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New Method of Controlling Grinding Accuracy with Dynamic Compensatory

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Abstract

Based on time series analysis, the control technique of grinding accuracy with dynamic compensatory is proposed. In the new technique, the optimal spectrum measurement technique is used as the on-line high precision measurement of the stochastic motion error of the worktable on the guide-way grinder. Then, the mathematics model for the stochastic motion error is given here. The stochastic motion error is predicted by the adaptive predictor, and Kalman filter is used to improve the predicting accuracy. By defining a compensatory curve, real-time compensatory control is adopted to realize high grinding precision on the guide-way grinder. The results from experiments of actual measurement and system simulation show the new technique is effective.

Keywords **:***Compensatory control, on-line high precision measurement, guideway grinder***.**

1. Introduction

In recent years, more and more precision and efficiency are required for super-precision machine tools and NC machine tools. Since the property of the bed's guide-ways on the machine tools would directly affect the machining precision, it is the first task that improving the grinding accuracy of the bed's guide-ways[1-2]. As there is difficulty with the high precision grinding for guide of the machine tools, it has become the important subject which is urgently solved. Many factors influence grinding accuracy of guide. Beside error of the guide-way grinder, there are oil pressure, oil temperature, variation of the circumstance temperature, hot deformation of the machine tools and work-piece, elastic deformation of the machine tools system, assembling error, not uniform distribution of lode-sand , and so on[3]. There influence working accuracy, and they often have randomness so that the working error value is not easy to control.

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In the paper, optimal spectrum measurement technique is adopted to solve the problem of measurement and decomposition of the stochastic motion error and to establish the mathematics model of the stochastic motion error, respectively. Here, the adaptive predictor is employed to solve the problem of time delay in real-time control. Kalman filter is employed to improve prediction accuracy. The dynamic compensatory control technique is employed to improve the working accuracy on the guide-way grinder.

2. On-Line High Precision Measurement For Errors

Motion errors of the worktable may be described with six error components in Fig.1.

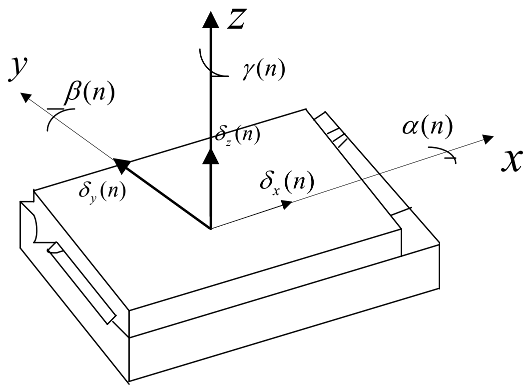

Fig.1 Distribution of the worktable motion errors

Assuming x to be motive direction of the worktable, $\delta_x(n), \delta_y(n)$ and $\delta_z(n)$ denote the motion error components in x, y, z coordinate axes, respectively. $\alpha(n)$, $\beta(n)$, $\gamma(n)$ the corner angular error components around x-axis, y-axis, z-axis, respectively. According to ISO standard, $\delta_z(n)$ and $\beta(n)$ are factors of the most importance for influencing working accuracy of the horizon straightness[4].

For on-line measuring, three sensor, Z_A , Z_B , Z_C , along the motive direction of the worktable, are parallel assembled in the front of primary axis of the machine tools, as Fig.2.

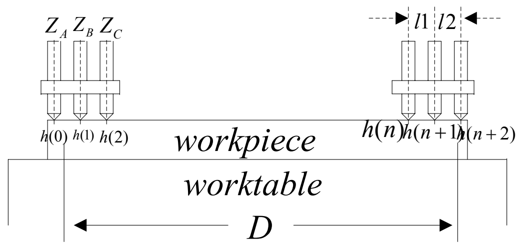

Fig.2 Measurement of the worktable motion error

Their interval is $L1$, $L2$ respectively. In measuring process, the output value of sensors is sampled once, whenever worktable runs ΔL distance. The relation between measurement values and error components is expressed by the following equations;

$$
\begin{aligned}
Z_A &= h(n) + \delta_z(n) \\
Z_B &= h(n+M1) + \delta_z(n) + M1 \times \Delta L \times \beta(n) \\
Z_C &= h(n+M1+M2) + \delta_z(n) + (M1+M2) \times \Delta L \times \beta(n)
\end{aligned}
\tag{1}
$$

