R. D. Hanson Graduate Student.

Tsu-Chin Tsao

Associate Professor

Department of Mechanical and Industrial Engineering, University of Illinois at Urbana-Champaign, Urbana, Illinois 6180*

Reducing Cutting Force Induced Bore Cylindricity Errors by Learning Control and Variable Depth of Cut Machining

In this paper, a method for on-line compensation of cylindricity errors in machined bores is formulated and demonstrated. The cylindricity errors addressed are those caused by the elastic deformation of the bore wall due to forces applied to the workpiece both during and after the machining process. Compensation is achieved using a piezoelectric boring bar servo capable of varying the depth of cut rapidly for on-line compensation at acceptable industrial machining speeds. Control of the boring bar servo consists of both learning and repetitive control. Learning control is used to determine the cutting tool reference trajectory required to achieve compensation, and repetitive servo control is used to accurately track the reference trajectory. The stability and convergence of the error dynamics of the learning control system are analyzed using a model for the flexure-induced machining errors. Experimental results demonstrate that the proposed method can significantly improve bore cylindricity in machined components.

Introduction

del of

re-

ent

are,

vell the idel

and

VCг-

tors

the

pect

tions Asia-990. indriem.''

, Au-

and

rence

991,

larcci

nting

matic

rking

ojgan,

Pro-

chool

ersity,

Parts.

nyang

eding

Engi-

Although the purpose of the boring operation is to produce cylindrical surfaces, often the machined surface lacks cylindricity due to several factors. These include spindle motion errors, workpiece and/or machine tool vibration, and deformation errors due to workpiece flexibility. For the last case, the cylindricity of the machined surface is limited by the degree of workpiece flexibility, the severity of the cutting conditions, and the manner in which the part is held by the machine tool fixture. In addition, workpiece flexibility can lead to cylindricity errors from post-machining deformation due to assembly or thermal stresses. A notable example in which flexure-induced cylindricity errors are a large concern is in the production of engine cylinder bores or liners (Kakade and Chow, 1993; Subramani et al., 1993) where the lack of cylindricity can lead to poor engine performance and excessive piston and cylinder wear.

The conventional approach to reduce flexure-induced cylindricity errors is to use low material removal rates and elaborate clamping and restraint fixtures. This costly approach may be followed by micro-sizing operations such as stress honing to further reduce the machining errors as well as to correct for post-machining deformation. However, if these errors are repeatable and can be quantified, either by off-line calculation or on-line measurement, they can be eliminated during the machining process by compensating tool motion. To achieve error compensation, the depth of cut must be dynamically varied since the flexure-induced errors vary around the bore circumference. In this paper, we propose a two-level control scheme to achieve compensation which consists of both learning and repetitive control. This method is illustrated in Fig. 1 in which wo consecutive machining cycles are represented. Note that the cylindricity errors, ϵ , are measured after each workpiece has been machined and are then used by a learning controller to the reference signal, r, for the subsequent workpiece. additionally, a repetitive controller is used during each machining cycle to accurately track the updated reference signal.

Variable depth of cut machining refers to machining systems that have the ability to vary the depth of cut rapidly by utilizing fast-tool servos. In recent years, researchers have investigated the application of variable depth of cut machining in the production of noncircular shapes on a lathe (Dow et al., 1991; Miller et al., 1994; Rassmussen et al., 1994; Tomizuka et al., 1987) and for dynamic error compensation. Most of the research in dynamic error compensation has targeted vibration or spindle motion errors in precision turning (Tomizuka et al., 1987; Fawcett, 1990; Okazaki, 1990; Wu, 1988) or the error motion of the rotating cutter in boring (Kim et al., 1987). The use of dynamic error compensation has also been considered in other machining operations such as end milling (Liang and Perry, 1992) and surface grinding (Wu, 1988).

Previous research in the area of dynamic error compensation has dealt with machining errors that could be monitored during the machining operation (Chen and Yang, 1989; Dow et al., 1991; Fawcett, 1990; Li and Li, 1992; Liang and Perry, 1992; Miller et al., 1994; Wu, 1988). For example, in the research addressing spindle motion errors, the error motion of the spindle was measured during the machining operation using position sensors (Chen and Yang, 1989; Wu, 1988). For reasons that will be explained in the following section, it is not possible to measure flexure-induced cylindricity errors during the boring operation. However, due to the repeatable nature of these errors, we will show that dynamic error compensation is still possible using the two-level control scheme described above.

