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Adaptive Modeling and Characterization for Machining Chatter

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Abstract

Adaptive AR models are used to fit actual recorded vibration data taken from the tailstock of a lathe while cutting a slender workpiece. The parameters of autoregressive (AR) model and critical value for chatter detection are determined on-line. The proposed method can be used to expedite the "forecasting control" and prevention of chatter.

Introduction

Several attempts have been made in the past to design an active machine tool chatter controller which can suppress chatter during machining process [1]. Implementation of the Dynamic Data System (DDS) [2] approach has already shown that the dynamics of the machining process can be identified under actual working conditions [3, 4]. Using this approach, a scheme for computer control of machining chatter based on the criterion of vibration signal range has been proposed [5].

The aim of this paper is to first introduce an on-line adaptive modeling technique which can be used to fit a time-varying autoregressive (AR) model of machining chatter, and then to employ it for predicting the occurrence of severe chatter.

Segmented AR Model of Chatter

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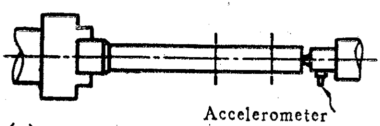
Since the chatter process is a nonstationary one, the usual method of determining its characteristics divides the whole record into short segments so that within each interval the data may be considered "piecewise stationary". After fitting each segment with a time-invariant AR model, *i. e.*,

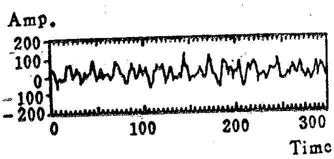
$$x_k = \phi_1 x_{k-1} + \phi_2 x_{k-2} + \cdots + \phi_n x_{k-n} + a_k \quad (1)$$

one thus obtains a series of models which may be combined to represent a nonstationary process. The ϕ_i's in Eq. (1) are autoregressive parameters and a_k are residuals.

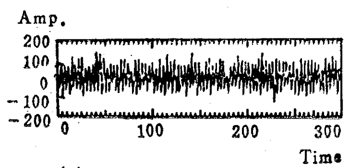
In this approach, the length of each segment should be as short as possible with the requirement that enough data would still be available for modeling. Besides this, there are advantages of having the order, n, of Eq. (1) as small as possible with the requirement that the resulting model still provides enough information for identifying the main features of the chattering. In order to make a choice of order n in advance, segmented AR models were fitted to different sets of acceleration data which were taken from the tailstock of a lathe while cutting a long slender workpiece. The data points in Fig. 1*b* and 1*c* are samples of acceleration signal representing the different levels of chatter. They were recorded while the turning tool was cutting at different positions along the workpiece, say *A* and *B*, (Fig. 1a) respectively. Since the most interesting frequency is the work-



(a)
Spindle-workpiece-tailstock system.



(b) No chatter



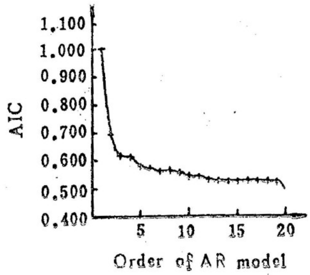
(c) Severe chatter

Fig. 1 Chatter signal plot. Sampling interval is 2 msec

piece's natural frequency, approximately 135 Hz in this case, for our sampling interval of 0.002 sec there are about 4 points per period.

The length of segment was chosen to be 20 samples long which divided the 1536 point nonstationarydata into 76 piece-wise stationary sections. By using the least-square method (LSM) each segment was fitted to an AR model. Akaike's Information Theoretic Criterion (AIC) was used to check the adequacy of the model. Figure 2 shows the AIC for order n from 1 to 20. According to the models fitted to the severe chatter the result indicates that AR(6) model is quite adequate. This is also true for the case of no chatter and mild chatter.