Where: ΔL is sample interval; $M1 = L1/\Delta L$, $M2 = L2/\Delta L$, and $M1, M2$ are the integrate; n is the ordinal number of sampling; h(n) is the shape error in μM of work-piece in the n'th sampling; $\beta(n)$ is the corner angular error component in $\mu M / MM$ around y-axis in the n'th sampling; Z_A, Z_B, Z_C in the n'th sampling, respectively.

Weighting to the three output value, the following equation is obtained

$$
\begin{aligned}
Z(n) &= Z_A(n) + C1 \times Z_B(n) + C2 \times Z_C(n) \\
&= h(n) + C1 \times h(n+M1) + C2 \times h(n+M1+M2) \\
&+ (1 + C1 + C2) \times \delta_z(n) + [C1 \times M1 + C2 \times (M1+M2)] \times \Delta L \times \beta(n)
\end{aligned}
\tag{2}
$$

where $C1$, $C2$ are unknown coefficient.

$1 + C1 + C2 = 0, \quad C1 \times M1 + C2 \times (M1+M2) = 0$

$C1$, $C2$ could be solved as: $C1 = -(1 + M1/M2)$, $C2 = M1/M2$. Substituted $C1$, $C2$ into (2), the following equation can be obtained

$$
Z(n) = h(n) - (1 + M1/M2) \times h(n+M1) + (M1/M2) \times h(n+M1+M2) \tag{3}
$$

Suppose the length D of work-piece is divided into N parts, *i.e.*$\Delta L = D/N$, and the followings equation can be obtained by using DFT to (3) equation

$$
\begin{aligned}
Z(k) &= h(k) + C1 \times h(k) \times \exp[J(2\pi/N) \times k \times M1] \\
&+ C2 \times h(k) \times \exp[J(2\pi/N) \times k \times (M1+M2)] \\
&= h(k)\{1 - (1 + M1/M2)\exp[J(2\pi/N) \times k \times M1] + (M1/M2) \times \exp[J(2\pi/N) \times k \times (M1+M2)]\} \\
&= h(n) \times w(k)
\end{aligned}
\tag{4}
$$

Where: k is the ordinal number of sampling in the frequency domain. $w(k)$ is the weighting function of "harmonic ware". It only relates to parameters ($L1$, $L2$, D, N) of the measuring system.

In order to get the best result in frequency domain, the parameters have to be selected so that the loss of harmonic to zero. When M1=M2=1, *i.e.*$L1 = L2 = \Delta L$, $w(k)$ can be written in following form:

$$
\begin{aligned}
w(k) &= 1 - 2\exp[j(2\pi/N)k] + \exp[j2(2\pi/N)k] \\
&= \{1 - \exp[j(2\pi/N)k]\}^2
\end{aligned}
\tag{5}
$$

From (5), no matter what is k (except k=0), $w(k) \neq 0$. Above-mentioned selection could minimize the loss of signal spectrum. It shows that selected parameters are optimal. If substituting these parameters into (1) and rearranging (1), the recursive equations for the optimal spectrum measurement technique can be obtained:

$$
\begin{aligned}
\delta_z(n) &= Z_A(n) - h(n) \\
\beta(n) &= [Z_B(n) - Z_A(n) - h(n+1) + h(n)]/\Delta L \\
h(n+2) &= Z_A(n) - 2Z_B(n) + Z_C(n) + 2h(n+1) - h(n) \\
n &= 1, 2, ..., N.
\end{aligned}
\tag{6}
$$

In initial moment, there exists:

$$
\delta_z(0) = 0, \beta(0) = 0, h(0) = Z_A(0), h(1) = Z_B(0), h(2) = Z_C(0)
$$

We have used the optimal spectrum measurement technique to get into actual measuring experiment on the M-52160 type double-housing guide-way grinder. The experiment conditions: the motion speed of the worktable is 20 M/Min , the length D of work-piece is 2.4 M, sample interval ΔL is 30 MM. In cases of $\pm 30\mu M$ as the range of sensors and 12 as the bits of the A/D converter's output is 0.015 μM . Fig. 3 shows a set result of the actual measuring experiment.

