

Active Control of Machine-Tool Vibration

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SUMMARY A new adaptive technique is presented for the increase of the dynamic stiffness of the cutting tool in a lathe by active control of the tool vibration in the cutting speed direction. Due to the statistic properties of tool vibration that are induced by the stochastic behavior of chip formation process, the controller is based on the filtered-x LMS algorithm which controls an adaptive filter that is based on Wiener filter theory. Hence, the adaptation of the filtered-x LMS algorithm is gradient-based and it is based on a classical optimization technique, the method of steepest descent. In the cutting experiments a tool holder construction with integrated actuators, i.e. secondary sources was used. The cutting experiments shows that the adaptive technique presented in this paper enables an increase in the dynamic stiffness of the cutting tool, i.e. tool vibrations are suppressed.

1 INTRODUCTION

In a turning operation it is well known that the relative dynamic motion between the cutting tool and the workpiece leads to poor surface finish, reduced accuracy, increased tool wear, and even tool fracture and damage to the machinery. The dynamic phenomena, which is induced by the stochastic behavior of the chip formation process is closely related to the dynamic stiffness of the structure of the machinery and workpiece material. It is widely accepted that increasing dynamic stiffness results in substantial reduction of the relative vibration between the cutting tool and the workpiece. The vibration problem may be solved in part by proper machine design which stiffens the structure resulting in increased dynamic stiffness. In order to achieve further improvements, the stiffness of the tool must be increased. Techniques have been developed which improve machine tool stiffness such as the use of dynamic dampers [1, 2, 3].

Other techniques that does not include the improvement of machine tool stiffness have been developed, such as active control of the position of the cutting tool relative to the workpiece in the cutting depth direction [4, 5, 6], and the control of cutting data with respect to the stability of machining [7, 8, 9, 10, 11, 12], i.e. the dynamic stiffness of the cutting tool and workpiece in the turning operation.

It is well known that mechanical properties of materials, such as chemical composition, inhomogeneities, microstructure and hardening have statistical variations in both the radial and the feed direction [13]. As a consequence of the statistical variation of the mechanical properties the deformation properties of the material will also show statistical variations. Since the chip formation process is in principal governed by the deformation properties of the workpiece material it will consequently have a stochastic nature. From the stochastic behavior of the chip formation process it follows that the tool vibration also have statistical properties, i.e. the tool

vibration define a stochastic process [14]. Practical experiments also show that the statistic properties of tool vibration are non-stationary [15] and this is probably a consequence of the statistical variations in mechanical properties of workpiece materials.

The tool vibration in a turning operation is in principal the composition of vibrations in two directions, i.e. the vibration in the cutting speed direction and the vibration in the feed direction. Consequently the control problem is related to multi-modal control and involves the introduction of two secondary sources, driven so that the vibration generated by these sources interferes destructively with the tool vibration, i.e. canceling the tool vibration [16, 17, 18]. The statistical properties of the tool vibration implies a controller which is based on a control law which uses the statistical dependence structure of the vibration [18, 19]. A classical but yet useful statistical criterion is the mean square error criterion [20, 21, 19, 14]. However, a controller based on this criterion can not solve the control problem, since a such controller is only "optimum" in a stationary environment [22, 19, 18]. A solution for this problem is an adaptive controller which is able to track the non-stationary environment [19, 18].

This paper is concerned with the active control of the tool vibration in the cutting speed direction, based on adaptive digital filtering. The single channel control system is illustrated in figure 1. A single-channel feedback controller which is based on the well known filtered-x LMS-algorithm [19, 23] is used. The tool holder in this application is a construction with integrated actuators (secondary sources) which has been developed at DPME¹ [24]. The construction of the tool holder is illustrated in figure 2.

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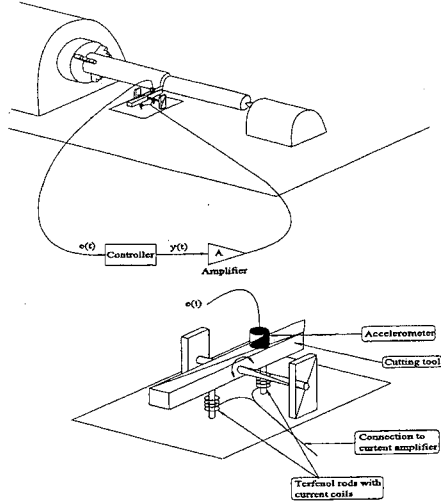


Figure 1: Vibration control system for the cutting process.