Our approach is demonstrated on an experimental system which was designed to operate at acceptable industrial machining speeds and is demonstrated using a 1000 rpm spindle speed. Many of the previous systems developed for dynamic error compensation (Li and Li, 1992; Liang and Perry, 1992; Kim et al., 1988) have been demonstrated at slow spindle speeds (less than 300 rpm) due to insufficient servo system bandwidth. Another important requirement for the fast-tool servo is that it must assure machining stability over a wide range of operating conditions. This servo feedback controller includes an innerloop H_{∞} -norm bounding controller and an outer-loop repetitive controller. The purpose of the former is to increase the dynamic stiffness and hence the cutting stability of the closed-loop sys-

Contributed by the Manufacturing Engineering Division for publication in the CORNAL OF MANUFACTURING SCIENCE AND ENGINEERING. Manuscript received to 1995. Associate Technical Editor: K. Danai.

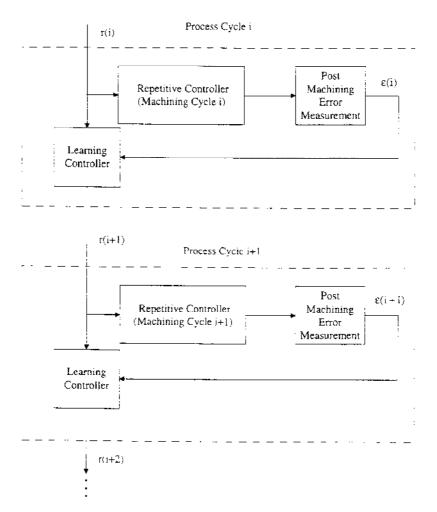


Fig. 1 Block diagram of proposed two-level control scheme

tem. The latter is included because flexure-induced errors contain significant periodic components, and it has been shown that repetitive control can be effectively used in metal cutting operations to track and/or reject periodic inputs (Hanson and Tsao, 1996; Li and Li, 1992; Rassmussen et al., 1994; Tsao and Tomizuka, 1988).

The remainder of this paper is organized as follows: First, sources of bore cylindricity errors are characterized, and a model for flexure-induced cylindricity errors is formulated. The boring servo system and servo feedback controller designs are described, followed by a presentation of the learning controller. Conditions to ensure stability and rapid convergence of the learning control system are given. Finally, experimental machining results which demonstrate the effectiveness of the proposed process feedback control strategy are presented.

Cylindricity Errors in Machined Bores

The cylindricity errors addressed by this research result from flexure of the workpiece due to cutting forces, machine tool fixturing forces, and permanent post-machining forces applied to the workpiece during the manufacturing process. As mentioned earlier, it is not possible to measure the flexure-induced cylindricity errors while the workpiece is being machined. One teason for this is that a portion of the errors is generated at other times such as during the final assembly. A second reason is that in-process measurement of workpiece deformation by the cutting and fixturing forces does not reflect the actual cylindricity error of the machined workpiece. Therefore, the errors are measured after a workpiece has undergone the complete

process which includes machine tool fixturing, machining, and final assembly. This measurement is then fed to a learning controller to determine the cutting tool trajectory for the subsequent part.

To analyze the stability and convergence of the learning control algorithm, a model is needed that relates the cylindricity errors (as output) to the cutting tool trajectory (as input). Let the cylindricity error, ϵ , at the point (θ, z) on the bore surface be defined as

$$\epsilon(\theta, z) = r_d - r_a(\theta, z) \tag{1}$$

where r_d is the desired bore radius, $r_u(\theta, z)$ is the actual bore profile after the machining process, and coordinates θ and z are defined in Fig. 2. The actual bore profile generated during the manufacturing process is written as

$$r_n(\theta, z) = r_n(\theta, z) + \operatorname{doc}(\theta, z) + \delta_{\text{exst-mach}}(\theta, z).$$
 (2)

In this expression, r_n represents the bore profile of the workpiece when mounted in the machine tool; i.e., it represents the uncut bore profile after the machine tool fixturing forces have been applied. Additionally, doe represents the true depth of cut and corresponds to the amount of material removed during the machining process as shown in Fig. 2. Lastly, $\delta_{\text{post much}}$ represents any post-machining bore deformation which may be caused by the removal of machine tool fixturing forces, the application of assembly forces, or thermal distortion of the workpiece.

The true depth of cut is defined as the distance the cutting tool penetrates the workpiece, i.e.

 δ_{flex} +

 $doc(\theta)$

where

amour forces of cut The magni depth cylind doc of

(ii)

relatio

These in the induc sump

where the confiser depth direct

wher at po Com of cu

Whe

Jou

Transactions of the ASME

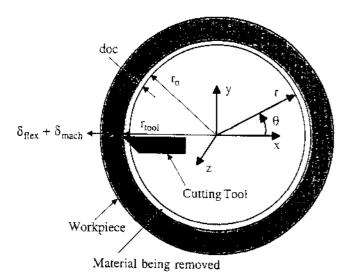


Fig. 2 Coordinate system used to describe bore profile

 $doc(\theta, z) = r_{tool}(\theta, z)$

$$= (r_{\theta}(\theta, z) + \delta_{\text{flex}}(\theta, z) + \delta_{\text{mach}}(\theta, z)) \quad (3)$$

where $r_{\rm toos}$ is the cutting radius of the boring bar, $\delta_{\rm flex}$ is the amount of radial flexure of the workpiece induced by the cutting forces, and $\delta_{\rm mach}$ represents any additional change in the depth of cut such as spindle motion errors or thermal deformation.