Fig. 2 Using AIC as criterion to check the adequacy of AR(n) model. $n=1$ to 20



Adaptive AR Model of Chatter

The algorithm of adaptive modeling is based on the method of steepest descent. Let $\Phi(k)$ represent the vector of AR parameters at any time k, where

$$\Phi(k) = [\phi_1(k), \phi_2(k), \cdots, \phi_n(k)]^T \tag{2}$$

In seeking the minimum mean-square error by the method of steepest descent, one begins with an initial guess as to where the minimum point of $E(a_k^2)$, the expected value of a_k^2, may be. Here a_k^2 can be the square of the forward (prediction) error a_{fk} (one-sided algorithm) or the sum of squares of backward (prediction) error a_{bk} as well as forward error a_{fk} (a two-sided algorithm) where

$$a_{fk} = x_k - \sum_{i=1}^{n} \phi_i x_{k-i} \qquad k = n+1,\ n+2, \cdots, N$$

$$a_{bk} = x_{k-n} - \sum_{i=1}^{n} \phi_i x_{k-n+i} \qquad k = n+1,\ n+2, \cdots, N \tag{3}$$

The latter two-sided algorithm is

$$a_k^2 = a_{fk}^2 + a_{bk}^2 \tag{4}$$

The updated vector of AR parameters is obtained from

$$\Phi(k+1) = \Phi(k) - \eta \nabla E(a_k^2) \tag{5}$$

where $\nabla E(a_k^2)$ is the gradient of the expected error-squared function with respect to $\Phi(k)$. The second term of Eq. (5) makes a change in the present vector $\Phi(k)$ in the direction of the gradient vector $\nabla E(a_k^2)$. The positive value of η scales the amount of readjustment of the parameters in one time step.

Since the true gradient is seldom available in practice, it is replaced by the gradient of a single time sample of the squared errors $\nabla(a_k^2)$ which can be shown to be an unbiased estimate of $\nabla E(a_k^2)$.

Differentiating Eq. (4) with respect to $\Phi(k)$ gives

$$\nabla(a_k^2) = -2\{a_{fk}[x_{k-1}x_{k-2}\cdots x_{k-n}]^T + a_{bk}[x_{k-n+1}x_{k-n+2}\cdots x_k]^T\} \tag{6}$$

The iterative correction of the parameters are now described by

$$\begin{aligned}\Phi(k+1) &= \Phi(k) - \eta\nabla(a_k^2)\\ &= \Phi(k) + \mu[a_{fk}X(k-1) + a_{bk}X(k-n+1)]\end{aligned} \tag{7}$$

where

$$\mu = 2\eta \tag{8}$$

$$X(k-1) = [x_{k-1}x_{k-2}\cdots x_{k-n}]^T \tag{9}$$

$$X(k-n+1) = [x_{k-n+1}x_{k-n+2}\cdots x_k]^T \tag{10}$$

The calculations required per time step for both adaption and error computation is a total of $2(2n+1)$ multiplcations and additions. (As for a one-sided algorithm the total number is $2n+1$ multiplications and additions.

In addition to estimating the order n, the choice of adaptive coefficient μ is an acute problem in iterative calculations.

If μ is chosen very small, the adjustment will take place very slowly. If μ is chosen too large, the adjustment will overshoot the minimum several times before Φ finally settles to its desired value. The mild chatter data were used to determine the constraint on μ. By using trial and error, in the case of $V_{ar}(x_k) = 1$, values of μ in the range 0.01—0.05 are shown to provide excellent results for chatter modeling.

Since μ is inversely proportional to the power of the data sequence, Σx_i^2, it is necessary to vary the value of μ because of nonstationary vibration. This adjustment will meet the needs of convergency for iterative algorithm. In our chatter example, where the order n is six, μ is taken initially to be 0.05. It is recommended to check the product

$$c=\mu\left(\sum_{i=k-30}^{k}x_i^2\right) \tag{11}$$

after every 1000 new sampled data point come in. The upper and lower bound of c are set to be 0.08 and 0.02 by experience. If c is beyond this range, μ will be changed to $0.05/\Sigma x_i^2$. Figure 3 shows μ with the growth of chatter for a 4096 data points interval which indicates the necessity of periodic checks.

