3-2007

Real-Time System Identification for Impact-Based Part Positioning

Laine Mears
Clemson University, mears@clemson.edu

Jeannie Falcon
National Instruments Corporation

Real-Time System Identification for Impact-Based Part Positioning

M. Laine Mears[1] and Jeannie Falcon[2]

[1]International Center for Automotive Research, Clemson University, Clemson, SC USA
[2]National Instruments Corporation, Austin, TX USA

Abstract
Simplified part positioning in manufacturing has been achieved using pushing or tapping actuation in place of more complex pick-and-place systems. However, positioning by impact introduces a new source of uncertainty: interfacial frictional effects of sliding, which can result in an uncontrollable and often poorly-predictable actuation distance. The described work provides a friction-based dynamic model of the sliding distance after impact that is used to predict static friction characteristics. A prototype system is simulated and validation data used to improve the model. A control algorithm is also described, tested and validated over a range of actuated masses.

Keywords:
Friction, Positioning, Impact

1 INTRODUCTION

Motion control of frictional systems has been extensively studied due to inherent difficulties of completely modeling and compensating for nonlinear frictional effects. Such effects include description of force in the transition region from static to nonzero velocity (*stiction*), hysteresis or directionality of friction forces, and time- and position-dependence of static friction effects. Poor modeling of such effects in motion systems can lead to *limit cycling* behavior, whereby desired system state is continually overshot without convergence.

A number of friction models and compensation schemes have been developed to describe these effects in the context of positioning. It is important to understand that friction is a time-varying phenomenon, and can change dramatically within a system through wear or introduction of contaminants. It is therefore desirable not only to provide an accurate control model, but also to continuously quantify the parameter(s) of the friction model through a system identification scheme. A result of this identification is the ability to track frictional state with time and derive process knowledge from this information.

This work presents implementation of a real-time friction identification scheme for sliding in an impact-based positioning system, and an optimal state estimation scheme for tracking friction in time and material domains to provide additional process diagnostic knowledge. Subtle changes in friction can be detected and fed back to the machine controller to provide additional process knowledge. Simulated case studies are presented.

2 SMART MACHINING

The concept of smart machining incorporates the need for system intelligence to improve reliability as applied to both output variance consistency and equipment health. Sensor information is used to model unobservable parameters, and subsequently detect changes to predict and improve cycle performance or long-term operational dependability. This identification and tracking is envisioned to occur in real-time, rather than by post-process discrete part evaluation as in traditional quality control methods.

One instance of parameter modeling and identification is in friction model classification, where parameters cannot be directly measured, and are typically time-variant. Examples of sensing and derived friction identification appear in the literature [1], [2]. However, these typically require additional sensing capability or have not been directly applied to manufacturing systems. In this work, we describe friction identification using single axis force and positioning sensing, and demonstrate it in a pertinent manufacturing application - positioning by sliding.

3 IMPULSIVE ACTUATION

3.1 Motivation

The majority of precision positioning of workpieces in manufacturing is accomplished by robotic pick-and-place equipment, positioning stage tables, or by manual human actuation. Each of these methods requires either high capital investment or high operating cost, resulting in a high specific positioning cost (cost per part positioned). An alternative method explored in the past 2 decades is positioning by sliding a workpiece using a single lateral force with position and force feedback. This method results in less expensive positioning, and can achieve accuracy comparable to robotic methods if friction is well understood. Positioning by sliding was dynamically evaluated by Peshkin [3], and constraints and stability quantified by Lynch et al. [4], [5].

An aspect of friction knowledge for the positioning system is accurate quantification of friction model parameters. A number of friction models have been proposed in the literature and are comprehensively surveyed by both Olsson et. al. [6] and Åström [7]. Additionally, friction models departing from classical models have been proposed by Canudas de Wit [8] and most recently by Makkar [9].

