Process Modeling and Adaptive Control for a Grinding System

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Introduction: Grinding Process

- Grinding is the final machining step in much of today’s precision component manufacturing.
- We must control position, force, and velocity for:
  - achieving a desired shape
  - eliminating surface and sub-surface damage
  - minimal surface variation
Typical Grinding Cycle

Current grinding control is primarily position and velocity control.

Force control is needed to prevent material damage and to allow accurate surface following in fine finishing, and to provide dimensional repeatability.
Methodology and Approach

- Select & validate a grinding process model
- Develop real-time model parameter estimators
  - Develop understanding of grinding process variation
  - Investigate performance of estimation algorithms
  - Multiple sensor inputs
- Develop adaptive control scheme
  - Cancel grinding process dynamics
  - Assess stability
- Perform benchmark experiments
  - Plunge grinding force control (assess force fidelity)
  - Traverse grinding force control (assess surface following)
Theoretical Grinding Models

- **Chip Thickness**
  \[
  h_{MAX} = \left[ \frac{4}{\sqrt{C_r}} \frac{V_w}{V \text{ wheel diameter}} a_c \right]^{1/2}
  \]
  - Based on undeformed chip thickness theory and power relations (Merchant, 1945).
  - Difficult to be deterministic because of the large number of cutting points and variation (average properties used).
  - Very general form and transportable applicability
  - Chip size effect for specific material power

- **Contact Length**
  - Relation to other rolling bodies
  - Hertzian contact (affected by loading)
  \[
  Q = V_{ap} C_r h_{MAX}^2 \frac{l_c}{4}
  \]
  (Shaw, 1956, Kalker, 1968, Malkin, 1989)
Models for Real-time Implementation

\[ F_N \text{ or } F_T = K_o \left( \frac{V_{\text{feed}}}{V_C} \right)^{e_1} a_{e_2} d_{e_3} u_{e_4} \]

General form (Konig 1989)

\[ Q = \frac{F_{N,C} V A}{k_1 u_C} \]

Malkin (1989)

\[ Q = \left( \frac{q_w}{q_a + q_w} \right) K F_N V \]

Coes (1972)

\[ Q = K_P F_N V \]

Preston (1927)

\[ Q = \Lambda (F_N - F_{TH}) \]

Hahn and Lindsay (1971)

\[ Q = K_P (F_N - F_{TH}) V \]

Combined Model

\[ Q = \text{material removal rate} = V_f A = \dot{x_f} A \]
Adaptive Force Controller
Grinding Force Control Approach

- Traditional fixed-gain PID type force control systems are limited because of the grinding process variations.
- Adaptive control grinding
  - Internal diameter grinding with a fixed reference model force controller with a changing process parameters
  - Real-time process variations considered in controlling the normal grinding force.
Experimental Grinding System with Force and Position Sensors

- Z Axis Servo Motor
- Force Transducer
- Tool End
- PC
- Controller
- workpiece
- Y Axis Servo Motor
- Motor Control
- PMAC Controller
- sampled at 2.26 kHz
- position sensor
- X Axis Servo Motor
System Dynamic Identification: Shaker Tests
System Close-up
Detailed View of Test Apparatus
Plunge Grinding

Grinder

Wheel

\( \omega \)

\( X_{\text{measured}} \)

\( F_{T2} \)

\( X_{\text{surf}} \)

\( F_N \)

\( F_{T1} \)

Part
**Desired Result:** Stable Force Control

Increased Accuracy and Productivity in Fine Finishing
Position Controller Model
Use a least squares fit for parameters of velocity as a first order transfer function of control voltage input

$$\begin{bmatrix} \hat{G}_N, \hat{H}_N \end{bmatrix} = \min \sum_{t=1}^{N} e^2(t)$$

$$y(t) = G(q)u(t) + H(q)e(t)$$

$$e(t) = H^{-1}(q)[y(t) - G(q)u(t)] = \text{error}$$

The resulting first order system $L M(s)$ is given as

$$\frac{V(s)}{U(s)} = L M(s) = \frac{397}{s + 2.95} \left[ \frac{\text{mm/s}}{\text{volt}} \right]$$
Anti-Aliasing Filter for sensor input
Cut-off frequency is 500 Hz

Butterworth analog filter

Frequency (Hz)
Magnitude
0 0.5 1 1.5
10^1 10^2 10^3

Frequency (Hz)
Phase Angle (deg)
0 -200 -400 -600
10^1 10^2 10^3
Identified Model of Position Control Loop

\[ G_{PC}(s) = \frac{X_e(s)}{X_d(s)} = \frac{203}{s + 224} \]