The radial flexure of the workpiece, δ_{flex} , depends on the magnitude of the cutting forces, which in turn depend on the depth of cut. Since we propose to eliminate the flexure-induced cylindricity errors by varying the depth of cut, the effect of the doc on δ_{flex} must be included in this model. In developing this relationship, the following two assumptions are made:

- (i) For a given spindle speed, feedrate, cutting tool geometry and workpiece material, the principle cutting forces (components of the resultant cutting force in the radial, tangential, and axial directions) are linearly related to the depth of cut.
- (ii) The radial flexure of the workpiece due to the application of a principle cutting force is proportional to this force and the effects of the principle cutting forces are additive.

These assumptions were validated by Subramani et al. (1993) in the development of a process model to predict cutting-force induced cylindricity errors in machinined bores. Note that assumption (i) can be expressed as

$$f'_{\text{cut}}(\theta, z) = k'_{\text{cut}}(\theta, z) \operatorname{doc}(\theta, z) - f/_{\infty}$$
 (4)

where $k_{\rm out}^j$ and $f_{\rm out}^j$ are the cutting stiffness and magnitude of the cutting force in the j-th direction, respectively, $f_{i,j}^j$ is an offset which depends on the cutting tool geometry and nominal depth of cut, and j represents the radial, tangential or axial direction. Additionally, assumption (ii) can be written as

$$\delta_{\text{flex}}(\theta, z) = \sum_{i} \frac{f_{\text{cut}}^{j}(\theta, z)}{k_{\text{struct}}^{j}(\theta, z)}$$
 (5)

where k_{struct}^j represents radial stiffness of the fixtured workpiece at point (θ, z) due to a force applied in the j-th direction. Combining Eqs. (4) and (5), the relationship between the depth of cut and the workpiece flexure can be expressed as

$$\delta_{\text{flex}}(\theta, z) = k_y(\theta, z) \text{ doc } (\theta, z) - \delta_{\text{tg}}(\theta, z)$$
 (6)

where

$$k_{\gamma}(\theta, z) = \sum_{j} \frac{k_{\text{cut}}^{j}}{k_{\text{sinict}}^{j}(\theta, z)}$$
 (7)

and

$$\delta_{r_{\mathcal{L}}}(\theta, z) = \sum_{i} \frac{f_{i_{\mathcal{R}}}^{f_{i_{\mathcal{R}}}}}{k_{simin}^{f_{i_{\mathcal{R}}}}(\theta, z)}.$$
 (8)

Combining Eqs. (1), (2), (3) and (6), the final expression representing the control-oriented model for cylindricity errors in machined bores can be written as

$$\epsilon(\theta,z) = k_{\rho}(\theta,z) (r_{\rm tool}(\theta,z) - r_{\rho}(\theta,z)) + r_{d} - r_{\rm tool}(\theta,z) +$$

$$(1 - k_p(\theta, z))[\delta_{\text{much}}(\theta, z) - \delta_{rs}(\theta, z)] - \delta_{\text{proposition}}(\theta, z)$$
 (9)

where the process gain k_n is defined as

$$k_p(\theta, z) = \frac{k_p(\theta, z)}{1 - k_p(\theta, z)}.$$
 (10)

Insight that is useful in the design of the control system can be gained by analyzing the system represented by Eq. (9). Previous research in the area of dynamic error compensation has dealt with machining errors associated with the machine tool such as spindle error motion, machine tool compliance, and cutter runout. Note that these errors represent external disturbances applied to the system (δ_{mach}). In the case of flexure-induced errors, not only do the errors enter as disturbances ($\delta_{\text{post-mach}}$), but they are also generated by the process itself. Note from Eq. (9) that if all disturbances are zero (all δ 's = 0) and if the cutting tool trajectory coincides with the desired bore radius ($r_{\text{cool}}(\theta, z) = r_d$), cylindricity errors still result due to the presence of the first term representing the cutting-force induced errors. Further note that the process gain associated with this term is position-varying (or time-varying).

From Eqs. (7) and (10), it can be seen that the process gain varies due to the position dependence of $k_{\rm since}$ which represents the radial stiffness of the mounted workpiece. The position dependence of $k_{\rm since}$ may be due to the geometry of the workpiece itself or due to the manner in which the workpiece is mounted in the machine tool. For example, consider the boring of engine cylinders. The variation in wall thickness of the cylinders due to the complex geometry of the engine block causes the radial stiffness of the cylinders to be position dependent. As another example, consider machining a thin walled workpiece with a uniform wall thickness that has been mounted in a 3-jaw chuck as shown in Fig. 3. Although the radial stiffness of the workpiece is not position dependent prior to being mounted in the 3-jaw chuck, the structure of the workpiece/fixture unit is position dependent.

