interest and importance. The authors develop a methodology that meets many of the needs of practitioners. They propose a flexible model based on a solid statistical foundation. Nonparametric local regression methods and random effects form the core of their approach. The random effects provide a convenient way of modeling covariance between responses observed at different points along the curve, a common feature of functional data. The procedure is quick in Phase II and appears to readily adapt to a variety of profile shapes.

To organize our discussion, we attempt to outline a list of desirable attributes and questions we can ask of a profile monitoring methodology. After describing each, we examine Qiu, Zou, and Wang in the context of that attribute or those questions. Before presenting our list, we briefly discuss a motivating example.

Example. To help fix ideas and provide a broader basis for discussing desirable attributes, we briefly describe a profile monitoring problem familiar to us. Mosesova (2007) provides additional details. The data arise from a manufacturing process in which a ram force-fits a steel valve seat into an aluminum cylinder head. Every insertion yields a force–time profile, three of which are displayed in Figure 1. In this particular process, a feedback controller adjusts the force in an attempt to maintain constant ram velocity during insertion. After an initial rise in

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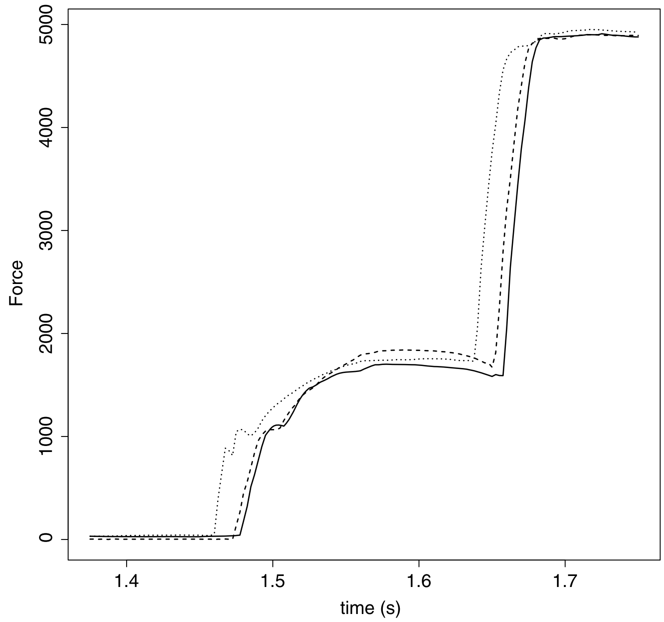

Figure 1. Three force–time profiles.

force corresponding to contact of the ram and the valve seat, the insertion force remains roughly constant as the seat is inserted. Once fully inserted, the force is increased in an attempt to maintain constant velocity. Every head has four cylinders, each with an intake and exhaust valve. The insertions displayed in Figure 1 correspond to three consecutive insertions of the intake valve in the same cylinder. Data are available on all eight valves for thousands of heads, ordered by time and date of manufacture.

1. FLEXIBILITY OF PURPOSE

The general goal of any process monitoring methodology is to detect changes that stand out above the common cause variation. Profiles can change in many ways, and ideally, the methodology can be adapted to be sensitive to prescribed changes. We may want to:

(a) Detect changes in particular features of the profile such as the maximum value, the location of the maximum, or the time point at which a specified event occurs (e.g., force begins increasing from 0 in Figure 1).

(b) Detect changes away from the "normal" profile toward one of several prespecified "bad" profiles. This might be accomplished via measures of closeness to representative profiles, or specification of a model in which some parameters identify departures toward the bad profiles.

(c) Detect unspecified changes in the mean profile.

(d) Detect changes in the variation (or covariance) of the residual profiles. This variation can be either functional ("wiggle") or noise (background randomness).

(e) Detect both persistent changes and single outlying profiles.

Purposes (c), (d), and (e) arise in conventional monitoring applied to a single response variate. Purposes (a), (b), and the idea of functional variation in (d) are unique to profile monitoring and arise from the functional nature of the data. Qiu, Zou, and Wang focus on purpose (c). Their methodology is designed to detect persistent changes of the mean profile. In Phase I, the authors obtain an estimate of the in control (IC) mean profile. In Phase II, at each observation point, they obtain an estimate of the current mean profile using an exponentially weighted moving average (EWMA) scheme combined with a local linear kernel estimate that allows for nonconstant variance at each point along the profile as estimated in Phase I. The monitoring statistic in Equation (11) is based on the differences between the estimates of the current and the IC mean profiles.