Actual and Model Displacement

Corresponding Measured Force
Dynamic System Model

\[ F_N - F_{TH} = \frac{A}{K_p V} \dot{x}_f \]

Position Transfer Function:
\[ \frac{x_f(s)}{x_e(s)} = \frac{K_P K_S V/A}{s + K_P K_S V/A} \]

Equivalent Damping:
Adaptive Force Controller with Real-Time Estimation

Desired Result: Stable Force Control, Increased Fidelity, Productivity, Greater Surface Following for Fine Finishing
**Fixed PI Force Controller**

\[
G_{FC}(s) = K_{\text{prop}} \left( s + \frac{K_{\text{int}}}{K_{\text{prop}}} \right) \frac{1}{s}
\]
Fixed PI Force Controller: Root Locus

Zero at -30

Zero at -20
**Fixed Gain PI Control Digital Design (Ignoring Grinding Process Model)**

\[ G_{FC}(z)G_{PC}(z)G_{TWP}(z) = K_{PROP}\left(\frac{(1+\alpha)z-1}{z-1}\right)\left(\frac{0.3543K_s}{z-0.6091}\right) \]

**Rise Time vs Gain**

(for \(K_i/K_{PROP}=1, 50, 100, 150, 200, 250\))
**Fixed-Gain Force Loop Block Diagram**

- Desired Force: $F_d$
- Force Error: $e$
- Force Control: $G(s)_{FC}$
- Commanded Position: $X_d$
- Position Loop: $G(s)_{PC}$
- Actual Position: $X$
- Tool-work-process Impedance: $G(s)_{TWP}$
- Measured Force: $F_m$
- Force Sensor: $G(s)_{FS}$
- Actual Force: $F_a$
Fixed PI Force Controller: Step Force input

Simulation

Experimental Results
Position Control Experiment: Identified Parametric Model vs. Actual Data

\[ \frac{x_f(s)}{x_e(s)} = \frac{\eta}{s + \eta} \]; where \( \eta = \frac{K_p K_s V}{A} \)

Actual and Model Displacements
Add Grinding Process To System

\[
R_m = [F, z, v, ..]^T
\]
**Force Control Experiment:**

**Typical Force and Displacement**

- **$F_N$** Normal Force
- **$x_f$** Measured Infeed Displacement

\[
\bar{K}_p = \frac{A \ddot{x}_f}{V(F_N - F_{TH})}
\]
Force Control Experiment: Experimental Results

\[ K_P = \frac{A \dot{x}_f}{V(F_N - F_{TH})} \]

\[ \forall F_N > F_{TH} \]
Multi-Sensor Data May Be Used to Improve Model Parameter Estimation

- Multi-sensor approaches have yielded encouraging results for improving on-line estimation of wear.
  - Several indirect measurement sources of wear have been successful, indicating that successful integration of several sensors may be more reliable than any single sensor method.

- Candidate Methods for Real-time Use of Multiple Sensors
  - Basis Functions
    - Require apriori basis structures
  - Neural Networks
    - Require bounded training sets
    - Training times can be long
  - Recursive Methods
    - Recursive Least Square
      - Forgetting Factors
    - Kalman Filtering
      - Windowing
Adaptive Force Controller with Real-Time Estimation

Desired Result: Stable Force Control, Increased Fidelity, Productivity, Greater Surface Following for Fine Finishing
Windowing of Sensor Data for Variable Parameter Estimation

Sensor Data

Collect data

Estimate parameters
Determine Gains

Collect data

Estimate parameters
Determine Gains

Collect data

...
Dual Processing Structure and Information Flow

PMAC (DSP)
(Servo-control, data acquisition)

Displacement Sensors
Force Sensors
Spindle Tachometer
Motors Encoders

Dual-Ported RAM
Controller Gains
Windowed Data

PC
(Estimation calculations, adaptive controller design)

PC-Bus
Actual Grinding and Model Results without Estimation Improvement
Estimated and Actual Grinding Wheel Displacements

Both Methods yield similar improvements. RLS is selected for real-time estimation for computational efficiency.
Window Size Effect on Kalman Filter Estimation: Model Error

Relative Error $P/P_{\text{max}}$
Effect of Sensor Inputs on Estimation and Model Error

Relative Error $\frac{P}{P_{\text{FT-sensor}}}$

Sensors used for estimation input
Adaptive Force Controller with Real-Time Estimation

Desired Result: Stable Force Control, Increased Fidelity, Productivity, Greater Surface Following for Fine Finishing
Adaptive Control Strategy