As a final observation, note that if the disturbances and process gain depend only on θ , the cylindricity error will depend only on θ . Cylindricity errors that depend only on θ will be referred to as periodic errors since the errors repeat every revolution along the helical path traversed by the cutting tool. Con-

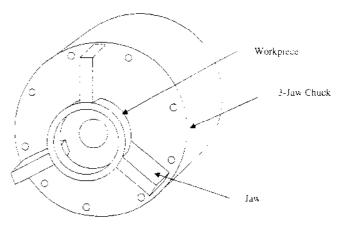


Fig. 3 Workpiece mounted in 3-jaw chuck

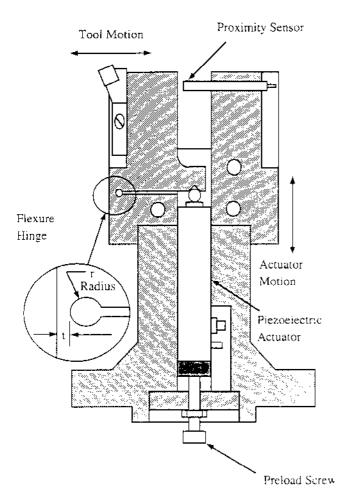


Fig. 4 Cross section of the boring bar servo

sider the previous example in which the workpiece was mounted in a 3-jaw chuck. The flexure-induced cylindricity errors generated using conventional boring methods (constant depth of cut) should be essentially periodic due to uniformity of the workpiece geometry in the axial direction. Even for situations in which the workpiece geometry varies in the axial direction, if the variations are not abrupt, the flexure-induced cylindricity errors along the cutting tool trajectory will change only slightly from one revolution to the next. The fact that flexure-induced cylindricity errors are essentially periodic or contain significant periodic component is used to advantage in the servo controller design.

Experimental System

To dynamically compensate for cylindricity errors, a boring bar servo capable of variable depth-of-cut machining is required. The boring bar servo that we have designed, which is shown in Fig. 4, utilizes a piezoelectric actuator to generate precise tool motions in the radial cutting direction. The open-loop static and dynamic stiffness of the boring bar servo are 12.8 N/ μ m and 1.35 N/ μ m, respectively, and the maximum unconstrained tool travel is 120 μ m.

A schematic diagram of the servo feedback loop is shown in Fig. 5. The radial tool position of the boring bar is measured using a proximity sensor attached to the boring bar servo. The output of the proximity sensor is passed to a digital controller. The spindle position which is obtained using a rotary encoder is also input to the controller. The digital controller processes this information and generates a control signal which is sent to the power amplifier driving the boring bar servo.

Closed-Loop Servo Controller

The control strategy proposed in this paper is to utilize process feedback and learning control to determine the reference signal (desired cutting tool trajectory) needed to compensate for the cylindricity errors and to use this reference signal as input to a closed-loop servo controller for the boring bar servo. The purpose of the closed-loop servo controller is to track the reference signal, reject the cutting force disturbance, and have sufficient closed-loop dynamic stiffness so that cutting stability is maintained over the desired range of cutting conditions. The servo control system designed to accomplish these objectives is represented in Fig. 6, where r is the reference command. e is the tracking error, $G_a(s)$ is the continuous-time transfer function of the power amplifier, and $G_b(s)$ is the continuous-time transfer function of the boring bar servo. In addition, $G_i(z^{-1})$ and $G_i(z^{-1})$ represent the inner-loop and repetitive portions of the digital controller, respectively.

The purpose of the inner-loop controller is to increase the closed-loop dynamic stiffness and hence increase the cutting stability. The inner-loop controller utilized is a 7-th order H_{∞} -norm bounding controller. Additionally, the repetitive controller is used to achieve asymptotic tracking of periodic inputs as well as to reject periodic disturbances. As mentioned previously, the ability to track periodic signals is advantageous in this situation since the cylindricity errors caused by component flexibility contain significant periodic components.