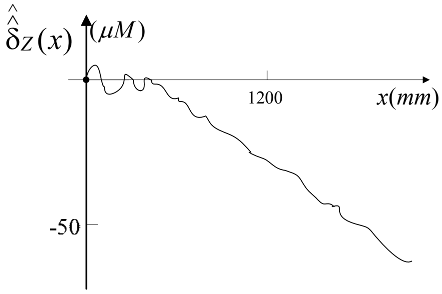

Fig. 3. Measuring curve of the motion error component

3. Building of The Mathematics Model For Error

From Fig. 3, the stochastic motion error component $\delta_z(x)$ is tending to fall down. In order to eliminate tendency and change the original series into the smooth stochastic series, difference process is employed here. Usually, the difference order d is decided by the shape of autocorrelation function curve of the series. If falling rate of autocorrelation function curve of the series is very slow, and could not be controlled by negative exponential function, the series have characteristic of trend[5].

Fig. 4 give curves of autocorrelation function $\hat{P}(r)$ of the stochastic motion error component $\delta_z(n)$ as d value is different.

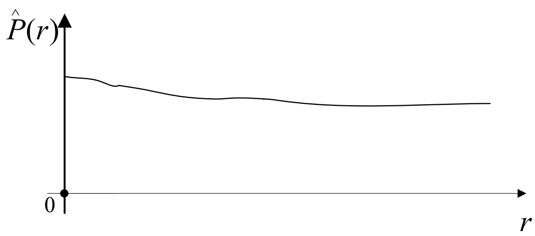

Fig. 4.a The curve of autocorrelation function of the series as d=0

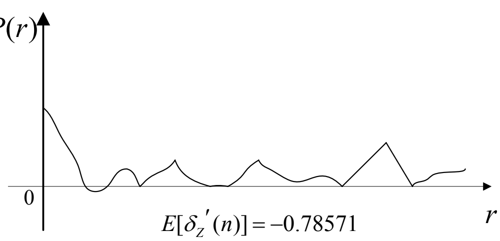

Fig.4.b The curve of autocorrelation function of the series as d=1

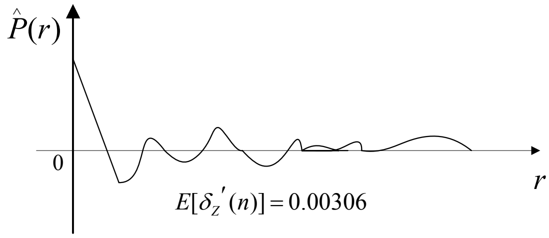

Fig.4.c The curve of autocorrelation function of the series as d=2

It is shown in Fig.4 that decay rate of autocorrelation function $\hat{P}(r)$ is very slow as d=0, this explains the series have characteristic of trend; decay rate of autocorrelation function $\hat{P}(r)$ speeds up as d=1, out the mean value of the series is not zero; the reason is that autocorrelation function $\hat{P}(r)$ could be controlled by negative exponential function and the mean value of the series approaches to zero as d=2, the series $\delta_z'(n)$ have been become zero mean and smooth stochastic series, i.e. the following equation exists:

$$\delta_z'(n) = (1-B)^2 \delta_z(n) \tag{7}$$

Where: B is backward shift operator, $\delta_z'(n)$ is the zero mean and smooth stochastic series.

AR(n) model which order is very big can be approximated to any reversible ARMA model at any precision[6], so we set up AR(n) model for the series $\delta_z'(n)$ and use the minimum Final Prediction Error criterion (FPE) to decide the order n of the AR(n) model. Table 1 gives different n values corresponding to FPE values.