In this work, we use a classical piecewise model of the form

$$F=\begin{cases} F(v)\,, & v\neq 0 \\ F_e \,, & v=0 \; and \; |F_e|<F_S \\ F_S \,, & otherwise \end{cases} \tag{1}$$

where F(v) is the force required to maintain a constant velocity, F_e is the static actuation force and $F_S = \mu_s mg$ is the static friction breakaway force. F(v) is modeled as

$$F_C = \mu_k F_N + k_v v \tag{2}$$

where F_C is the dynamic friction force, μ_k is the dynamic friction coefficient, F_N is the normal force and k_v is the proportionally constant of force resistant to velocity. Simultaneous identification of μ_k and k_v through decrement analysis has previously been treated by Feeny and Liang [10]. In this work the objective is to simply predict the static friction parameter μ_s.

3.2 Impulse Planning

A one-dimensional model of the impulsive system with friction is shown in Figure 1, with friction simulated by (1).

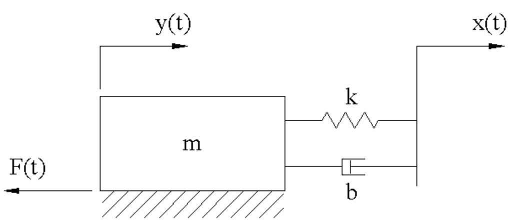


Figure 1 - Idealized Impulsive System Model

The governing system equation is given by

$$\begin{aligned} &m\ddot{x}+b\left(\max\left(\dot{y}-\dot{x},0\right)\right) \\ &\quad +k\left(\max\left(y-x,0\right)\right)=-F\left(t\right) \end{aligned} \tag{3}$$

and is solved using a modified Euler numeric scheme. Parameters of the prototype system are determined and validated through experimental testing.

3.3 Derived Parameters

Simulated position and force response plots of constant-velocity actuation are shown in Figure 2 and Figure 3 respectively.

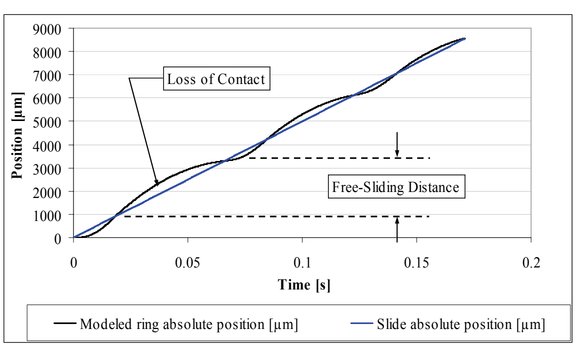


Figure 2 - Simulated Position Response, m=18.9 kg, v=3000 mm/min

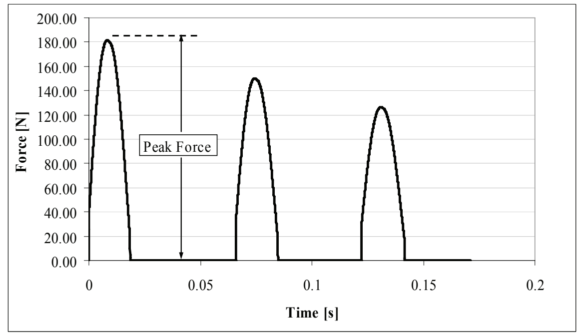


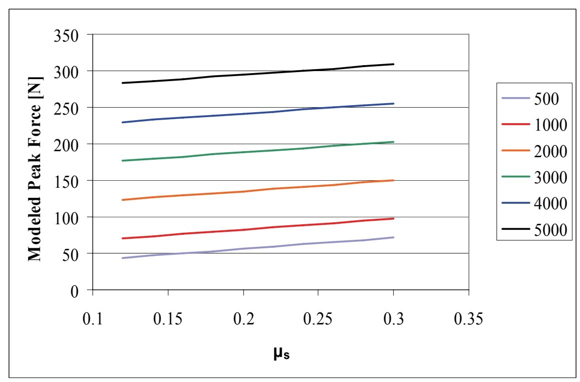
Figure 3 - Simulated Force Response, m=18.9 kg, v=3000 mm/min

For each plot, a characteristic dimension is defined, which is to be used in the subsequent friction predictor model. Free-sliding distance d is defined for position response as the distance the part travels from loss of contact with the actuator until coming to a stop under the influence of friction. For force response, the peak force F_p is defined as the maximum force observed over the actuation.

