Impulse Disturbance Rejection in Adaptive Feedforward Control for an Active Vibration Isolation System

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Introduction

Adaptive disturbance feedforward control is an effective control method for Active Vibration Isolation Systems (AVIS). Numerous applications can be found in the literature which typically uses either a filtered error or filtered reference formulation, which is solved using a least mean squares or recursive least squares method [1,2,3].

In the noise- and disturbance-free case, the optimal weights of the adaptive feedforward controller to suppress floor acceleration only depend on the mechanical parameters in the system. However, sensor noise and direct disturbance forces affect the optimal solution depending on their relative spectra [1]. Moreover, it is known from active noise control (ANC) systems, which use similar adaptive feedforward algorithms, that the performance after an impulse disturbance is severely degraded since the estimated weights shift to another solution [4]. Eventually, the algorithm converges back to the initial solution, but over an extended period, the performance of the active vibration isolation is degraded. Here, a scheduling method of the adaptation gain is proposed, which limits the adaptation gain when a statistical threshold is exceeded.

Problem formulation

The ideal physical model of an AVIS can be seen in figure 1. The sensitive payload with mass m is suspended with a passive suspension system that uses a spring k and a viscous damper d. The absolute position of the floor and the payload are x_0 and x_1 respectively. The acceleration of x_0 and x_1 are measured with accelerometers. The nominal dynamics of the AVIS are described by

$$P_1(s) = \frac{a_1(s)}{a_0(s)} = \frac{ds + k}{ms^2 + ds + k}, \tag{1}$$

$$P_d(s) = \frac{a_1(s)}{F(s)} = \frac{s^2}{ms^2 + ds + k}, \tag{2}$$

$$P_a(s) = \frac{F(s)}{V(s)} = \frac{\omega_a}{s + \omega_a}, \tag{3}$$

with $P_2(s) = P_d(s)P_a(s)$, and $F(s) = F_a(s) + F_d(s)$, where F_a is the actuator force related to the actuator voltage V_a. F_d is the direct disturbance force, which can without loss of generality be considered a voltage disturbance V_d. The blockscheme which describes the closed loop system with FeRLS adaptation can be found in figure 2, with sensor noises n_0 and n_1.

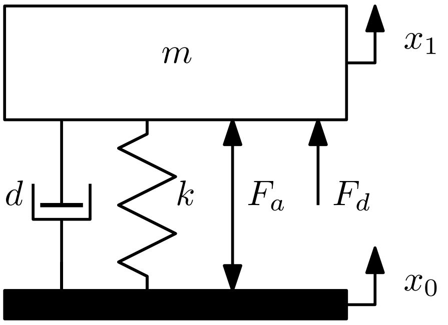

Figure 1. Ideal physical model of an AVIS.

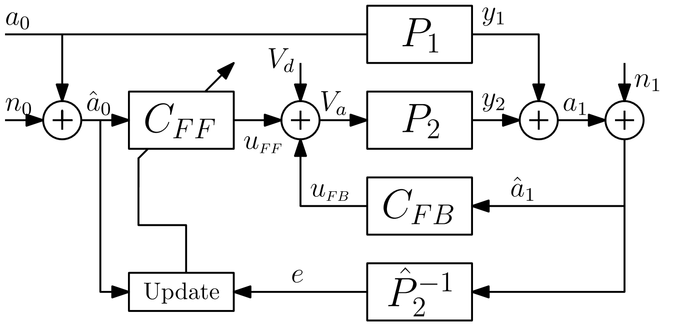

Figure 2. Blockscheme AVIS.

The feedback controller is a skyhook damper described by

$$C_{FB}(s) = -\frac{\omega_i}{s+\omega_i}k_v, \tag{4}$$

The feedforward controller is given as a generalized FIR filter, whose output in discrete time is

$$u_{FF}(k) = \underbrace{[\hat{a}_0(k) \quad H(q)\hat{a}_0(k) \quad H^2(q)\hat{a}_0(k)]}_{\boldsymbol{\psi}^T(k)} \boldsymbol{w}(k), \tag{5}$$

with q the delay operator, $\boldsymbol{w}(k) \in \mathbb{R}^3$ the estimated weight vector, and