Table 1. Relation between n and FPE

n	1	2	3	4	5
FPE	3.214	2.726	2.677	2.574	2.682

It is shown in Table I that FPE values reach the minimum when n=4. Therefore, AR(4) is the best construction of the series $\delta_z'(n)$. As stated above, the optimal mathematics model of the stochastic motion error component $\delta_z(n)$ of the worktable of the guide-way grinder is

$$\Phi(B)(1-B)^2 \delta_z(n) = \varepsilon(n) \tag{8}$$

Where $\Phi(B) = 1 + \sum_{i=1}^{4} a_i B^i$, a_1, a_2, a_3, a_4 are model parameters, $\varepsilon(n)$ is the white noise series.

4. High Precision Adaptive Prediction for Error

From (8), it includes 4 unknown parameters obviously. The series least squares method is adopted to identify these unknown parameters on-line. Contrasting (7) and (8), the following equation can be obtained:

$$\Phi(B)\delta_z'(n) = \varepsilon(n) \tag{9}$$

(9) can be rewritten in vector form:

$$\delta_z'(n) = A^T X(n) + \varepsilon(n) \tag{10}$$

Where: $A^T = [-a_1, -a_2, -a_3, -a_4]$,

$$X(n-1) = [\delta_z'(n-1), \delta_z'(n-2), \delta_z'(n-3), \delta_z'(n-4)]$$

The following equations can be obtained by the series least squares method:

$$\hat{A}(n) = \hat{A}(n-1) + P(n)X(n)[\delta_z'(n) - X^T(n)\hat{A}(n-1)] \tag{11}$$

$$P(n) = P(n-1) - \frac{P(n-1)X(n)X^T(n)P(n-1)}{1 + X^T(n)P(n-1)X(n)} \tag{12}$$

Where: $\hat{A}(0) = 0, P(0) = 100I$ (I is the unit matrix). (11) and (12) gives a set of the recursive conditions, so that identification for parameters is used to solve for model parameters.

From (10), the linear smooth least variance predictor is adopted in dynamic prediction. Prediction equation is

$$\hat{\delta}_z'(n) = \hat{A}^T(n-1)X(n-1) \tag{13}$$

The error of prediction is

$$e(n) = \delta_z'(n) - \hat{\delta}_z'(n) = \varepsilon(n) \tag{14}$$

The variance of prediction error $e(n)$ is

$$Var[e(n)] = q(n) \tag{15}$$

Obviously, the prediction error is model residual error. This describes the variance of prediction error has reached minimum. Further, the adaptive prediction value $\hat{\delta}_z(n)$ of the stochastic motion error component $\delta_z(n)$ can be obtained by (7):

$$\hat{\delta}_z(n) = \hat{\delta}_z'(n) + 2\delta_z(n-1) - \delta_z(n-2) \tag{16}$$

From analyzing theoretically and measuring actually, the results show the repetitive accuracy exists in worktable motion [7]. To improve predictive precision, Kalman filter is used, on the basis of the measuring value of the stochastic motion error component and the adaptive prediction value of it.

As stated above, we can get the following two equations:

$$\delta_z(n) = \hat{\delta}_z(n) + \varepsilon(n) \tag{17}$$

$$Z(n) = \delta_z(n) + v(n) \tag{18}$$

where: $\delta_z(n)$ is the real value of the stochastic motion error component in the n'th sampling, $Z(n)$ is the measuring value of the stochastic motion error component in the (n-1)'th sampling, $v(n)$ is the repetitive error value of the worktable motion, and the white noise series. Thus,