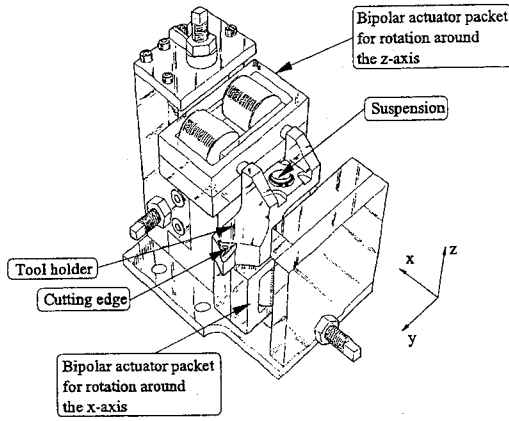


Figure 2: Tool holder with integrated actuators for the control of tool vibration in the metal cutting process [24]

2 MATERIALS AND METHODS

2.1 The Adaptive FIR-filter for Single Channel Control

A common and widely used adaptive filter algorithm is the LMS algorithm, which is an adaptive solution of the well known Wiener filtering problem [21, 23]. Given some signal $x(n)$, $n \in \{0, \dots, N-1\}$ and a desired signal $d(n)$ at time n , the problem is to determine the optimal weights of the linear filter according to this minimization criterion, generally referred to as the Wiener filter problem [21, 14]. In the case of a FIR filter the filter output $y(n)$ is given by;

$$y(n) = \mathbf{w}^T \mathbf{x}(n) \quad (1)$$

where

$$\mathbf{x}(n) = [x(n), x(n-1), \dots, x(n-M+1)]^T \quad (2)$$

is the input signal vector and

$$\mathbf{w} = [w_0, w_1, \dots, w_{M-1}]^T \quad (3)$$

is the coefficient vector of the FIR filter. Thus the statistical FIR filtering problem is shown in figure 3 If it is as-

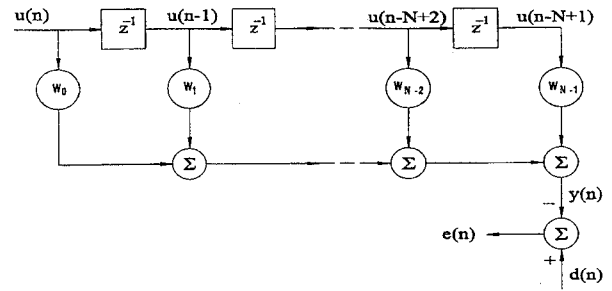


Figure 3: Block diagram of the statistical FIR filtering problem.

sumed that both the input signal $x(n)$ and the desired signal $d(n)$ are at least weakly stationary processes. Then the stationary Wiener FIR filter is obtained by the coefficient vector which minimizes the mean-squared error $E[e^2(n)]$ (the estimation error is defined by $e(n) = d(n) - y(n)$), i.e. the optimal coefficient vector \mathbf{w}_o [21, 14]. This is equivalent to minimizing the quadratic function J_f [21, 14]:

$$J_f = E[e(n)^2] = E[(d(n) - \mathbf{w}^T \mathbf{u}(n))(d(n) - \mathbf{u}^T(n) \mathbf{w})] \quad (4)$$

and the minimum can be obtained from:

$$\mathbf{R} \mathbf{w}_o = \mathbf{p} \quad (5)$$

which is the matrix formulation of the Wiener-Hopf equations, \mathbf{R} is the $M \times M$ correlations matrix of the input signal vector and \mathbf{p} is the cross-correlation vector between the input signal vector $\mathbf{x}(n)$ and the desired signal $d(n)$. To solve the Wiener-Hopf equations it is assumed that the \mathbf{R} correlation matrix is nonsingular, and the optimal coefficient vector \mathbf{w}_o is given by [21, 14]:

$$\mathbf{w}_o = \mathbf{R}^{-1} \mathbf{p} \quad (6)$$

The LMS algorithm is basically a combination of two processes, an adaptive process and a filtering process. The filtering process involves the linear FIR filtering of the input signal and the generation of the estimation error. The adaptive process involves the automatic adjustment of the coefficient vector towards its equilibrium and it is based on the information obtained from the estimation error and the input signal [20, 21, 23]. Figure 4 illustrates the structure of the LMS algorithm. The Wiener solution of the coefficient vector is obtained by minimizing the quadratic function [20, 21, 23]:

$$J_f(n) = E[e(n)^2] = E[(d(n) - \mathbf{w}^T(n) \mathbf{u}(n))(d(n) - \mathbf{u}^T(n) \mathbf{w}(n))] \quad (7)$$