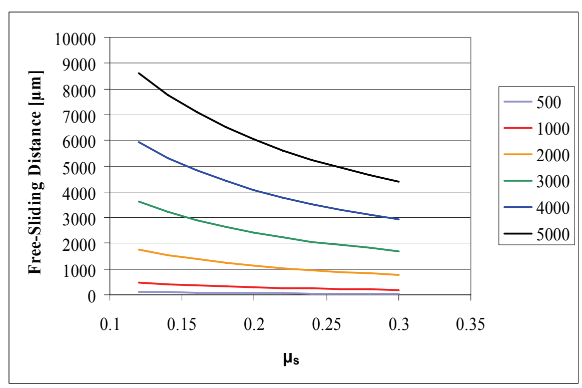
4 FRICTION PREDICTION

4.1 Approach

The peak force and free-sliding distance are dynamically modeled across a range of friction parameters and velocities as shown in Figure 4.



(a)



(b)

Figure 4 - Friction-Based Curve Families by (a) Peak Force and (b) Free-Sliding Distance

These models are inverted and fit through a least-squares technique to a static friction coefficient first-order predictor function in actuation velocity v and peak force F_p

$$\mu_s = \frac{F_p - 0.0529v}{146.2} \tag{4}$$

and a second-order predictor in actuation velocity v and free-sliding distance d

$$\mu_s = 0.3415 - \sqrt{\frac{d - 0.00041v^{1.8997}}{0.07379v^{1.6428}}} \tag{5}$$

The models are combined through a gradient-weighted estimator of the form

$$\mu_s^* = \mu_{s,force} \frac{\frac{\partial F}{\partial \mu}}{\frac{\partial F}{\partial \mu} + \frac{\partial d}{\partial \mu}\frac{\Delta F}{\Delta d}} + \mu_{s,dist} \frac{\frac{\partial d}{\partial \mu}\frac{\Delta F}{\Delta d}}{\frac{\partial F}{\partial \mu} + \frac{\partial d}{\partial \mu}\frac{\Delta F}{\Delta d}} \tag{6}$$

which gives higher weight to the predictor with greater model sensitivity to changes in the friction parameter.

4.2 Results

Friction identification results are determined for a range of actuation velocities of an 18.9-kg turned steel part sliding on carbide. The gradient-weighted combined estimator (6) is found to give an average error of 3.6% at velocities above 3000 mm/min.

5 REAL-TIME SYSTEM IDENTIFICATION

Given the result of the described friction estimation scheme, it is next undertaken to implement it in a real-time actuation system, and to track frictional behavior of the system in time and material domains.

5.1 Implementation

The described method is implemented on the prototype system shown in Figure 5.

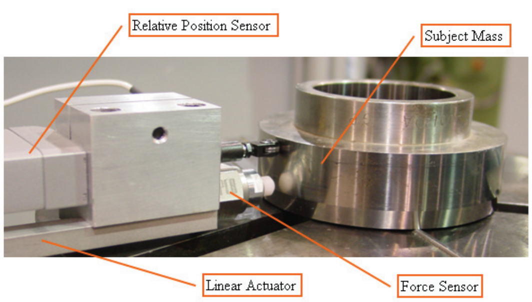


Figure 5 - Friction Measurement Test Setup

The system hardware consists of a linear actuator with precision positional and force feedback. The force is sampled using a filed-programmable gate array (FPGA), which allows high achievable sampling rate (up to 1 MHz), and subsequently more data for modeling. Data acquisition for force is implemented on the FPGA board, and used to identify the static friction parameter in real time by the foregoing scheme.

6 FRICTIONAL DIAGNOSTICS

Real-time identification of sliding friction is important for maintaining the accuracy of sliding control systems in positioning. However, it also enables a new domain of process characterization – *frictional diagnostics*. The frictional state of a sliding system can be tracked and estimated in different domains to identify gradual or event-based changes in state.