$E[\varepsilon(n)v(m)] = 0$, $E[\varepsilon(n)] = 0$,

$E[v(n)] = 0, E[\varepsilon^2(n)] = q(n), E[v^2(n)] = r(n),$

$E[\delta_z(0)\varepsilon(n)] = E[\delta_z(0)v(n)] = 0.$

If Kalman filter[8] is applied to the discrete dynamic system which is described by (17) and (18), the following filter algorithms can be obtained:

$$P(n/n-1) = P(n-1) + q(n-1) \tag{19}$$

$$K(n) = P(n/n-1)/[P(n/n-1) + r(n)] \tag{20}$$

$$P(n) = [1 - K(n)]P(n/n-1)$$

$$P(0) = Var[\delta_z(0)] \tag{21}$$

$$\hat{\hat{\delta}}_z(n) = \hat{\delta}_z(n) + K(n)[Z(n) - \hat{\delta}_z(n)]$$

$$\hat{\hat{\delta}}_z(0) = E[\delta_z(0)] \tag{22}$$

Where: $P(n/n-1)$ is the variance matrix of the one-step prediction error, $P(n)$ is the variance matrix of the filtering error, $K(n)$ is the gain matrix of the optimal filter.

(19) — (22) are recursion filter formulas. $\hat{\hat{\delta}}_z(n)$ is the final prediction value of the stochastic motion error component $\delta_z(n)$. Fig.5 gives the final prediction curve of the stochastic motion error component shown in Fig.3., based on the method of the modeling and prediction. The computing results show the variance value of prediction error is not more than 1 μM . This explains the predictive precision of the adaptive predictor with Kalman filter satisfies the demand of working accuracy.

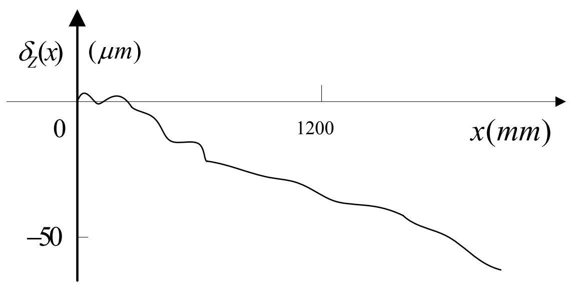

Fig.5 The final prediction curve of the stochastic motion error component

5. Dynamic Compensatory Control For Error

Factors which influence working accuracy on the guide-way grinder, generally, come from two ways: one is system error of the guide-way grinder and working error caused by the stochastic disturbance of circumstance, and it is described by the stochastic motion error component $\delta_z(n)$ of worktable; the other is working error caused by the hot deformation of work-piece, as $g(n)$. If $\delta_z(n+1)$ and $g(n+1)$ can be fixed at n moment of the grinding process, headstock position of the guide-way grinder can be controlled beforehand. Then, the effect of precision compensation is obtained.

If the surface of work-piece is demanded to be ground as $f(t)$ curve shape, the headstock of the guide-way grinder can move along path $F(n+1)$ show by (23). Like this, the error's influence to working accuracy can be decreased, so as to achieve the high precision grinding.

$F(n+1) = f(n+1) + g(n+1) + \hat{\hat{\delta}}_z(n+1)$, as $F(n+1)$ and $F(n)$ are the same sign

$F(n+1) = f(n+1) + g(n+1) + \hat{\hat{\delta}}_z(n+1) + C$, as $F(n+1)$ and $F(n)$ are the different sign (23)

Where: C is the reversal interval compensatory value of gear.

In the grinding process, the grinding heat is important factor which cause temperature differential between upper layer and lower layer of work-piece, and the hot deformation of work-piece. Theoretic computation and actual experiment show the hot deformation error of work-piece is mainly decided by feed value and feed times of the grinding wheel. This makes the quantitative compensation of the hot deformation error of work-piece become possible.

6. Conclusion

In this paper, we put forward a new technique for on-line high precision measurement, dynamic building model, high precision adaptive prediction and dynamic compensatory control, in order to improve working accuracy on the guide-way grinder. This technique has the following advantages; high measuring precision, simple algorithms, short computing time, good adaptive function, high prediction precision, flexible control. System simulation shows this new technique can improve working accuracy on the guide-way grinder. It is a controlling technique of advance and practical precision working, and has wide applied range.

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