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Advanced filtering strategies for residual error mitigation in vibration sensors for precision manufacturing

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Abstract
Vibration monitoring in machine tools is essential for ensuring precision and quality in industrial manufacturing. However, vibration sensors, including both general-purpose and MEMS-based sensors integral to Industrial Internet of Things (IIoT) systems which offer compact and cost-effective solutions for continuous monitoring, are prone to residual errors that persist even after application of systematic compensation and calibration techniques. These errors can degrade the accuracy of predictive maintenance and quality control systems, which are vital in the era of Industry 4.0 and smart manufacturing. This research investigates various filtering techniques to minimize these residual errors, with a focus on their applicability to the non-stationary and complex vibration signals typical in machine tool environments. Several adaptive filtering methods, including Savitzky-Golay (SG), Wiener filtering, Wavelet denoising, Adaptive Recursive Least Squares (RLS), and Kalman Filtering (KF), were evaluated using a simulated dynamic noisy vibration signal representative of an industrial CNC machine. The evaluation criteria included Signal-to-Noise Ratio (SNR) improvement, Mean Squared Error (MSE), and convergence time, ensuring real-time suitability for practical industrial applications.
Extensive Monte Carlo simulations were conducted to compare the effectiveness of these techniques in reducing noise and improving signal estimation accuracy. Significant differences were observed in their ability to manage the non-linear and non-stationary characteristics of machine tool vibrations. Advanced Kalman filtering techniques, in particular, showed potential for processing non-linear systems in vibration signal processing. The findings contribute to the field of precision engineering by offering a comprehensive comparison of filtering techniques and proposing advanced methods for residual error compensation in vibration sensors. This work has important implications for enhancing measurement accuracy, machine tool performance, and quality control in industrial manufacturing, while also improving IIoT-based condition monitoring and more precise predictive maintenance strategies, and overall optimization of smart manufacturing processes as they are dependent on high quality sensing.

Measuring Instruments, Vibration Sensors, Residual Error Compensation, Adaptive Filtering, Machine Tool Metrology, Precision Engineering, Industrial Metrology

1. Introduction

In the era of Industry 4.0, precision manufacturing increasingly depends on advanced vibration monitoring systems to uphold the stringent accuracy requirements of modern machine tool metrology [1]. These systems are essential for ensuring product quality and operational stability in smart manufacturing [2]. However, vibration sensors—particularly general-purpose and MEMS-based sensors integrated into Industrial Internet of Things (IIoT) frameworks—remain susceptible to residual errors that persist even after systematic calibration and compensation [3, 4]. These errors compromise measurement accuracy and hinder the implementation of robust predictive maintenance and quality control strategies critical to high-precision manufacturing environments.

Vibration sensors inherently experience both deterministic and stochastic error sources [5]. Deterministic errors, such as offset biases, scale factor deviations, and cross-axis sensitivity, are typically addressed through well-established calibration protocols [4]. In contrast, stochastic errors, including hysteresis, drift, and environmental noise, demand more sophisticated compensation methods [6]. Residual uncertainties—defined as the errors persisting post-calibration—present significant challenges for achieving the sub-micrometre precision required in contemporary machine tool operations . These residual errors can arise from various sources, including environmental factors, thermal deformation, and limitations in measurement methods. Such inaccuracies can adversely affect IIoT-enabled condition monitoring systems .

Recent advancements in signal processing have provided promising approaches to mitigate these challenges [7]. Traditional techniques, including Empirical Mode Decomposition (EMD) and Principal Component Analysis (PCA) , have demonstrated utility in noise reduction . However, their performance often diminishes when applied to the dynamic and non-stationary vibration signals characteristic of machine tool environments. This necessitates the development and evaluation of advanced filtering strategies capable of addressing these complexities. Methods such as Savitzky-Golay (SG) filtering [8], Wiener filtering [9], Wavelet denoising , Adaptive Recursive Least Squares (RLS) [10], and Kalman Filtering (KF) [11] offer potential for improved residual error mitigation, particularly in dynamic operational scenarios.

