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ROBUST CONTROL OF MACHINE-TOOL VIBRATION IN A LATHE

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ABSTRACT

In the turning operation the relative dynamic motion between cutting tool and workpiece, or vibration, is a frequent problem, which affects the result of the machining, and, in particular, the surface finish. Tool life is also influenced by vibration. Severe acoustic noise in the working environment frequently occurs as a result of dynamic motion between the cutting tool and the workpiece. These problems can be reduced substantially by active control of the machine-tool vibration. Adaptive feedback control based on the filtered-x LMS-algorithm, enables a reduction of the vibration by up to 40 dB at 1.5 kHz and by approximately 40 dB at 3 kHz. The active control performeds a broadband attenuation of the sound pressure level by up to 35 dB. However, the process of machining a workpiece usually involves a variety of cutting data which in turn are likely to cause substantial variations in the spectral properties of the tool vibrations. Hence, variations in the spectral properties originates from changes in the excitation of the tool holder and changes in the structural response of the tool holder. To handle the potential large variations in the spectral properties of tool vibration in the turning operation the robustness of the control system has to be improved. By applying the leaky version of the filtered-x LMS algorithm in the active control of machine tool vibration it was found that the robustness of the adaptive control system was improved substantially to large variations in the spectral properties of tool vibration.

1. INTRODUCTION

In the turning operation the tool and tool holder shank are subjected to dynamic excitation due to the deformation of work material during the cutting operation. The stochastic chip formation process usually induces vibrations in the machine-tool system. Energy from the chip formation process excites the mechanical modes of the machine-tool system. Modes of the workpiece may also influence tool vibration. The relative dynamic motion between cutting tool and workpiece will affect the result of the machining, in particular the surface finish. Furthermore, the tool life is correlated with the amount of vibration and the acoustic noise introduced. The noise level is sometimes almost unbearable.

It is wellknown that vibration problems are closely related to the dynamic stiffness of the structure of the machinery and workpiece material. The vibration problem may be solved in part by proper machine design leading to an increased dynamic stiffnes in the machine structure. In order to achieve further improvements the dynamic stiffness of the tool holder shank can be increased more selectively. One solution to these problems is active control of the tool vibrations.

Generally, machine-tool systems are classified as narrow-band systems [1] and as a consequence tool shank vibrations can usually be described as a superposition of narrow-band random processes at each modal frequency [1, 2]. These when added to together form a more wide-band random process [1]. The tool vibrations in a turning operation mainly comprise vibrations in two directions: the cutting speed direction and the feed direction [1, 3]. Usually, the vibrations in the cutting speed direction and the feed direction are linearly independent, except at some of the eigenfrequencies [1]. Consequently, the control problem involves the introduction of two secondary sources, driven in such a way that the anti-vibrations generated by means of these sources interfere destructively with the tool vibration [3]. However, in external longitudinal turning, most of the vibration energy is usually induced in the cutting speed direction [1, 3]. It is thus likely that the control of tool vibration in the cutting speed direction is an adequate solution the vibration problem [3, 4] A complication in the turning operation is that the original excitation of the tool vibration the chip formation process cannot be observed directly and thus cannot be used as a feedforward control signal.

The statistical properties of the tool vibration imply a controller which utilizes the statistical correlation of the vibrations [5]. A classical statistical criterion is the mean square error criterion [6]. However, a controller based on this criterion cannot generally solve the control problem, since a such controller is only "optimum" in a stationary environment [7]. The statistical properties of the tool vibrations may vary during the machining process. Changes in cutting data and material properties influence the statistical properties of tool vibrations [1, 3]. Variation within the allowed cutting data interval may also influence the structural response of the tool holder [3]. In the case of constant cutting data, adaptive feedback control of machine-tool vibration based on the wellknown filtered-x LMS-algorithm seems very promising [3]. However, variations within the excitation and the structural response of the tool holder influence the stability of the adaptive feedback control system. The stability of the feedback control systems is affected by the ability of the filtered-x LMS-algorithm to control the adaptive FIR filter, the time varying controller response, without violating the closed loop stability requirements, i.e. the Nyquist stability criterion [8]. A solution to the controller problem is to control the adaptive FIR filter with the leaky version of the wellknown filtered-x LMS-algorithm [4]

This paper discusses the single-channel feedback control of tool vibration in the cutting speed direction. The single channel control system is illustrated in Fig. 1 below.