The LMS algorithm is a gradient-based adaptation which is based on a classical optimization technique, the *method of steepest descent* [20, 21, 23]. The algorithm for the adaption of the coefficient vector uses an instantaneous estimate of the gradient vector $\nabla_{\mathbf{w}(n)} J_f(n)$ which is given by [20, 21, 23]:

$$\nabla_{\mathbf{w}(n)} J_f^*(n) = \nabla_{\mathbf{w}(n)} e(n)^2 = -2 \mathbf{u}(n) e(n) \quad (8)$$

This leads directly to the definition of the LMS algorithm and which is given by the following three equations [20, 21, 23]:

$$y(n) = \mathbf{w}^T(n)\mathbf{u}(n) \quad (9)$$

$$e(n) = d(n) - y(n) \quad (10)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{u}(n)e(n) \quad (11)$$

Usually adaptive filters are designed for problems such as conventional electrical noise canceling where the output signal from the filter is an estimate of the signal to be canceled. In case of active control the adaptive filter work as a controller and controls a dynamic system containing actuators and amplifiers etc., so the estimate in this case can be seen as the output signal from the dynamic system, i.e. the "secondary" source. Because of the dynamic system between the filter output and the estimate, the selection of adaptive filter algorithms are rather limited. A well known algorithm such as the LMS algorithm is likely to be unstable in this application due to the phase shift introduced by the dynamic system [18]. The filtered-x LMS-algorithm is specially developed for such applications in active control [18, 19, 23].

The filtered-x LMS-algorithm is developed from the LMS algorithm, where a model of the the dynamic system between the filter output and the estimate, i.e. secondary path is introduced between the input signal and the algorithm for the adaptation of the coefficient vector [18, 19, 23]. Figure 5 shows an active control system with a controller based on the filtered-x LMS algorithm. We assume that the transfer function for the secondary path can be modeled with a I th-order FIR filter, which coefficients are c_i , $i \in \{0, \dots, I-1\}$, so that:

$$e(n) = d(n) - \sum_{i=0}^{I-1} c_i \sum_{m=0}^{M-1} w_m(n-i)u(n-i-m) \quad (12)$$

The Wiener filter solution of the coefficient vector is then obtained by minimizing the quadratic function [25, 18, 19, 23]:

$$J_f(n) = E[e(n)^2] \quad (13)$$

The differential of this function with respect to each coefficient is;

$$\frac{\partial J_f(n)}{\partial w_m(n)} = 2E \left[e(n) \frac{\partial e(n)}{\partial w_m(n)} \right] \quad (14)$$

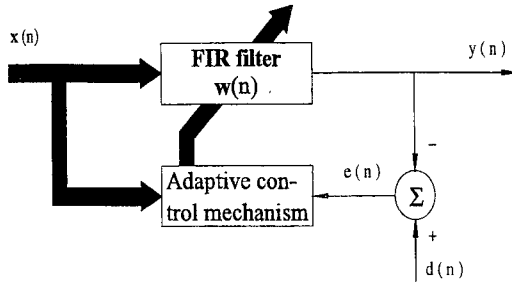


Figure 4: Block diagram of adaptive FIR filter.

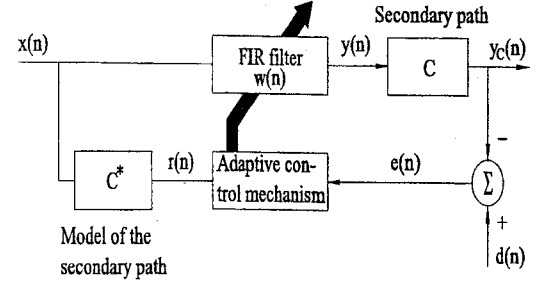


Figure 5: Active control system with a controller based on the filtered-x LMS-algorithm.

and if it is assumed that w_m , $m \in \{0, \dots, M-1\}$ is time invariant, the differential of the estimation error with respect to a coefficient is given by:

$$\frac{\partial e(n)}{\partial w_m(n)} = \sum_{i=0}^{I-1} c_i u(n-i-m) \quad (15)$$