The theoretical values for static and dynamic stiffness of the closed-loop servo system are infinity and 2.83 N/µm, respectively. In addition, the control system was designed to operate using a sampling rate of 4000 Hz. For a spindle speed of 1000 rpm, this corresponds to sampling at 240 equally spaced points around the circumference of the workpiece.

anc

r_e(Eq

an

us

For a detailed discussion of the design of the boring bar servo and closed-loop servo controller, the reader is referred to (Hanson and Tsao, 1996)

Learning Control

The purpose of the learning controller is to determine the reference cutting tool trajectory (or process input) necessary to compensate for the flexure-induced cylindricity errors. Based on the process error from the previous cycles, learning control modifies the reference signal to reduce the process error in the subsequent cycle. Learning control has received considerable attention in the field of robotics where it has been utilized to improve the tracking performance of robot manipulators performing repetitive tasks (Casalino and Gambardella, 1986; Furuta and Yamakita, 1986; Togai and Yamano, 1986). The form of the discrete-time learning control algorithm presented in these papers (with the exception that a time-varying learning gain is allowed for here) can be expressed as

$$r_{i+1}(k) = r_i(k) + k_l(k)\epsilon_i(k) \tag{11}$$

where $e_i(k)$ and $r_i(k)$ are the process error and process input at time k on the i-th cycle, respectively, and $k_i(k)$ is the learning gain at time k.

To determine the values of the learning gain that will ensure stability and rapid convergence for this application, the model of the flexure induced cylindricity errors will be utilized. It is convenient to rewrite Eq. (11) in terms of the coordinates (θ_i , z_i), which represent the cutting tool location corresponding to the sampling instant, as

$$r_{i+1}(\theta_k, z_i) = r_i(\theta_k, z_k) + k(\theta_i, z_k)\epsilon(\theta_i, z_i)$$
 (12)

where k = 0, 1, 2, ..., M - 1 and M is the total number of sampling instances.

For ease in analyzing the stability of the learning algorithm, let us define the discrete vector valued signal, v(r), as

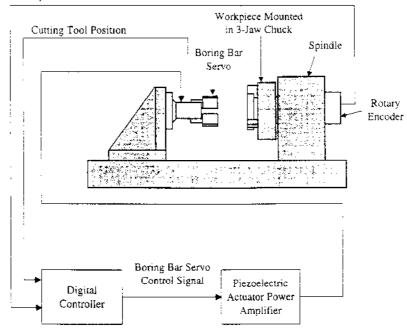


Fig. 5 Schematic of the feedback system

 $\mathbf{r}(i) = [r_i(\theta_0, z_0), r_i(\theta_1, z_1), \dots, r_i(\theta_{M-1}, z_{M-1})]'$ (13) and define the discrete vector valued signals $\boldsymbol{\epsilon}(i), \mathbf{r}_{\text{nod}}(i), \mathbf{r}_{d}(i), \mathbf{r}_{d}(i), \boldsymbol{\delta}_{\text{mach}}(i), \boldsymbol{\delta}_{\text{post-mach}}(i), \text{ and } \boldsymbol{\delta}_{i,g}(i) \text{ in an identical fashion.}$ Equations (9) and (12) may now be rewritten as

$$\boldsymbol{\epsilon}(i) = K_p[\mathbf{r}_{\text{net}}(i) - \mathbf{r}_n(i)] + \mathbf{r}_d(i) - \mathbf{r}_{\text{tool}}(i) + (I - K_p)(\boldsymbol{\delta}_{\text{mach}}(i) - \boldsymbol{\delta}_{\text{t.e.}}) - \boldsymbol{\delta}_{\text{post-mach}}(i)$$
(14)

and

٧

te

0

ts

аг

to

he

to

æd

rol

the

ble Lto

er-

Fu-

orm

l in

iing

10

nput

ning

isure

nodel It is (θ_{i})

ng to

(12)

er of

rithm.

ASME

$$\mathbf{r}(i+1) = \mathbf{r}(i) + K_i(\epsilon)(i), \tag{15}$$

respectively, where

$$K_p = \operatorname{diag}(k_p(\theta_n, z_n), k_p(\theta_1, z_1), \dots, k_p(\theta_{M-1}, z_{M-1})), (16)$$

$$K_l = \text{diag}(k_l(\theta_0, z_0), k_l(\theta_1, z_1), \dots, k_l(\theta_{M-1}, z_{M-1})),$$
 (17)

and l is the identity matrix of dimension $M \times M$. Finally, let us assume that the servo tracking error is negligible which implies

$$\mathbf{r}(i) = \mathbf{r}_{\text{mod}}(i). \tag{18}$$

By substituting Eqs. (14) and (18) into Eq. (15) and rearranging, we obtain the governing equation for this system which can be expressed as

$$\mathbf{r}(i+1) = [I - K_i(I - K_p)]\mathbf{r}(i) - K_iK_p\mathbf{r}_n(i)$$

$$+ K_i(I - K_p)(\boldsymbol{\delta}_{much}(i) - \boldsymbol{\delta}_{t,e}(i))$$

$$+ K_i(\mathbf{r}_d(i) - \boldsymbol{\delta}_{post-mach}(i))$$
 (19)

From this equation, it can be seen that if the system is stable and the inputs are stationary, then $\mathbf{r}(i+1) \to \mathbf{r}(i)$ as $i \to \infty$ which implies $\mathbf{e}(i) \to 0$ as $i \to \infty$ from Eq. (15). The system can be made stable if K_l is chosen such that the eigenvalues of $[I - K_l(I - K_p)]$ are inside the unit disk. The inputs are stationary if all the input terms in Eq. (19) do not change with the index i, implying that these terms are repeatable from one workpiece to another. The above discussion can be summarized as follows: If the process variation is zero and the learning gain is chosen such that the eigenvalues of $[I - K_l(I - K_p)]$ are inside the unit disk, then the cylindricity errors due to workpiece flexibility will asymptotically approach zero.