The tool holder in this application has integrated actuators, i.e. secondary sources, which have been developed at DPME[1] [9]. The construction of the tool holder is shown in Fig. 2.

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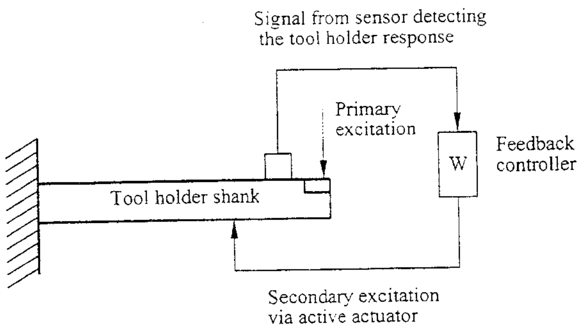

Figure 1: A machine-tool feedback control system[3].

2. MATERIALS AND METHODS

2.1. EXPERIMENTAL SETUP

The cutting experiments have been carried out on a Köping lathe with 6 kW spindle power using a tool holder construction with integrated actuators [9] and an accelerometer mounted on the cutting tool make it possible to measure the vibrations in the cutting speed direction. The tool holder construction is based on two bipolar actuators. The bipolar design is motivated by a desire to achieve linear behaviour, and is composed of two actuators that work with 180° phase difference. In order to operate the bipolar actuator, a large current amplifier(5kW) was used. A digital signal processor controller was used and the measurements were carried out on a two-channel signal analyzer. Furthermore, a two channel low-pass filter was used to adjust the input level to the A/D converter and the output level from the D/A converter.

2.1.1. WORK MATERIAL - CUTTING DATA - TOOL GEOMETRY

The workpiece material SS 2541-03, chromium molybdenum nickel steel [1], was used in the experiments. This work material excites the machine-tool-system with narrow bandwidth in the cutting operation. After a preliminary set of trials a suitable combination of cutting data and tool geometry were selected (see Table 1).

Cutting data set	Geometry	Cutting speed v (m/min)	Depth of cut a (mm)	Feed s (mm/rev)
No. 1	DNMG 150604-PF 4015	80	0.9	0.25
No. 2	DNMG 150604-PF 4015	68, 70, . . . , 82	0.9	0.25

Table 1: Cutting data and tool geometry.

Cutting data set No. 1 was selected for the production of significant tool vibrations. These resulted in an observable deterioration in the workpiece surface as well as severe acoustic noise. Cutting data set No. 2 was selected to introduce substantial variations in the spectral properties of the tool vibration in a controlled manner. Eight different cutting data settings were selected. The experiment was carried out with gradually increasing cutting speeds from 68 m/min to 82 m/min with a step of 2 m/min. The diameter of the workpiece was deliberately chosen large (over 100 mm), in order to render the workpiece vibrations negligible.

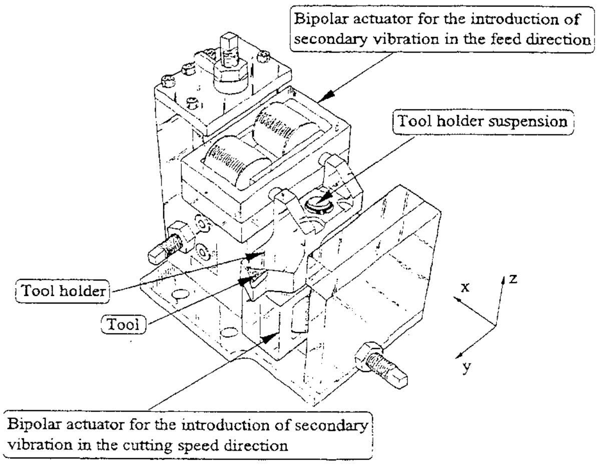

Figure 2: Tool holder with integrated actuators for the control of tool vibration in the metal cutting process [9].