The assumption of time invariance is in accordance with a slow coefficient change in comparison with the timescale of the response of the system to be controlled, and in practice the filtered-x LMS-algorithm is stable even if its coefficients change significantly within the timescale associated with the dynamic response of the secondary path [25, 18, 19, 23]. The filtered-x LMS-algorithm is given by the following four equations [25, 18, 19, 23];

$$y(n) = \mathbf{w}^T(n)\mathbf{u}(n) \quad (16)$$

$$e(n) = d(n) - y_c(n) \quad (17)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{r}(n)e(n) \quad (18)$$

and

$$\mathbf{r}(n) = \sum_{i=0}^{I-1} c_i^* \mathbf{u}(n-i) \quad (19)$$

where c_i^* , $i \in \{0, \dots, I-1\}$ is an estimate of the impulse response of the secondary path.

2.2 The adaptive controller

Adaptive digital FIR filters based on the method of steepest descent are popular in active control of sound [18, 26, 27] and in other applications, such as electrical noise canceling, system identification, adaptive beamforming, etc. [23]. This is due to the simplicity of the implementation and their unimodal error surface in the feedforward application. Thus a feedforward active controller which is based on a adaptive filter such as the LMS algorithm will "always" converge towards the optimum solution [20, 21, 19, 23]. Usually adaptive FIR filters are used in feedforward control [18, 26, 27] but they have also been used in feedback control [28], even though there is no guarantee that the error surface will be unimodal under these conditions[29]. Similar error surfaces can also be observed in feedforward control systems, when the control problem is not well conditioned. A method to control such systems is to add a leaky term

to the adaption algorithm [20, 30, 21, 31]. This will also prevent an accumulative build-up of bias in the coefficient update algorithm in the adaptive filter [32].

The controller used in the experiments reported here is a feedback controller based on the well known filtered-x LMS-algorithm [28]. The block diagram of the feedback controller and the filtered-x LMS algorithm used for the adaption of the coefficient vector $\mathbf{w}(n)$ of the FIR filter is shown in figures 6 (a) and (b). In these figures C is the plant under control, i.e. the electro-mechanic response of the secondary path and C^* is a model of the response of the secondary path. The secondary path was estimated in an initial phase with an another adaptive FIR filter, and subsequently used to filter the input signal to the algorithm for the adaptation of the coefficient vector in the filtered-x LMS algorithm.

Due to the lowpass character of the algorithm for the

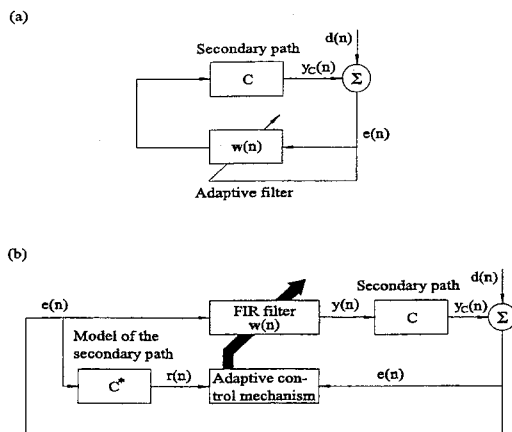


Figure 6: The equivalent block diagram of the feedback controller (a) and the filtered-x LMS algorithm used for the adaption of coefficient vector $\mathbf{w}(n)$ of the FIR filter(b).

adaption of the coefficient vector the sampling rate of the digital filter was chosen rather high (20 kHz). To minimize the delay in the loop (according to the well known Nyquist theorem) no anti-aliasing or reconstruction filters were used. However, due to a rather nasty resonance in the tool holder construction at approximately 1.6 kHz, a lowpass filter was introduced in the loop to eliminate the influence of this resonance to the adaptive filter.

Both simulation and practical cutting experiments were conducted. The simulation was performed in the dynamic system simulation software SIMULINK [33], where an ARMA process was used to model the tool vibration and a FIR filter modeled the secondary path.

2.3 Materials

In the cutting experiments quenched and tempered steel AISI 4130 was used.