From Eq. (19), it is clear that the optimal convergence rate will occur when K_l inverts $I = K_p$. This is the suggested choice for K_t when the cutting stiffness is of the same order of magnitude as the radial stiffness of the workpiece. However, if it is known that $|K_p| \le 1$, which is the case for the engine cylinders considered in (Subramani et al., 1993) where $||K_o|| < 0.05$, the complexity of determining K_n can be avoided. In this situation, by simply setting K_i equal to the identity matrix, rapid convergence of the learning control scheme will occur since this choice of K_t is close to optimal. Note from Eqs. (7) and (10) that this situation arises when the magnitude of the cutting stiffness is much less than the radial stiffness of the workpiece. The above conclusions can be restated in terms of the original learning gain $k_i(\theta_k, z_k)$ as follows: To achieve a stable process feedback system with the optimal convergence rate, the learning gain should be set equal to $k_l(\theta_k, z_k) = 1/(1 - k_p(\theta_k, z_k))$; and if it is known that $k_o(\theta_k, z_k) \leq 1$ for all k, then it is sufficient to set $k_l(\theta_k, z_k) = 1$.

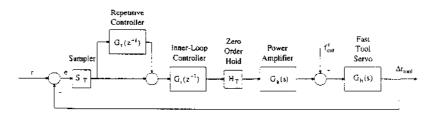


Fig. 6 Block diagram of the servo feedback control system

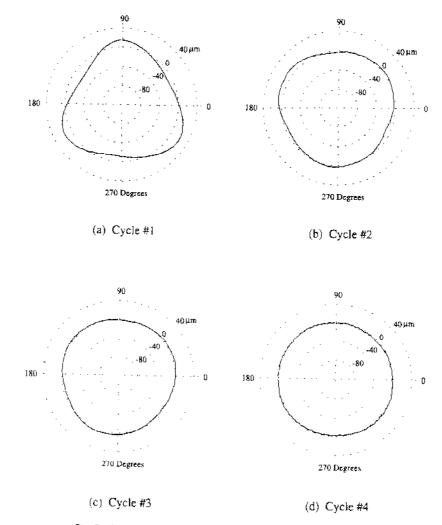


Fig. 7 Cylindricity error profiles obtained in machining experiment

In the above analysis, it is assumed that the process variation is zero and that all non-repeating errors, such as those due to spindle error motion, are zero. Obviously, this ideal case will not be the situation in practice, and the process variation and nonrepeating errors will enter into the above process. Although the cylindricity errors can no longer be expected to decay to zero, if the magnitude of these errors is relatively small in comparison to the magnitude of the error associated with workpiece flexibility, a large reduction in the cylindricity errors can still be expected.

Experimental Results

The objective of the experiment described below is to demonstrate the effectiveness of the proposed approach in compensating for flexure-induced cylindricity errors. For this experiment, thin-walled workpieces that were mounted in a 3-jaw chuck as shown in Fig. 3 were machined. The workpieces consisted of 12.5 mm lengths of 102 mm diameter schedule 80 aluminum pipe. For the combined workpiece/3-jaw chuck structure, the radial stiffness of the structure is at its maximum at the 3 locations where the jaws come in contact with the workpiece and at its minimum at the 3 midpoints between the maxima. If a workpiece was machined using a conventional boring bar and the resulting cylindricity error profile was measured while the workpiece was still mounted in the 3-jaw chuck, a 3 lobed surface resulted as shown in Fig. 7(a). The goal of this experiment was to produce a cylindrical bore in the workpiece/3-jaw

chuck structure; i.e., to drive the cutting force induced machining errors to zero.

A series of 8 workpieces was machined in this experiment. After each workpiece was machined, the cylindricity errors were measured and used in the learning control algorithm to modify the reference signal for the subsequent cycle. The cylindricity errors generated in this experiment were treated as 1-dimensional errors (depending only on θ) due to the constant workpiece/fixture geometry in the axial direction, and the cylindricity errors were measured at the mid-section of the workpiece only.