2.2. ADAPTIVE CONTROL OF TOOL VIBRATION

The original excitation of the tool vibrations originating from the material deformation process cannot be directly observed. Consequently, the controller for the control of machine-tool vibration is based on a feedback approach. The response of the tool holder can be measured with a sensor mounted on the machine-tool. By the introduction of secondary anti-vibrations with a secondary source an actuator the response of the tool holder can be modified [3]. The actuator is steered by a controller fed with the accelerometer signal which senses the vibrations of the tool holder (see Fig. 1).

The objective of the control is to minimize the mean square error. The use of the error signal as input signal to the adaptive FIR filter controlling the plant, will cause the adaptive FIR filter to act as a feedback controller. This will complicate the relation between the mean square error and the filter coefficients, i.e. the mean square error will not be a quadratic function of the filter coefficients. In fact the mean square error function may be multimodal in the filter coefficients [10]. The search for a minimum on the mean square error surface can be performed by the wellknown filtered-x LMS algorithm defined by [4]:

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

$$e(n) = d(n) - y_C(n) \tag{2}$$

$$\mathbf{x}_{C^*}(n) = \mathbf{c}^{*T}\mathbf{x}(n) \tag{3}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}_{C^*}(n)e(n) \tag{4}$$

where

$$\mathbf{x}_{C^*}(n) = \begin{bmatrix} \sum_{i=0}^{I-1} c_i^* x(n-i) \\ \sum_{i=0}^{I-1} c_i^* x(n-i-1) \\ \vdots \\ \sum_{i=0}^{I-1} c_i^* x(n-i-M+1) \end{bmatrix} \tag{5}$$

and c_i^* is the coefficients of an estimated FIR filter model of the forward path:

$$h_{C^*}(n) = \begin{cases} c_n^* & \text{if } n \in \{0, \ldots, I-1\} \\ 0 & \text{else} \end{cases} \tag{6}$$

A block diagram of the feedback control system with the filtered-x LMS algorithm is shown in Fig. 3.

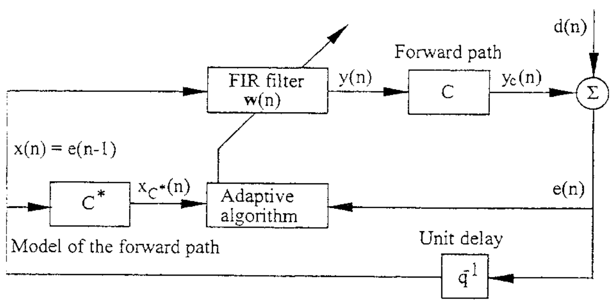

Figure 3: Equivalent block diagram of the feedback control situation with the filtered-x LMS algorithm[3].

In Fig. 3 the box with the unit delay operator q^{-1} at the input to the controller handle the fact that we are dealing with an adaptive digital filter in a feedback control system. Observe the feedback relation from $x(n) = e(n-1)$. Furthermore, C represents the dynamic secondary system (forward path) under control, i.e. the electro-mechanic response. The estimate of this path is denoted C^*. It is in practice customary to use an estimate of the impulse response for the forward path. As a result, the reference signal $\mathbf{x}_{C^*}(n)$ will be an approximaton, and differences between the estimate of the forward path and the true forward path influence both the stability properties and the convergence rate of the algorithm [5, 7, 11, 12].