2.4 Equipment

The cutting experiments have been carried out on a K ping lath with 6 kW spindle power. The equipment

that has been used in the experiments are:

1. A tool holder with integrated actuators constructed and developed at DPME² [24].
2. Accelerometer *Br el & Kj r model 4374*
3. Current amplifier *Techron 7700 series*, 5 kW 50 kHz, power supply for the actuators.
4. Frequency Analyzer *HP 3565A Dynamic Signal Analyzer*, Band width: 102 kHz one channel, 51 kHz two channels.
5. Signal processing unit *Burr - Brown, PCI-20202C*, digital signal processor carrier with TMS320C25 signal processor (40MHz).
6. A/D-converter *Burr - Brown, PCI-20023M-1*, 180 kHz, 8-inputs with 12 bits resolution.
7. D/A-converter *Burr - Brown, PCI-20003M*, 120kHz, 2-outputs with 12 bits resolution.
8. Computer *Silicon Graphics, Iris Crimson*.

The accelerometer was mounted on the cutting tool in order to measure the vibration in the cutting speed direction.

3 RESULTS

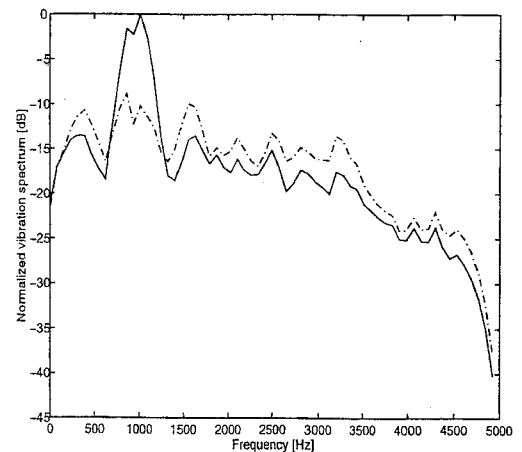


Figure 7: Simulated cutting tool vibration spectrum with (dashed) and without (solid) feedback control.

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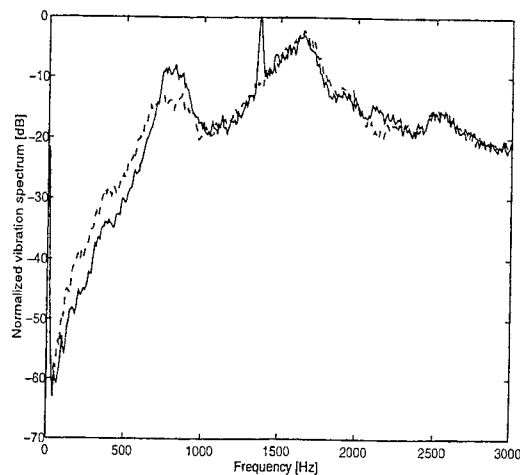


Figure 8: Cutting tool vibration spectrum with (dashed) and without (solid) feedback control, the cutting speed v was 60 m/s, the feed s was 0.3 mm/rev and the depth of cut a was 0.8 mm.

4 DISCUSSION

This paper introduces a new adaptive technique to increase the dynamic stiffness of the cutting tool in a lathe. The technique involves the active control of tool vibration in the cutting speed direction with an adaptive controller that is based on the filtered-x LMS algorithm. The cutting experiments show that it is possible to increase the dynamic stiffness of the cutting tool, i.e. cancel cutting tool vibration.

In comparison with other existing techniques which increase the dynamic stiffness in the cutting tool, this technique is adaptive, i.e. it automatically adjusts itself to the properties of the tool vibration. Further, the technique does not reduce cutting data and consequently not the material removal rate.

The experiments have been rather "nasty" due to the ill conditioned control problem and due to the resonance in the tool holder construction. Since there was not a leaky term in the adaptive algorithm there was a problem with accumulative build-up of biases in the coefficient update of the adaptive filter, which often resulted in adaptation hangup and even worse, in instabilities. Further, the resonance in the tool holder construction caused big problems, since the influence of the resonance on the adaptive filter had to be eliminated to control the tool vibration introduced by the chip formation process. Thus the influence of the resonance had to be filtered out and this was done with a lowpass filter which was introduced in the loop. Unfortunately, the lowpass filter that was used had a rather low rolloff rate, which in combination with its phase delay resulted in a nearly unacceptable loop delay. Even with these rather serious problems it was possible to show that the dynamic stiffness of the cutting tool could be increased, i.e. canceling cutting tool vibration with this technique is promising.

We plan to improve the control system by implementing the filtered-x LMS algorithm with a leaky term and update the filter equipment for the elimination of the resonance in the tool holder construction in the near future.

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