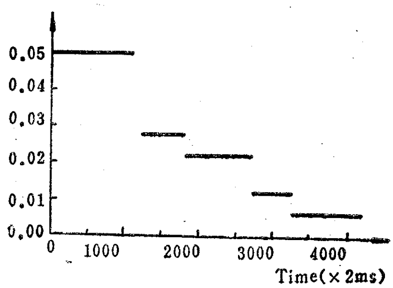
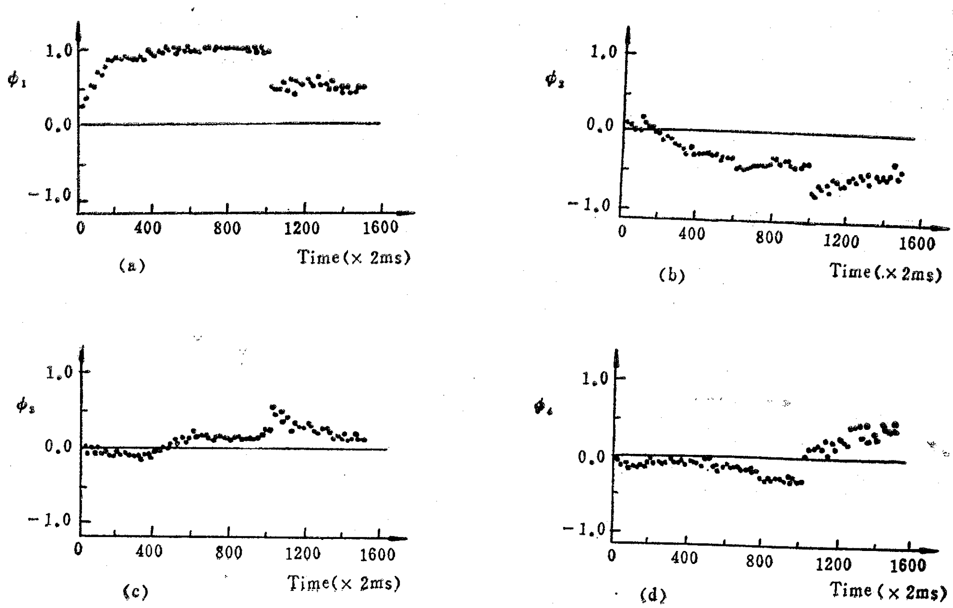


Fig. 3 Values of μ obtained from period checking at every 30 sampled data points.

In order to test the efficiency of the adaptive approach to on-line modeling, the real data taken from mild chatter and severe chatter were artificially linked at $k=1000$ to form a whole piece of nonstationary process. Furthermore, all the initial values of ϕ_i's are set to be zero at $k=0$. Fig.4 gives the results of $\phi_1-\phi_6$ in adaptive fitting. Note that there are sudden changes at $k=0$ and $k=1000$. These



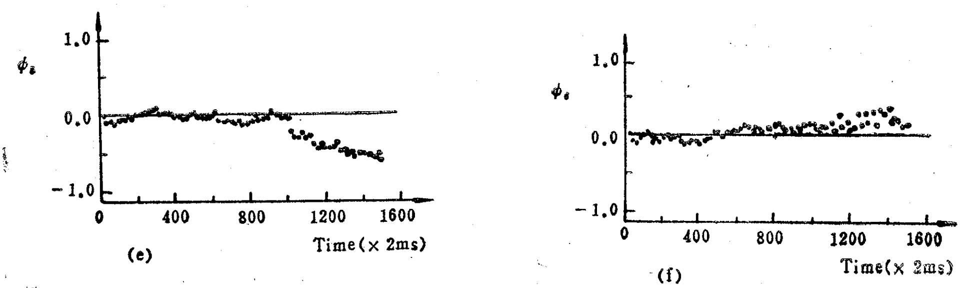


Fig. 4 Parameters of AR(6).

results show that the adaptive algorithm can track the changing signal with rapid response.

A typical result obtained from simulation is shown in Fig. 5a. Real data are also shown for comparison (See Fig. 5b). As the initial values of parameters are all set to zero, the simulated records are small in amplitude during the first 60 data points but become closer to the real process thereafter. This response lag also indicates how fast the adaptive fitting tracks the changes of the signal.

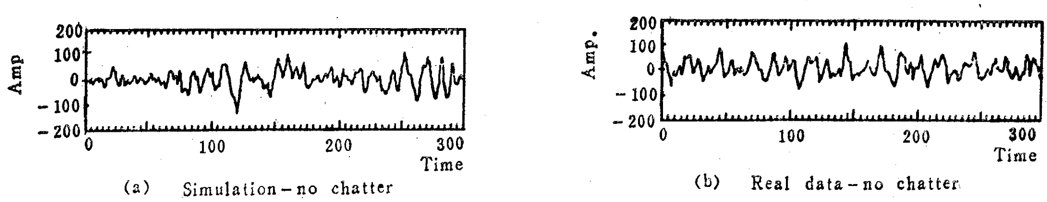


Fig. 5 Comparing the simulation data with the real data.