This research systematically investigates these advanced filtering techniques using simulated noisy vibration signals based on experimental data from industrial CNC machines. Performance metrics, including Signal-to-Noise Ratio (SNR) improvement, Mean Squared Error (MSE), and convergence time, are utilized to evaluate their efficacy [12]. The analysis is supported by extensive Monte Carlo simulations, providing a robust comparative framework to determine their suitability for real-time industrial applications .

The results of this study contribute to the domain of machine tool metrology by addressing the critical issue of residual error compensation in vibration sensors. By enhancing measurement accuracy and reliability, this research supports the evolution of IIoT-based predictive maintenance and quality control solutions [13], thereby reinforcing the foundational principles of smart manufacturing and advancing the capabilities of next-generation precision manufacturing systems [14].

2. Comparison of Filtering Techniques for Sensor Compensation

Previous research has shown that vibration sensors are susceptible to both internal and external noise, which cannot be fully eliminated through calibration or compensation alone [3, 15]. In instrumentation and sensors, noise, comprising intrinsic and extrinsic elements, remains a challenging and expanding area requiring ongoing research.

While sensor calibration minimizes systematic errors, noise persists post-calibration due to the complex nature of measurement systems. Comprising components such a sensing elements, pre-amplifiers, cabling, and a data acquisition systems, in the sensor measurement chain also exhibit an inherent noise in addition to external noise sources [5]. Mathematically it can also be shown that for the vibration output ($x_{meas}(t)$) is actually sum of actual signal of vibration ($a_{true}(t)$) and noise ($n(t)$), as shown in equation below

$$x_{meas}(t) = a_{true}(t) + n(t) \qquad (1)$$

Here $n(t)$ represents the residual noise component which is a major source of residual error. Therefore selection of an appropriate filtering or estimation technique should provide adequate coverage for practical machine tool scenarios while improving sensor response [16] through the reduction of computed residual error. The residual error or noise in this research is assumed to be Gaussian in nature, as described by its noise variance value, which can then be used to estimate its intrinsic error value .

Therefore in order to improve sensor response in vibration monitoring, a thorough evaluation and comparison of various digital filtering methods is essential. However, several considerations must be addressed prior to evaluation. Vibration signals in machine tools are often complex due to the interaction of various subsystems, and the noise characteristics can change with different operational modes of the machine. Consequently, filtering techniques must be designed to effectively reduce noise variance and residual errors, enabling real-time signal enhancement for practical machine vibration monitoring [16, 17].

3. Methodology for Filter Implementation and Selection

In principle, applying a filter that suppresses noise while leaving the signal relatively unchanged is a common method for estimating a signal corrupted by residual noise (both deterministic and stochastic) [7]. The bandwidth of measured vibration signals and noise in machine tools is typically shared with the induced effect of the background noise as well, which makes it difficult to eliminate the noise [18, 19]. Active fixed filters, such as Notch, Sallen-Key, and Butterworth filters, for example, cannot be used in this scenario because their design relies on prior knowledge of both the signal and the noise [7]. Therefore, to deal with the unknown signal estimation problem, adaptive filters must be used for noise reduction [9].

Adaptive filters have the ability to adjust their own parameters automatically , and their design requires little or no knowledge of signal or noise characteristics [9]. In fact, practically all adaptive filters do require the use of initial signal noise spectrum samples for initialization and convergence i.e. optimal minimization of mean squared error (MSE). Moreover, they also have a better signal-to-noise (SNR) performance ratio when compared to fixed filters within the same working conditions [7]. In brief, adaptive filters can be understood as self-designing filters operating recursively on the noisy signal within unknown signal characteristics [20].

Adaptive filtering utilises a primary signal, which contains the corrupted signal, and a noise reference source. It is assumed that the estimated noise is correlated to the actual noise in some unknown way. The goal of the adaptive filter is reducing noise variance in the measured signal. The block diagram of adaptive noise cancelling filter can be seen in Figure 1. The $[k]$ notification represents a sampled version of signal described by Equation 1. Mathematically the adaptive filter produces an output $n_{est}[k]$ with the overall filter system output being the error signal $e[k]$ as in Equation 2, minimized recursively by the adaptive algorithm.