The estimation error is given by the recursive difference equation:

$$e(n) = -c(n) * \sum_{m=0}^{M-1} w_m(n) e(n-m-1) + d(n) \tag{7}$$

This expression can be rewritten in a more convenient form using delay-operator notation as follows:

$$e(n) = -C(q) W(n,q) q^{-1} e(n) + d(n) \tag{8}$$

which can be expressed as the filtering operation:

$$e(n) = \frac{1}{1 + C(q)W(n,q)q^{-1}} d(n) \tag{9}$$

From this expression it is obvious that the poles of filter, i.e. the poles of the transfer function between the desired signal $d(n)$ and the estimation error $e(n)$, are affected by the controller response. The stability of the feedback control systems thus depends on the ability of the filtered-x LMS-algorithm to control the adaptive FIR filter, the time varying controller response, without violateing the closed loop stability requirements, i.e. the Nyquist stability criterion [8]. In feedback control, limiting the energy in the control signal to the plant yields a more robust behaviour. By introducing leakage in the filtered-x LMS-algorithm the "memory" of the adaptive algorithm is reduced thereby reducing the energy in the response of the adaptive FIR filter and also the energy in the control signal to the plant.

The leaky version of the filtered-x LMS-algorithm is obtained through a modification of the algorithm for the coefficient vector adaption of the filtered-x LMS-algorithm with a leakage factor γ. As a result, the algorithm for the coefficient vector adaption of the leaky version of the filtered-x LMS-algorithm is given by [12]:

$$\mathbf{w}(n+1) = \gamma\mathbf{w}(n) + \mu\mathbf{x}_{C^*}(n)e(n) \tag{10}$$

The leakage factor γ is a real positive parameter which satisfies the condition:

$$0 < \gamma < 1 \tag{11}$$

The secondary path was estimated in an initial phase and was carried out by a second adaptive FIR filter steered by the LMS algorithm. In the estimation, a broadband Gaussian-distributed training signal was used. The fixed FIR filter estimate of the forward path was subsequently used to prefilter the input signal to the algorithm for the adaptation of the coefficient vector in the filtered-x LMS algorithm. For the control of tool vibration a 20-tap adaptive FIR filter was used together with a 16-tap FIR filter estimate of the secondary path [3]. These filter lengths were at the limit for the processing capacity of the signal processor used. A 15 kHz sampling rate was chosen for the digital filter. In order to minimize delay in the loop, no anti-aliasing or reconstruction filters were used. Obviously, this necessitates extra care being taken in order to avoid aliasing.

3. RESULTS

The tool shank vibrations considered in this section originate from the cutting speed direction of the tool holder shank in the tool holder construction. To enable an investigation of both the filtered-x LMS algorithm and the leaky filtered-x LMS algorithm in the feedback control of tool vibrationas in a "stationary" environment, the experiment was designed to introduce significant tool vibrations with constant cutting data in accordance with cutting data set No.1. To illustrate the effect of feedback control of tool vibration in the cutting speed direction, the spectral densities of the tool vibrations with and without feedback control are shown in the same diagram. Fig. 4 shows a typical result obtained with adaptive feedback control of tool-vibration. It performs a broad-band attenuation of the tool-vibration and manage to reduce the vibration level with up to approximately 40 dB simultaneously at 1.5 kHz and 3 kHz. An important property of adaptive control of tool vibrations is the robustness of the control to substantial variation in the spectral properties of the tool vibrations. In order to render an examination of the robustness of the adaptive control to substantial variation in the spectral properties of the tool vibrations, the second cutting experiment was designed to introduce considerable variation in the spectral properties of the tool