Two main sources of change in frictional systems are degradation with time and influence of material transport across system boundaries. Abrasive or contamination-based wear can be considered a time-dependent phenomenon, while transport effects are strictly material-based. These effects can be separated and tracked in multiple domains to identify sources of change.

These effects are simulated with Gaussian-distributed noise to represent uncertainty in the friction estimation scheme. The true friction of the process is estimated using a variance-based optimal estimator.

6.1 Optimal Estimation of Frictional State

Friction prediction using a simplified estimator is inherently subject to variability which must be accounted for in estimating the true frictional state of the machine. One estimation technique that is shown to be optimal for systems with Gaussian-distributed disturbance is the Kalman filter [11]. This technique accounts for both true process fluctuation and inherent error in measurement.

6.2 Friction Identification with Time

Tracking and estimating friction in the time domain allows identification of long-term effects on machine surfaces. Phenomena that are essentially independent of material effects, such as contamination, wear or machine element degradation can be identified and potentially compensated for over long term operation in order to remove cycle variability induced by variation in friction over time.

A simulation of friction identification data and the optimally estimated state using Kalman filtration for a system undergoing continuous wear is shown in Figure 6.

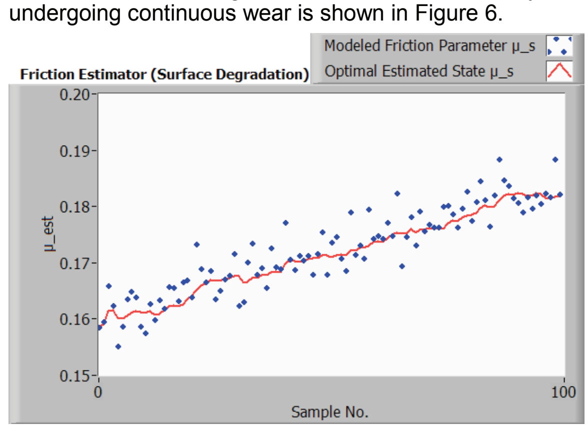


Figure 6 - Simulation of System Degradation Effect on Friction Model Parameter

The system can be seen to change over time by the optimal estimator. Such a change can be continually compensated in a positioning system through motion controller modifications. Alternatively, the wear state can be monitored and an alarm actuated above a threshold limit.

6.3 Friction Identification with Material Batch

With additional data on material changes (batch or material type), material-specific frictional effects can be separated and identified. In Figure 7, simulation shows a detectable system state change with a coincident material batch change.

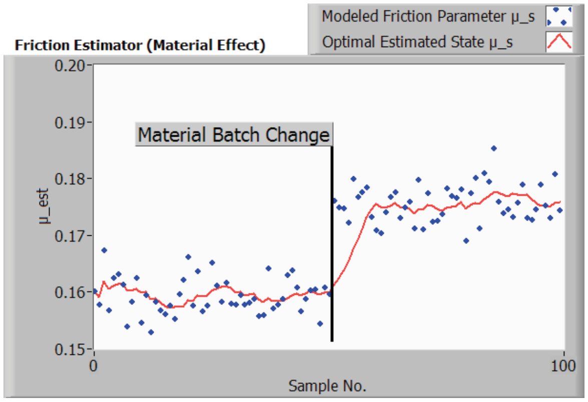


Figure 7 - Simulation of Friction Estimation Process Shift with Material Change

Such state shift can be automatically detected and compensated to provide identical system output for varying material batches.

6.4 Friction Identification over Machine Cycle

In addition to long-term frictional variation, the friction during a single machine cycle can be identified quasi-continuously using high rate sampling and real-time estimation. This allows for establishing a frictional signature of machine operation over the course of a single cycle as simulated in Figure 8.