$$x_{est}[k] = x_{meas}[k] - n_{est}[k] \qquad (2)$$

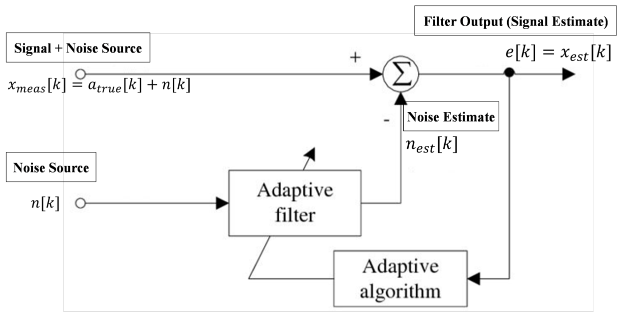

Figure 1. Block diagram of an adaptive noise filter

With the aim to improve response of vibration sensors for machine tools several active denoising and adaptive filtering algorithms were reviewed for application. Few of the noteworthy methods explored included Savitzky-Golay (SG) [8], Wiener filtering, Wavelet denoising [16], Adaptive Least Mean Squares (LMS) [10, 21] , Adaptive Recursive Least Squares (RLS) [7, 10], Kalman Filtering , etc. Many factors influence the selection of an appropriate adaptive filtering algorithm, including computational efficiency, robustness, tracking, rate of convergence, and numerical implementation [20]. Another aspect that must be addressed by filtering algorithm is an efficient response to non-stationary machine tool vibration signals as well i.e., variation in signal amplitude, frequency , noise etc. Adaptive filters are suitable for this as they are not only able to remove noise from unknown signals but also predict future values of a steady state, slowly varying or periodic signals in real-time.

To evaluate the performance of the filters [22], implementation was done using a simulated dynamic noisy vibration signal generated based on experimental observations. The signal was modelled as a sinusoidal wave with an amplitude of $A = \pm 1\ g$ and frequency of $f = 135\ Hz$ ($8100\ RPM$) sampled at a rate of $f_s = 1500\ Hz$. A Gaussian or white noise was added to the signal with a noise variance of $\sigma = 0.5\ g$. The frequency of the signal was chosen to represent a value close to the highest spindle RPM of the three-axis Cincinnati Arrow 500 machine tool on which the validation is intended, while the sampling rate was chosen to be close to the nominal rate of the investigated MEMS vibration sensors. A section ($t = 0.25$ sec) of the generated reference signal with and without noise can be seen in Figure 2. The reference signal is represented by a solid red line, while the noisy signal is represented by a dot-dash blue line. The results from the implementation of the filters are presented in the next section of the research paper.

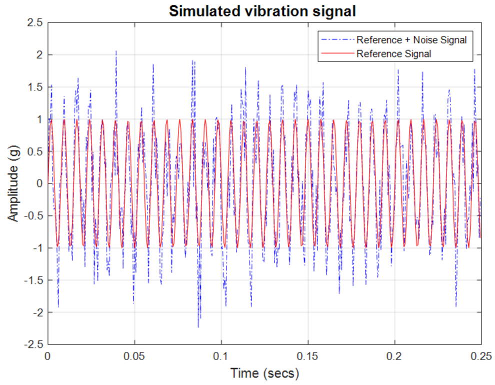

Figure 2. Simulated noisy signal for filter comparison and selection

4. Results and Discussion

Adaptive filters work in applications by adjusting their coefficients with the goal of achieving an optimal state. When the mean square of the error signal between the adaptive filter output and the desired signal converges to the minimum value , the optimization criterion is satisfied. Resultantly at this state, the filter is adapted, and the coefficients have converged to a solution. The filter output, $x_{est}[k]$, is then said to match very closely to the desired signal, $a_{true}[k]$. Potentially any change in input data characteristics, such noise , amplitude and frequency of the signal, the filter adapts to the signal characteristics by generating a new set of coefficients for the new data [20].