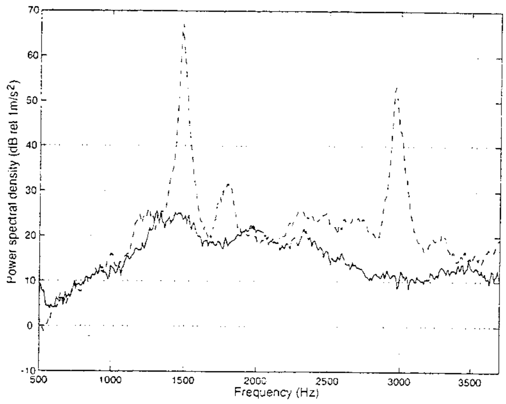

Figure 4: The spectral density of tool vibration with 20 tap FIR filter feedback control (solid) and without (dashed). Cutting speed $v = 80$ m/min, cut depth $a = 0.9$ mm, feed rate $s = 0.25$ mm/rev, tool DNMG 150604-PF, grade 4015[4].

vibrations. The cutting data used were thus varied in a controlled manner, according to cutting data set No. 2. The results reported here are presented with waterfall diagrams. Fig. 5 shows the spectra for the tool vibration without adaptive feedback control at the eight different cutting speeds.

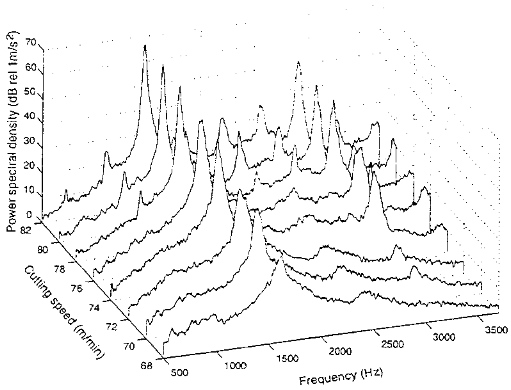

Figure 5: The spectral density of tool vibration at eight different cutting speeds $v = 68$ - 82 m/min, cut depth $a = 0.9$ mm, feed rate $s = 0.25$ mm/rev, tool DNMG 150604-PF, grade 4015.

By using the step length $\mu = 0.1$ in the filtered-x LMS algorithm the feedback control resulted in the vibration spectrum shown in Fig. 6. From the waterfall diagram, it is obvious that the control system is unstable for the two highest cutting speeds, i.e. 80 m/min and 82 m/min.

Leakage was then introduced in the filtered-x LMS algorithm, $\gamma = 0.99$. Feedback control of tool vibration based on the cutting data set No.2 was repeated with different step lengths, starting with $\mu = 0.1$. The step length was then gradually increased up to the maximal step length setting

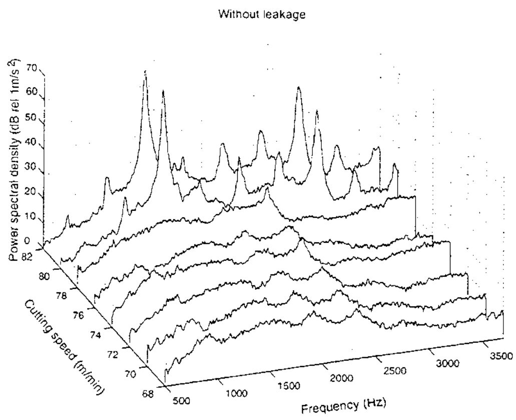

Figure 6: The spectral density of tool vibration with adaptive feedback control, $\mu = 0.1$, at eight different cutting speeds v = 68 - 82 m/min, cut depth a = 0.9 mm, feed rate s = 0.25 mm/rev, tool DNMG 150604-PF, grade 4015.

$\mu = 1$. For the maximal step length setting $\mu = 1$ and the leakage factor $\gamma = 0.99$ the adaptive control of tool vibration resulted in the vibration spectrums shown in the waterfall diagram in Fig. 7. As a result, the adaptive control system maintained stable even for the maximal step length setting, $\mu = 1$, in the leaky filtered-x LMS algorithm, leakage factor $\gamma = 0.99$.