Although all the ingredients of process monitoring are present in the proposed chart, they are assembled in a nonstandard way. A more conventional approach is to calculate a discrepancy measure for each profile, and then use EWMA (or another charting method) to combine the discrepancies. For example, if we have a new profile $\mathbf{y}_i$ then we can define the discrepancy $(\mathbf{y}_i - \mathbf{g}_0(x_i))^T \boldsymbol{\Sigma}_i^{-1} (\mathbf{y}_i - \mathbf{g}_0(x_i))$, where $\boldsymbol{\Sigma}_i$ is the covariance matrix for $\mathbf{y}_i$ calculated using the results from Phase I. The embedding of the EWMA in the estimation process will make it more difficult to swap EWMA for other kinds of charting, such as cumulative sum (CUSUM) or Shewart charts. We feel it will be difficult to adapt the Qiu, Zou, and Wang approach to detecting single outlying profiles. In addition, practitioners may be more willing to use a new monitoring method if the elements of that method resemble existing strategies.

The need for multiple charts for different purposes is common in process monitoring where we are looking to detect changes other than persistent shifts in the mean, e.g., $\bar{X}$ and s charts for a single characteristic. Shewhart charts have greater power to detect a single outlying observation, while EWMA or CUSUM's are good for quickly detecting relatively small persistent changes or drifts. Ideally, in any methodology, there should be flexibility to detect a variety of possible process changes. The statistic being charted can be designed for specified departures from the IC condition and simultaneous charting used for combinations of departures. An important question (beyond the scope of this discussion) is to determine when the unconventional method proposed by the authors is better than the more conventional approach we describe.

Although the proposed method focuses on purpose (c), one may ask whether it can be modified to detect changes in (a) specific features, (b) departures in specified directions, or (d) unspecified changes in variation. Note, as suggested by the authors, inclusion of the weight function $\Gamma_1(s)$ in the monitoring statistic $T_{t,h,\lambda}$ in Equation (11) allows for increased sensitivity to detect changes in specified sections of the mean profile that correspond to features of interest. To detect specified departures, the mean Phase I curve $\mathbf{g}_0$ can be replaced by "bad" curves in the calculation of Equation (11), although this will require a change in control limits. An out-of-control process will be flagged by profiles close to the "bad" baseline. It is not clear how to adapt the proposed methodology to detect changes in the covariance structure (d).

2. FLEXIBILITY OF APPLICATION

Process monitoring is an inherently applied discipline. A successful profile monitoring method will see widest application if it can be adapted to a wide variety of contexts:

(a) Does the method require retooling for different profile shapes?

(b) What happens if the data are collected in subgroups?

(c) Within each profile, must observations be made at equally spaced time points? Must different profiles be observed at the same time points?

(d) Do the profiles need registration? For instance, the curves in Figure 1 cannot be easily monitored until they are aligned by an affine transformation of the "time" axis. Similar registration of the vertical (e.g., force) axis may also be required. In some circumstances, nonlinear time warping functions (Ramsay and Silverman 2005) may be required to align multiple points of interest along curves.

(e) How much of the procedure can be automated? Is computation in Phase II quick? In some applications, the data stream might be huge and fast, and even setting up the chart might require automation.

(f) Are there automatic or semiautomatic choices of tuning constants (e.g., EWMA weight λ or kernel bandwidth h)?

(g) Are covariates observed that will affect each curve? For instance, in our application, there can be cylinder and valve effects. While eight separate analyses (four cylinders by two valve types) can be carried out, a combined model with covariate effects (e.g., additive shifts for cylinder number and valve type) may increase power by borrowing strength across multiple data streams. In general, covariates can be fixed for each curve (as in our valve seat insertion example), or vary over time as the curve is observed.

The methodology of Qiu, Zou, and Wang does well at (a) and (c). The nonparametric curve estimation is very flexible, does not require equally spaced data, and should be applicable to any shape of curves. Registration (d) is not discussed in the article, although we suspect the authors are implicitly assuming curves are registered. The authors pay special attention to the design of Phase II modeling, gaining computation speed (e) by dropping random effects from the model and employing quick updating formulae. The choice of tuning parameters (f) is discussed, though fine tuning may still be somewhat of an art form. Tuning constants are difficult to set automatically since they will depend on the nature of the out-of-control condition one wishes to detect. For instance, in Figure 1, the out-of-control condition might be the shape of "wiggle" near time $= 1.5$ (requiring a small smoothing bandwidth) or the height of the flat section around time $= 1.6$ (requiring a large smoothing bandwidth). Practitioners may have little information about such a condition.

Subgrouping (b) is a common technique employed in univariate control charting. It also may be an issue in the AEC example in Qiu, Zou, and Wang where there was sampling of profiles from batches of AEC's. In the Phase I modeling or the Phase II charting, there is no explicit recognition that within batch variation may be different than between batch variation.

Qiu, Zou, and Wang did not consider adjustment for covariates (f). Such adjustments are not common in conventional monitoring. Extensions to this case will require that the locally linear model be augmented to include regression terms for the covariates with either fixed or random effects.

3. MODELING ASSUMPTIONS

All modeling requires assumptions, often to simplify computation or theoretical derivations, or to focus attention on aspects of the problem that are particularly relevant. In profile monitoring, three key questions are:

(a) Is there heteroscedasticity at different time points within a curve?