Figures 6a, 6b, 6c are the spectra of adaptive AR(6) models fitted after receiving the 20th, 280th and 1040th data point respectively.

It should be noted that all the spectra in this paper are calculated by the modified equation given by

$$S_x(f, k) = \frac{1}{\left|1 - \sum_{i=1}^{n} \phi_i(k) \exp(-2\pi j i f)\right|^2} \qquad (12)$$

to simplify their calculations.

A Proposed Criterion for Chatter Detection

Although the autoregressive parameters of the time-varying AR (6) models can be determined on-line, they cannot be used directly as a criterion for chatter detection. What is needed is a comprehen-

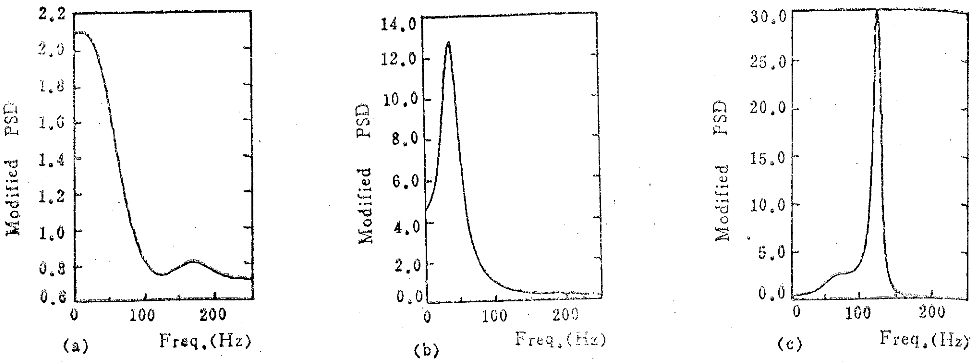


Fig. 6 Spactre of adaptive AR(6) model.

sive index which characterizes the level of chatter in a sensitive way and is also computaionally simple.

It is well known that the dynamic performance of a lathe is dominated by the response of the spindle–workpiece–tailstock system, and when the frequency response of the system reaches a certain high level at the workpiece natural frequency f_0, severe chatter vibration will result. The occurrence of chatter vibration is usually not an abrupt phenomenon, but develops gradually with time. Figure 7 shows the spectrum growing up with the level of chatter. For this reason, the occurrence of chatter can be forecast by detecting the workpiece's natural frequency.

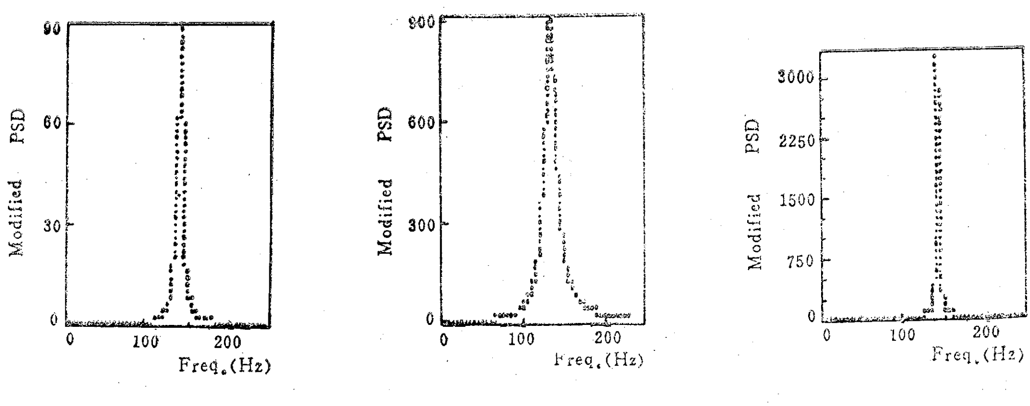


Fig. 7 Spectra with different level of chatter.