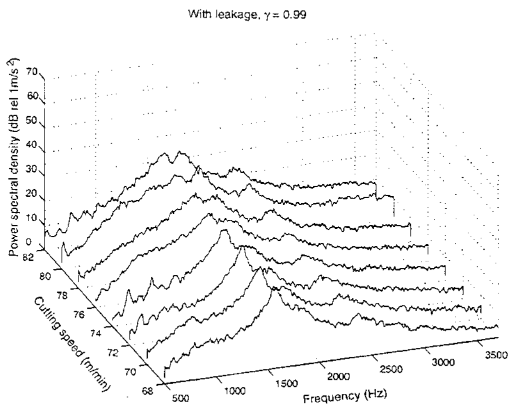

Figure 7: The spectral density of tool vibration with adaptive feedback control, $\mu = 1$ and $\gamma = 0.99$, at eight different cutting speeds v = 68 - 82 m/min, cut depth a = 0.9 mm, feed rate s = 0.25 mm/rev, tool DNMG 150604-PF, grade 4015.

In order to illustrate the influence of leakage on the stability of the feedback control system, the significant part of the Nyquist plot, i.e. the part of the Nyquist plot closest to the point $(-1, 0)$, is given for estimates of the open loop frequency response with and without leakage in the filtered-x LMS algorithm. Fig. 8 shows the Nyquist plot for the case of no leakage; and Fig. 9 shows the Nyquist plot for the case of leakage in the filtered-x LMS algorithm. The absolute-calibrated

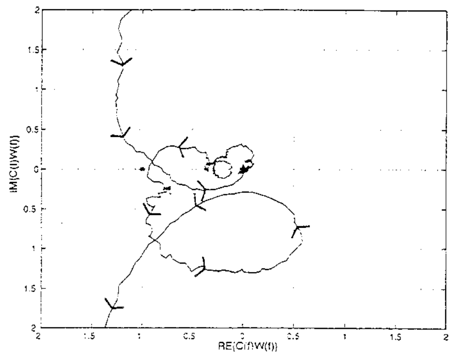

Figure 8: Nyquist diagram for the feedback control system without leakage, step length μ = 0.05[4].

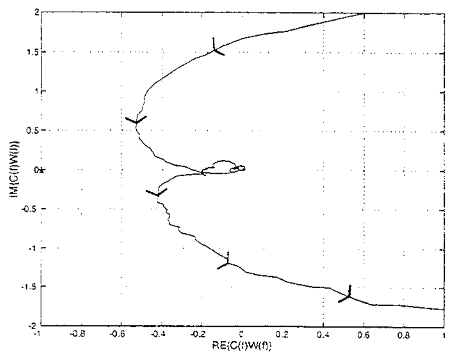

Figure 9: Nyquist diagram for the feedback control system with leakage, $\gamma = 0.999$, step length $\mu = 0.05$[4].

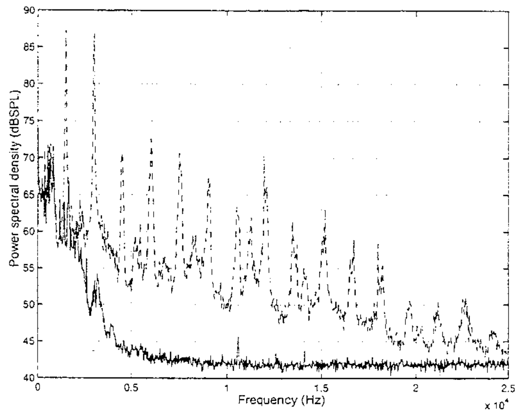

Figure 10: The Power spectral density of sound pressure with 20-tap FIR filter feedback control (solid) and without (dashed). Step length $\mu = 0.05$, cutting speed $v = 80$ m/min, cut depth $a = 0.9$ mm, feed rate $s = 0.25$ mm/rev, tool DNMG 150604-PF, grade 4015[13].

sound pressure level was measured in the lathe operator area and a typical result obtained with adaptive feedback control of tool-vibration is shown in Fig.10. It performs a broad-band attenuation of the sound pressure in the frequency band 1.5 kHz to 25 kHz, with up to approximately 35 dBSPL at 3 kHz.