(b) Do correlations exist between measurements made at different time points on the same curve?

(c) Do dependencies exist between different curves?

Qiu, Zou, and Wang model heteroscedasticity (a) in both Phases I and II. In Phase I, they allow for within-profile correlation (b) via a random effects term. However, the correlations are not used explicitly for monitoring, as random effects are dropped from the Phase II model. Also, the weighted local likelihood before Equation (9) uses only variances (i.e., diagonals of the covariance matrix). Will it be straightforward to replace the sum in Equation (11) by a quadratic form that includes an inverted covariance matrix? We believe detection power might be enhanced by explicitly accounting for such covariances in Phase II.

The authors make the standard assumption that profiles are independent over time (c). However, autocorrelation is common, especially if 100% inspection is employed. Profiles sampled within the same batch or close together in time are apt to be more alike than profiles sampled from different batches or far apart in time.

4. PHASE I ISSUES

The availability of in-control data for Phase I modeling is a key component of any monitoring methodology since it enables calibration of statistics that are to be used for detection of process changes in Phase II. Considerations in Phase I include:

(a) Phase I calculations are done off-line providing plenty of modeling and computation time.

(b) The data used Phase I must be sampled from an IC process to enable accurate calibration. Methods are needed to check the Phase I data for outliers or other anomalies that should be removed before calculating the control limits.

(c) A combination of theory and analysis of Phase I data must provide control limits for use in Phase II.

Qiu, Zou, and Wang effectively exploit the availability of offline IC data (a) for estimating the IC mean profile and for developing Phase II control limits. They assume that IC data are available, but as noted in their discussion, provide no methodology to identify anomalies (b). Without such tools, it is difficult to imagine implementing the proposed chart in Phase II.

Calculation of control limits (c) with specified IC average run lengths (ARL's) is a key component of any monitoring procedure. Qiu, Zou, and Wang adopt an empirical approach that requires a large IC Phase I dataset. In determining the IC ARL's, the authors need to remove the effect of the initial conditions for the EWMA. As the EWMA weight for τ profiles in the past is $(1-\lambda)^{\tau}$ using $\tau = 30$ is unlikely to be sufficient. With $\lambda = 0.02$ (the smallest recommended value), $(1-\lambda)^{30} = 0.55$, which is the weight of the initial value in the EWMA statistic.

In Table 1, the authors compare random and fixed effect modeling. The fixed effect model does not have the desired in-control ARL. To make the comparison fair, we see no reason why the control limits for the fixed effects approach cannot be set to achieve the desired IC ARL.

5. PROPERTIES OF THE PHASE II ALGORITHM

In Phase II, we see the fruits of our labor with a method that will signal when the process goes out-of-control. We require:

(a) Simple and quick calculations as new profiles arrive.
(b) Good detection properties for relevant departures (as described previously under flexibility of purpose).
(c) Interpretability.

The authors demonstrate promising indications on all these criteria. The absence of random effect terms in Phase II of the model (as noted earlier) means that the Phase I and II models are different. We wonder whether such a difference will have any impact on detection properties (b). The proposed method is interpretable, in that the EWMA-smoothed curve that signalled the departure can be directly compared to the IC mean profile. However, the complex form of the model will make it difficult to pinpoint the cause of a signal if it is not evident in the displayed curve.

6. CLOSING THOUGHTS

The need for profile monitoring is increasing due to the availability of high-resolution data from many processes. This stimulating article shows how flexible nonparametric statistical methods can be used in a specific profile monitoring framework. The approach of Qiu, Zou, and Wang has many essential attributes that we feel a profile monitoring methodology should have and promises extensions in many directions.

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Comment

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I would like to congratulate Qiu, Zou, and Wang on an interesting and innovative article that addresses a fundamental profile monitoring problem in statistical process control (SPC). I think this is a timely discussion because there is an urgent need for SPC techniques in various industries (not only in manufacturing, but also in service) that can handle complex functional monitoring and surveillance on a real-time basis. The proposed methodology focuses on the single covariate case, but it should be possible to extend it to a more practical case with multiple covariates. In my discussion I will focus on the profile monitoring cases with high-dimensional multiple covariates.

Due to the technological progress in hardware and software, most companies and organizations record and process huge amounts of data about production, business transactions, and service operations. These data streams contain very useful information that can be extracted through data modeling, characterization, monitoring, and forecasting. To remain competitive, it is important for organizations to develop enterprise systems that allow managers to characterize relationships among performance and variables and to detect and prevent abnormal activities in operation.

Statistical monitoring and surveillance was widely recognized as an important and critical tool for detecting and identifying abnormal behavior (Tsung, Zhou, and Jiang 2007). Conventional approaches such as using statistical process control (SPC) techniques for system monitoring and surveillance often assume that the state of a system can be represented by a single random variable or a random vector of low dimensionality. However, many systems are far more complicated and

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