$$H(s) = \frac{1-\left(\frac{\alpha}{s+\alpha}\right)^5}{s}, \tag{6}$$

The weight vector is estimated by

$$\boldsymbol{w}(k+1) = \boldsymbol{w}(k) - \boldsymbol{P}(k)\boldsymbol{\psi}(k)e(k), \tag{7}$$

with

$$\boldsymbol{P}(k) = \lambda^{-1}\left[\boldsymbol{P}(k-1) - \frac{\boldsymbol{P}(k-1)\boldsymbol{\psi}(k)\boldsymbol{\psi}^T(k)\boldsymbol{P}(k-1)}{\lambda + \boldsymbol{\psi}^T(k)\boldsymbol{P}(k-1)\boldsymbol{\psi}(k)}\right], \tag{8}$$

which yields the RLS algorithm [3]. The convergence properties can be influenced by the forgetting factor λ. For further details about the used controllers, the reader is referred to Beijen *et al.* [1,3].

Method

Impulsive noise is characterized by a low probability but a high amplitude. When this impulsive noise enters the system directly, *i.e.* as a disturbance force, it causes an a_1 which is not correlated to a_0. This causes a shift in the weights $\boldsymbol{w}(k)$. This shift degrades the performance of the AVIS until the weights are converged back toward a good set. The decay rate of the effects of this impulsive disturbance is therefore governed by the time constant of the adaptive algorithm. For systems without adaptive feedforward, the decay rate of the effects of this impulsive disturbance is governed by the mechanical time constant which represents a lower bound on the achievable impulse suppression. Typically, the mechanical time constant is several orders of magnitude lower than the time constant of the adaptive algorithm. This is also a prerequisite for the stability of the FeRLS algorithm. To reduce the effect of these impulsive disturbances, it is proposed to use an error clipping method to reduce the step size during the impulse. This is well established for ANC systems, and an overview can be found in Lu *et al.* [4]. Several error clipping methods are investigated and it was found that Hampel's algorithm performed best for AVIS. Hampel's algorithm is defined as

$$e'(k) = \begin{cases} e & \text{if } |e| < c_1\sigma_e(k) \\ c_1\sigma_e(k) & \text{if } c_1\sigma_e(k) < |e| < c_2\sigma_e(k) \\ \dfrac{-c_1}{c_3 - c_2} e + c_3\sigma_e(k) & \text{if } c_2\sigma_e(k) < |e| < c_3\sigma_e(k) \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where $c_1 < c_2 < c_3$ are multipliers determining the proportions of the clipping function. The clipping window is scaled by σ_e, and is chosen as the standard deviation of the "impulse free" e [5]. This can be estimated using

$$\sigma_e^2(k) = \lambda_\sigma \sigma_e^2(k-1) + (1-\lambda_\sigma)C_1 med(A_e(k)), \quad (10)$$

where λ_σ is the forgetting factor, $med(.)$ is the sample median operator, $C_1 = 1.483\left(1 + \frac{5}{N_w+1}\right)$ is a finite sample correction factor, $A_e(k) = [e^2(k), \ldots, e^2(k - N_w + 1)]$ and N_w is the window length of the sample median operator. The median estimator has a limited sensitivity to the errors caused by the impulsive disturbance, making it an estimator of the standard deviation of the "impulse free" e. The error $e(k)$ in equation (7) can be replaced by the clipped error $e'(k)$.

Evaluating the median operator has a high computational complexity. To mitigate this, the sample median m_k = $med(A_e(k))$ is approximated by an online median estimator [6].

$$\widehat{m}_{k+1} = \begin{cases} \widehat{m}_k + \mu_m & \text{if } e_t^2 > \widehat{m}_k \\ \widehat{m}_k & \text{if } e_t^2 = \widehat{m}_k \\ \widehat{m}_k - \mu_m & \text{if } e_t^2 < \widehat{m}_k \end{cases} \quad (11)$$

with μ_m the step size of the estimator.