The cylindricity errors were measured using a surface gauge which was mounted stationary inside the bore of the machined workpiece. The probe mounted on the surface gauge had a ball tip having a diameter of 3 mm. Using such a probe, the rapid changes in the surface finish are not detected, and the measurement obtained is representative of form error rather than surface roughness. The change in the bore radius was digitally recorded at 240 equally spaced points around the bore circumference as the workpiece was slowly rotated about the spindle axis. Using this measurement system, it was only possible to measure relative changes in the bore radius, and as a result, static radius errors were not addressed in this experiment. The cylindricity errors shown in the subsequent plots represent the dynamic component of the true cylindricity errors computed as $y(\theta)$ + y_{mean} where $y(\theta)$ is the measurement obtained from the surface gauge and y_{mean} is the average measurement over one spindle rotation. The cylindricity errors obtained in this manner differ from the true cylindricity errors by a constant offset.

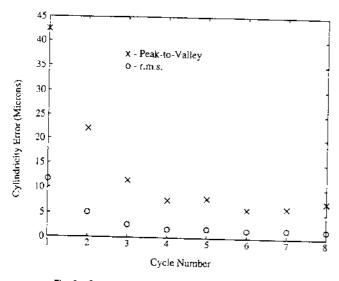


Fig. 8 Convergence of the learning control system

Each workpiece in this experiment was machined in the identical fashion with the exception of the reference signal used. First, an initial dress cut was made using a constant radial tool position to reduce the wall thickness of the workpiece to 6.35 mm. A second pass was then made in which the radial tool position was varied as specified by the reference signal. In this pass, the nominal depth of cut, feedrate, spindle speed and surface speed were 0.76 mm, 0.05 mm/rev, 1000 rpm and 638 m/min, respectively.

During the first machining cycle (designated cycle #1) a constant reference signal (constant radial tool position) was used, and the results obtained are therefore representative of conventional horing. The cylindricity errors that resulted in cycle #1 are shown in Fig. 7(a) in polar coordinates. In addition, the cylindricity errors measured for cycles 2, 3 and 4 are shown in Figs. 7(b), 7(c) and 7(d), respectively. In these figures, the jaws of the 3-jaw chuck contacted the workpieces at the 90, 210 and 330 degree locations. From this sequence of figures, the improvement in cylindricity that is obtained utilizing learning control is apparent. A plot showing both the r.m.s. (root-meansquare) error and peak-to-valley error (maximum radius minus minimum radius) for each machining cycle is shown in Fig. 8. As can be seen, the peak-to-valley error, which was 42.0 μm in the first machining cycle, decayed to no more than $8.1~\mu\mathrm{m}$ after the fifth cycle.

in-

nt.

ere lify

ity

nal

ce/

ors

uge

ned

ball

pid

ire-

ace

ded

e as

sing

ela-

dius city

mic

) -

face

ndle

iffer

ME

The learning gain used in this experiment was $k_t(\theta_k, z_k) = 1$ for all k since it was determined that $k_p(\theta_k, z_k) < 0.054$ for the workpiece/3-jaw chuck structure. The bound on the process gain was determined using results from cycle #1 of this experiment which represents conventional boring. To compute this bound, it was assumed the disturbances involved in Eq. (9) were negligible (δ 's = 0) and that the cutting radius of the boring bar was equal to the desired bore radius ($r_a = r_{\text{tool}}$). Making these assumptions, Eq. (9) can be rewritten as

$$k_{\rho}(\theta, z) = \frac{\epsilon(\theta, z)}{r_{\text{total}}(\theta, z) - r_{\rho}(\theta, z)}.$$
 (20)

Note that $r_{\text{tool}} = r_o$ represents the nominal depth of cut associated with conventional boring. Therefore, by knowing the nominal depth of cut and the maximum cylindricity error generated, a bound can be computed for k_p using Eq. (20). For the initial workpiece machined, the peak-to-valley cylindricity error was 42.0 microns. Since the nominal depth of cut used was 0.76 mm, a bound on k_p was computed as 0.054.

The fact that the cylindricity errors did not converge to zero in this experiment can be attributed to noise present in the feedback sensor signal, error motions of the machine tool structure and spindle, and process variations.

Discussion

In the experiment above, the errors generated were 1-dimensional errors produced by the cutting forces. The proposed approach could also be used to compensate for post-machining deformation if the process feedback measurement was made after all sources of flexure-induced errors were applied. Additionally, compensation for 2-dimensional errors could be achieved if the process feedback measurement system used was capable of measuring 2-dimensional error profiles. The measurement and compensation of post-machining and 2-dimensional error profiles is the subject of future research.

Conclusions

A model for bore cylindricity error has been developed for the purpose of process feedback control system design. This model relates the output variable (the cylindricity error) to the control input (the cutting tool displacement). The model indicates that the process gain varies with the variable workpiece/ fixture radial stiffness. Based on the model, a cycle-to-cycle process feedback learning control is designed, and its stability and convergence criteria, which relates to the (bound of) ratio of the cutting stiffness to the workpiece/fixture stiffness, is derived. A method to select learning gains for rapid stable error convergence is given. The resulting compensating tool motion is periodically varying with respect to the spindle rotation, and this tool motion is generated precisely by a piezoelectric driven fast tool servo using an H_* /repetitive control developed in Hanson and Tsao (1996). An experimental demonstration shows that the cylindricity error was reduced by more than 5 times compared to the conventional uncompensated machining opera-

Acknowledgment

This work was supported in part by the University of Illinois Manufacturing Research Center and by NSF Grant DMI9522815.