4. CONCLUSIONS AND FUTURE WORK

Summary and Conclusions

It is clear from the results presented that tool vibrations in a lathe during metal cutting can be controlled using an adaptive active control system. In the case of constant cutting data, adaptive feedback control of machine-tool vibration based on the well-known filtered-x LMS-algorithm yields promising results. In the process of machining a workpiece there is likely to be variations in cutting data, i.e. variations in the spectral properties of the tool vibrations. It is thus essential that the adaptive feedback control of machine-tool vibration handles the time varying environment. And indeed, the leaky filtered-x LMS algorithm appears to have great potential with respect to the feedback control of tool vibrations in the turning operation.

The adaptive feedback control performs a broad-band attenuation of the tool-vibration, and is able to reduce the vibration level by almost 40 dB simultaneously at 1.5 kHz and 3 kHz (see Fig. 4). When cutting data was varied, however, the stability of the adaptive feedback control system was affected (see Fig. 6). In order to improve the robustness of the feedback control with respect to variation in cutting data, leakage was introduced in the filtered-x LMS-algorithm.

With the leaky version of the filtered-x LMS-algorithm on the other hand, a substantial improvement was observed in the robustness of the control system with respect to variations in cutting data (see Fig. 7). The system was provoked numerous times with varying cutting data and remained stable. In comparison with the filtered-x LMS algorithm, the leaky filtered-x LMS algorithm improves the robustness of the adaptive feedback control to large variations in the spectral properties of tool vibration.

The estimate of the forward path and the actual forward path is likely to differ and in this way introduces complex eigenvalues in the filtered-x LMS algorithm correlation matrix. The leaky filtered-x LMS algorithm improves the positiveness of the correlation matrix, i.e. it adds a real positive constant to each eigenvalue of the filtered-x LMS algorithm correlation matrix. In other words, the leaky version of the filtered-x LMS algorithm is likely to allow larger variations in the power of the tool vibration than does the filtered-x LMS algorithm and thereby improve the robustness of the adaptive feedback control to variations in the spectral properties of tool vibration.

The leakage factor reduce the magnitude of the frequency response of the adaptive FIR filter, i.e. causes the loop gain of the control system to be reduced and is so doing increases the distance between the trajectory of the open loop frequency response and the point $(-1, 0)$. This can be observed by comparing the Nyquist diagram for the open loop response for the control system when the filtered-x LMS algorithm is used to control the response of the adaptive FIR filter shown in Fig. 8. Observe further the Nyquist diagram for the open loop response for the control system when the leaky filtered-x LMS algorithm is used to control the response of the adaptive FIR filter shown in Fig. 9. The control system is thus likely to be more robust in the Nyquist sense when the leaky filtered-x LMS algorithm controls the response of the adaptive FIR filter.

The reduction in the noise level introduced by the tool vibrations is also an important factor. In the operator area for the lathe, the vibration control thus results in a broad-band attenuation of the sound pressure in the frequency band 1.5 kHz to 25 kHz by approximately 35 dB sound pressure level at 3 kHz (see Fig. 10). Adaptive feedback control of the tool vibration introduce a significant improvement in the workpiece surface. It is also interesting to note that the adaptive technique does not affect the cutting data; it may indeed allow an increase in the material removal rate. It is also well-known that there is a correlation between tool vibration and tool life. It is thus likely that the adaptive feedback control of the tool vibration increases tool life.

Future work will include the development of a new generation active tool holder shanks based on embedded piezo cheramic actuators. There is also an urgent need for the production of a theoretical foundation for the behaviour of the filtered-x LMS algorithm in the application.

Acknowledgment

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