Results

The method described above is implemented on an experimental setup, see Beijen *et al.* [1] for details. For this validation, $c_1 = 4$, $c_2 = 5$, c_3 = 6, $\mu_m = 1 \times 10^{-11}$, $\lambda = e^{-0.05t_s}$, $\alpha = 4\pi$, $k_v = 3500$, $\omega_i = 1$ and a sample time of 2×10^{-4} s is used. In figure 3 the convergence of the weights can be seen, where at t_2 and t_3 an impulse is sent through the system. For the impulse at t_2 the error $e(k)$ is used, where $e'(k)$ is used at t_3. It can be seen that the influence of the impulse on the weights is negligible when using $e'(k)$. The resulting acceleration can be seen in figure 4 on a shifted time axis. The acceleration after t_2 takes a long time to settle back to the level before the impulse, whereas after t_3 this happens directly after the initial peak.

Conclusion

Here a method is presented to suppress the effects of direct impulsive disturbance on AVIS. This method is based on clipping the error after a statistical threshold is exceeded. Experimental validation of the proposed method shows a significant improvement in both the disturbance of the weights, as well as the acceleration after impulsive disturbance. Due to the online median estimator, this method is computationally efficient.

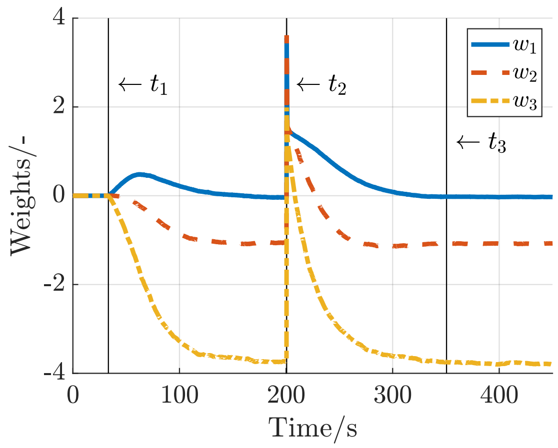

Figure 3. Measured convergence of $\boldsymbol{w}(k)$. At t_1 the adaptation is started, at t_2 an impulse is sent through the system without error clipping. At t_3 the same amplitude and duration impulse is added, but with error clipping.

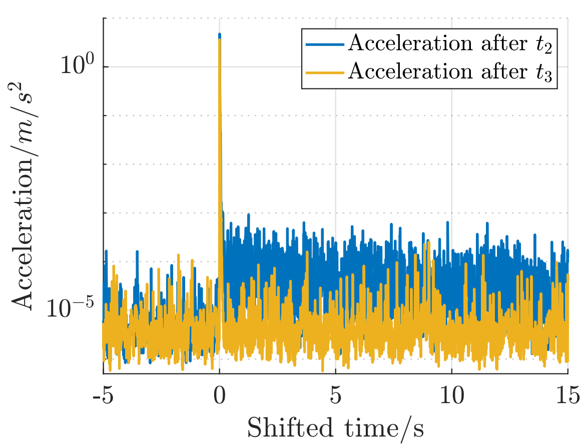

Figure 4. Measured acceleration in z direction. Time is shifted such that t_2 and t_3 are at 0. Acceleration is filtered with first order low-pass filter with cut-off frequency of 60 Hz.

Acknowledgements

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References

[1] Beijen M A, Heertjes M F, Van Dijk J and Hakvoort W B J 2018 Self-tuning MIMO disturbance feedforward control for active hard-mounted vibration isolators *Control engineering practice* vol 72 pp 90-103

[2] Van der Poel T, van Dijk J, Jonker B and Soemers H 2007 Improving the vibration isolation performance of hard mounts for precision equipment *2007 IEEE/ASME international conference on advanced intelligent mechatronics* pp 1-5

[3] Beijen M A and Hakvoort W B J 2019 Filtered-error recursive least squares optimization for disturbance feedforward control in active vibration isolation *IFAC-papersonline* vol *52* pp 448-53.

[4] Lu L, Yin K L, de Lamare R C, Zheng Z, Yu Y, Yang X and Chen B 2021 A survey on active noise control in the past decade—Part I: Linear systems. *Signal Processing* vol 183

[5] Chan S C and Zou Y X 2004 A recursive least M-estimate algorithm for robust adaptive filtering in impulsive noise: fast algorithm and convergence performance analysis. *IEEE Transactions on Signal Processing* vol 52 pp 975-91

[6] Bylander T and Rosen B 1997 A perceptron-like online algorithm for tracking the median. In *Proceedings of International Conference on Neural Networks* IEEE vol 4 pp 2219-24