References

Casalino, G., and Gamhardella, L., 1986, "Learning of Movements in Robotics Manipulators," *Proc. International Conference on Robotics and Automation*, San Francisco, pp. 572–578.

Chen, M., and Yang, C., 1989, "Dynamic Compensation Technology of the Spindle Motion of a Precision Lathe," *Precision Engineering*, Vol. 11, No. 3, pp. 135-139.

Dow, T., Miller, M., and Falter, P., 1991, "Application of a Fast Tool Servo for Diamond Turning of Nonrotationally Symmetric Surfaces," *Precision Engineering*, Vol. 13, No. 4, pp. 243–250.

neering, Vol. 13, No. 4, pp. 243-250 Fawcett, S., 1990, "Small Amplitude Vibration Compensation for Precision Diamond Turning," *Precision Engineering*, Vol. 12, No. 2, pp. 91-94.

Furuta, K., and Yamakita, M., 1986, "Iterative Generation of Optimal Input of a Manipulator," *Proceedings of the International Conference on Robotics and Automation*, San Francisco, pp. 579–584

Automation, San Francisco, pp. 579–584.

Hanson, R., and Tsao, T.-C., 1996, "The Design, Analysis, and Control of a Fast Tool Servo for Dynamic Variable Depth of Cut Machining," ASME JOURNAL OF MANUFACTURING SCIENCE AND ENGINEERING, submitted for review

Li, C., and Li, S., 1992, "On-Line Roundness Error Compensation via P-integrator Learning Control," ASME JOURNAL OF ENGINEERING FOR INDUSTRY, pp. 476–480.

Liang, S., and Perry, S., 1992, "Milling Cutter Runout Compensation By Control of Radial Depth of Cut," *Japan/USA Symposium on Flexible Automation*, Vol. 2, pp. 861–864.

Kakade, N., and Chow, J., 1993, "Finite Element Analysis of Engine Bore Distortion During Boring Operation," ASME Journal, of Engineering for Industry, pp. 379–384.

Kim, K., Eman, K., and Wu, S., 1987, "In-Process Control of Cylindricity in Boring Operations," ASME JOURNAL OF ENGINEERING FOR INDUSTRY, Vol. 109, No. 4, pp. 291–296.

Miller, M., Garrard, K., Dow, T., and Taylor, L., 1994, "A Controller Architecture for Integrating a Fast Tool Serve into a Diamond Turning Machine," Previ sum Engineering, Vol. 16, No. 1, pp. 42-48.

Okazaki, Y., 1990, "A Micro-Positioning Fool Post Using a Piezo Actuato: for Diamme Turning Machines." Precision Engineering, Vol. 12, No. 3, pp. 151–156.
Rasmussen, J., Tsao, T.-C., Hanson, R., and Rapoor, S., 1994. "A Piezoelectric Rasmussen, J., Pato, U.S., Hanson, R., and Kapoos, S., 1994. A Piezoelectric Tool Servo System for Variable Depth of Cut Machining," International Journal of Machine Tools & Manufacture, Vol. 34, No. 3, pp. 379–392. Subramani, G., Kapoor, S., and DeVor, R., 1993, "A Model for the Prediction of Bore Cylindricity During Machining," ASME JOURNAL OF ENGINEERING FOR

INDUSTRY, Von. 115, pp. 15-22.

Togai, M., and Yamane, O., 1986, "Learning Control and Its Optimality; Analysis and its Application to Controlling Industrial Robots," *Proc. Interna*tional Conference on Robotics and Automation, San Francisco, pp. 248-253.

Tomizuka, M., Chen, M., Renn, S., and Tsao, T.-C., 1987, "Tool Positioning for Noncircular Cutting with a Lathe," ASMF. *Journal of Dynamic Systems*.

Measurement and Control. Vol. 109, pp. 176-179.

Tsao, T-C., and Tomzuka, M., 1988, "Adaptive and Repetitive Digital Control Algorithms for Noncircular Machining," Proc. American Control Conference.

pp. 115-120.

Wu, S., 1988. "New Approaches to Achieve Better Machine Performance." Japan/USA Symposium on Flexible Automation. Minneapolis, pp. 1063-1068.

> 1 It

> pier duc CUII and

cha and mou SUC con ame pric case only cutt is e the not the to t qui Ĭ. дел be chi niq dift

net

ьте щo Fui sul in Tec dui or lig:

Dec