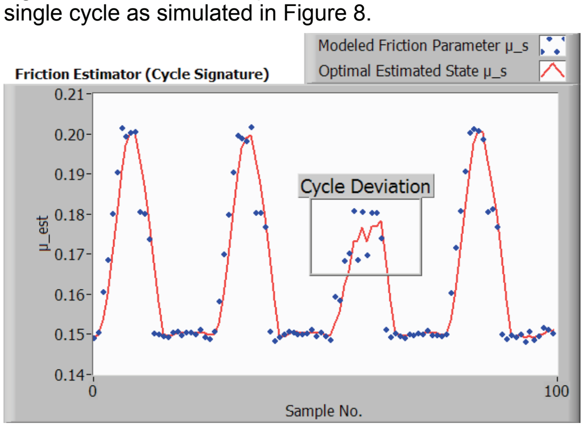


Figure 8 - Simulation of Friction Signature Showing Deviant Cycle

Variation in the signature signal enables detection of individual part differences, which can then be fed back to the operation in real time as an additional control variable. Direct control of friction adds a new dimension of process intelligence obtained with existing sensor technology.

7 SUMMARY

This paper reviews a friction identification scheme based on maximum force encountered and sliding distance of a part positioned by impulsive actuation. The method is implemented on a real-time control system

The described estimation scheme can be applied to friction identification in time, material, and cycle domains to identify and compensate for friction-based cycle variations as well as long-term frictional changes in the manufacturing process. The derived process knowledge inferred from friction estimation can be used as both a control feedback and diagnostic tool for reducing variability, improving operation efficiency and enhancing intelligence in manufacturing systems.

The results of this work are directly implementable in part positioning for machining, and it is anticipated that the techniques described can be later extended to polar positioning devices such as simple arms subject to friction in the rotating joint.

The described system incorporates an FPGA for force and position sampling due to the high sample rate achievable. It is anticipated in the future that the optimal estimation filtering and motion control routines will also be migrated to the FPGA for reduced loop time and implementation of more sophisticated motion controllers.

8 ACKNOWLEDGMENTS

We extend our sincere thanks to National Instruments and The Timken Company for providing financial support and equipment for this project.

9 REFERENCES

[1] Miyazaki, N., Ueno, S., Tamaki, H., Hironaka, R., Yamaguchi, T., Li, C., 2001, Development of High-Quality Multi-Axial Sensing System (MASS) for Direct Measurement of 4 Directional Forces and Coefficient of Friction in Real Time, SAE 2001 World Congress, Detroit, Michigan.

[2] Shiraishi, M., Sumiya, H., Aoshima, S., 2003, Friction Control in Positioning by AE Detection, Proceedings of the IASTED International Conference on Intelligent Systems and Control : 75-80.

[3] Peshkin, M.A., Sanderson, A., 1988, The Motion of a Pushed, Sliding Workpiece, IEEE Journal of Robotics and Automation, 4/6:569.

[4] Lynch, K., 1993, Estimating the Friction Parameters of Pushed Objects, Proceedings of International Conference on Intelligent Robots and Systems: 186-193.

[5] Lynch, K., Mason, M., 1996, Stable Pushing: Mechanics, Controllability, and Planning, The International Journal of Robotics Research, 15/6: 533-556.

[6] Olsson, H., Åström, K., Canudas de Wit, C., Gafvert, M., Lischinsky, P., 1998, Friction models and friction compensation, European Journal of Control, 4/3: 176-195.

[7] Åström, K., 1998, Control of Systems with Friction, (Technical paper), Department of Automatic Control, Lund Institute of Technology.

[8] Canudas de Wit, C., Olsson, H., Åström, K., Lischinsky, P., 1995, New model for control of systems with friction, IEEE Transactions on Automatic Control, 40/3:419-425.

[9] Makkar, C., Dixon, W.E., Sawyer, W.G., Hu, G.,A New Continuously Differentiable Friction Model for Control Systems Design, Proceedings of the 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM, Jul 24-28 2005, Monterey, CA, 1: 600-605.

[10] Feeny, B., Liang, J., 1996, A Decrement Method for the Simultaneous Estimation of Coulomb and Viscous Friction, Journal of Sound and Vibration, 195/1: 149-154.

[11] Kalman, R.E., 1960, New approach to linear filtering and prediction problems, American Society of Mechanical Engineers Transactions of Journal of Basic Engineering Series D, 82/1: 35-45.