Based on the results or the experiments and the analysis of the fitted models, a narrow width and sharp peak grows up around f_0 (in modified spectrum) when chatter is tending to be severe. The absolute value of the peak is not related to chatter signal amplitude due to the use of the modified spectrum estimate as defined in Eq. (12). To simplify the computation, the inverse power density

$$S_x^{-1}(f,k)=\left|1-\sum_{i=1}^{n}\phi_i(k)\exp(-2\pi jif)\right|^2 \quad (13)$$

is used. The value of $\sum_{i=0}^{n}\phi_i(k)\exp(-2\pi jif)$ with $\phi_0(k)=-1$ can be calcuated by a special simplified FFT algorithm. The number of calculations necessary to compute the summation in Eq. (13) can be greatly reduced, the precise number of computations depends on the order n. Figures 8a and 8b show the S_x^{-1} at $k=1060$ and 1320 respectively.

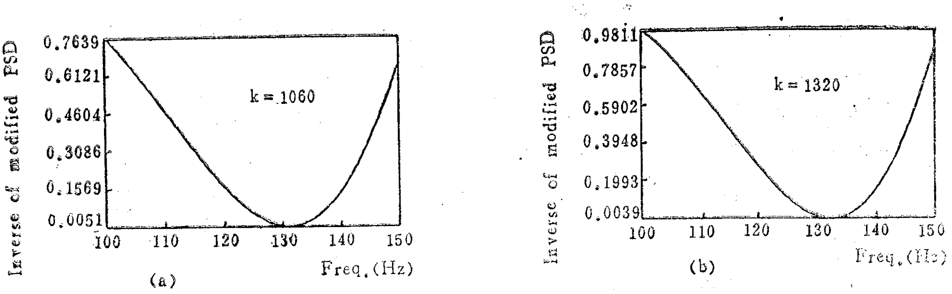


Fig. 8 $S_x^{-1}(f, k)$ at $k=1060$ and $k=1320$

A critical value of S_x^{-1} around f_0 is predetermined. Comparing this critical value, P_c, with the local minimum given by

$$P=\min[S_x^{-1}(f,k)] \quad f_0-\Delta f<f<f_0+\Delta f \quad (14)$$

the difference detween P_c and P could be used as a predictor of severe chatter. When P is larger than a critical value P_c, the machining process is stable and there is no severe chatter expected. However, whenever $P<P_c$, it indicates the likelihood of severe chatter and the cutting conditions of spindle speed and/or feed rate should be changed in advance to avoid the inevitable chattering.

The basic form of adaptive modeling and the P calculation is presented schematically in Fig. 9. The computation for ϕ_i's and P are performed periodically and the result of ϕ_i's in previous steps is stored up in output memory as the initial values for the next step computation (zeros can be used as initial values at the very beginning).

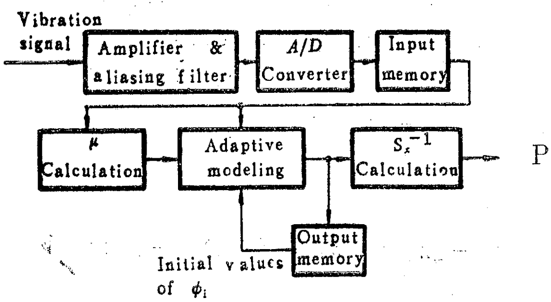


Fig. 9 Basic operating block diagram for adaptive modeling and chatter detection.

Conclusions

1. The time-varying AR models for representing nonstationary chatter can be determined by periodically updating the parameters in a time adaptive manner. An adaptive time-varying AR(6) model is sufficent for fitting the vibration data during the whole chatter process.
2. The adaptive AR modeling technique is suitable for on-line modeling. Since it requires only 26 multiplications and additions (if $n=6$ and use two-sided algorithm) for each update cycle, the implementation of the on-line modeling within the interval of several samples is possible.
3. The critical local minimum of inverse power density P_c is used as an index of the level of chatter. The local minimum of inverse power density P below this level is presumed to indicate the likelihood of severe chatter.
4. Only minimal prior knowledge regarding the nature of the vibration is required. The workpiece natural frequency needs to be identified in advance in order to search for the local minimum P.

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