- Grinding variation effects overall system gain and has slow dynamics, and can lead to oscillations.
- Controller can be unstable for some fixed-gains
  - Reduce gain before on-set of oscillation
- Control strategies
  - Pole-zero cancellation of grind process via PI-controller (Windowed update of gains)

Grinding Process

\[
G_{TPW}(s) = \frac{F_N(s)}{x_e(s)} = K_S \left( \frac{s}{s + \eta} \right)
\]

\[\eta = K_P K_S V/A\]

PI Controller

\[
G_{FC}(s) = K_{PROP} \left( s + \frac{K_I}{K_{PROP}} \right) \frac{1}{s}
\]
Force Controller Development

Position loop

\[ G_{PC}(s) = \frac{X(s)}{X_D(s)} = \frac{203}{s + 224} \]

Tool-work & Process

\[ G_{TPW}(s) = \frac{F_N(s)}{x_e(s)} = K_s \left( \frac{s}{s + \eta} \right) \]
\[ \eta = K_P K_S V/A \]

PI Force Control

\[ G_{FC}(s) = K_{PROP} \left( s + \frac{K_i}{K_{PROP}} \right) \frac{1}{s} \]
\[ \alpha = \frac{K_i}{K_{PROP}} \]

Combined Plant

\[ G_{FC}(s)G_{PC}(s)G_{TWP}(s) = \frac{F_N(s)}{E_F(s)} = 203K_s \left( \frac{s}{s + \eta} \right) \frac{K_{PROP}(s + \alpha)}{s(s + 224)} \]

Typically \( \eta << 224 \)  
Therefore let \( \alpha = \eta \)

Thus pole-zero cancellation via PI Control

\[ G_{FC}(s)G_{PC}(s)G_{TWP}(s) = \frac{F_N(s)}{E_F(s)} = \frac{203K_sK_{PROP}}{(s + 224)} \]
Digital Control Implementation

Using a digital controller

\[
G_{FC}G_{PC}G_{TWP}(z) = \frac{K_{\text{PROP}}f_2(\eta)}{1+\alpha} \left( \frac{z - \frac{1}{1+\alpha}}{\varepsilon - f_1(\eta) - C_0} \right)
\]

\[
f_1(\eta) = e^{-\eta T} \quad C_0 = e^{-24T}
\]

Let \[f_1(\eta) = \frac{1}{1+\alpha}\] for cancellation of grinding process (stable zero near unity)
Benchmark Tests: Combined Real-Time Estimation and Adaptive Control

- Two tests
  - Vertical plunge grinding
    - Control grinding normal force
    - Assess force fidelity (mean, range, and variance)
  - Traverse grinding
    - Constant horizontal force on “straight” surface
    - Control vertical force
    - Assess surface following ability
  - Compare adaptive pole-zero cancellation control with fixed-gain PI force controller
Surface Profile Measurement
Surface Grinding Profiles

Fixed-Gain Force Control

Adaptive Force Control

\[ X_f (\mu m) \]

Length (mm)

\[ X_f (\mu m) \]

Length (mm)
Plunge Grinding Normal Forces

Fixed-Gain Control

Adaptive Control

Time (s)

$F_N$ vs. Time (s)

$F_N$ vs. Time (s)
## Normal Grinding Force (Plunge Grind)
### Experimental Force Statistics

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</table>
Conclusions

• Grinding is time-varying process, and may be thought of as a damping equivalent.

• A two-parameter grinding model is a valid process representation
  ♦ $F_{TH}$ can be thought of as constant for a particular setup
    – Function of the wheel grit and part elastic modulus
  ♦ $K_P$ is best modeled in real-time
    – Average values have a linear correlation to the material hardness

• Grinding process variations are generally at significantly lower frequencies than machine vibrations.
  ♦ Low-pass filtering may be used to separate the process dynamics from the machine vibrations

• Applying recursive estimation techniques to multiple sensor data provides an improved estimate of the model coefficient.
  ♦ RLS-FF and the Kalman filter methods yield similar results
  ♦ Both produce a time-varying “optimal” filter for $K_P$
Conclusions (continued)

• There is a trade-off between the timeliness of sensor data and a meaningful statistical representation of process, leading to an optimum window of sampled data (or forgetting factor).

• Additional correlated sensors have diminishing improvements
  ◆ An additional sensor data for filtering $K_p$ has an order of magnitude improvement on model error covariance.
  ◆ An average a small (7%) improvement was seen by adding correlated additional sensor.
  ◆ Industrial application should not require extensive sensoring

• Adaptive pole-zero cancellation of the grinding process provides stable control under process variations.
  ◆ This yielded greater force control fidelity.
  ◆ An improved ability to track surfaces in fine finishing has been observed.
The End

- Thank you