Savitzky-Golay (SG), Wiener filtering, Wavelet denoising, Adaptive Recursive Least Squares (RLS) [7, 10] and Kalman Filtering (KF) methods were applied to compare their performance on the simulated signal described in section 3. In order to compare the effectiveness of filter in terms of signal quality before and after denoising, a quantitative performance evaluation index i.e. signal-to-noise ratio (SNR) is introduced to evaluate the denoising effect, which is defined as follows (Equation 3) [16], where $x_{meas}(i)$ is the measured vibration signal , $n(i)$ is the additive noise component to $a_{true}(i)$ true vibration signal, and N is the signal length :

$$SNR = 10 \log \frac{\sum_{i=1}^{N} x_{meas}^2(i)}{\sum_{i=1}^{N} n^2(i)} \qquad (3)$$

The optimal filter parameters for investigated filters were set according to reviewed literature describing similar experimental evaluations for example Savitzky-Golay (SG) requires setting of order filter and window length. Similar approaches were followed for Wiener filtering, Wavelet denoising , Adaptive Recursive Least Squares (RLS) and Kalman Filtering (KF). However, it is important to highlight that choice for optimal parameters for adaptive filters are a sprawling research area and requires due consideration of the specified applications and further investigation.

To evaluate the performance of filters, $N = 1000$ Monte Carlo type simulations were run in MATLAB to generate simulated signals with random noise, while recording the SNR of filtered signals. The stability of filter performance was evaluated by computing the standard deviation in the resulting SNR results. The results of the evaluation have been tabulated in Table 1. Overall filter performance was evaluated by means of evaluating the greatest SNR improvement percentage, along with the lowest MSE value and convergence time for executing the algorithm. SNR improvement demonstrates the ability of the filter to remove residual noise, while MSE represents the accuracy of the estimated signal with respect to the original noise-free signal. Similarly, the convergence rate demonstrates the suitability in terms of real-time execution. Based on the results, adaptive RLS and Kalman filters provide the best performance for the considered scenario, although they have a higher computational complexity, especially for adaptively reducing noise in non-linear dynamic vibration signals [21].

This can be appreciated by looking at representative results plotted in in Figure 3. from $N = 100$ simulations (x-axis) which compare filter performance in terms of its SNR (y-axis) with variation in residual noise in the reference signal.

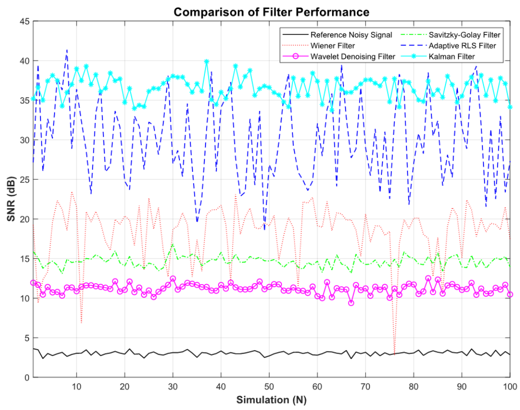

Figure 3. Results comparison of filters for residual noise reduction

Table 1 Results comparison of filtering techniques for reduction of residual noise (N=1000 simulations)

Parameter	Noisy Signal	Wiener Filtering	Wavelet Denoising	Savitzky-Golay Filter	Adaptive RLS Filtering	Kalman Filtering
Average SNR (dB)	3.08	18.17	11.13	14.57	30.85	36.18
Standard Deviation	0.26	3.50	0.57	0.73	5.46	1.9451
Mean Squared Error (MSE)	0.2465	0.0229	0.0362	0.0177	0.0014	0.0795
Percentage Improvement (%)	-	489.94	216.36	373.05	901.93	1074.68
Convergence Time (ms)	-	179.1	169.6	153.6	156.6	N/A
Order (N) / Frame length (L)	-	L=295	N=5	N=10 / L=99	N/A	N/A

6. Potential of Kalman Filtering for Vibration Sensors

Kalman filtering (KF) proves to be an effective tool for reducing residual noise in vibration signals , particularly in nonlinear and dynamic machine tool environments . As shown in the previous section, KF minimizes mean squared error by estimating system states amidst both measurement and process noise. In the context of this study, recent works have evaluated KF alongside other filtering methods [23], with the Unscented Kalman Filter (UKF) demonstrating their ability and superior performance in reducing noise and improving signal quality. The UKF generally performs better than the Extended Kalman Filter (EKF) in terms of accuracy, particularly in handling the nonlinear characteristics of machine tool vibrations, as reflected in the significant SNR improvement and lower MSE observed in the previously reported results [23]. This highlights the UKF's ability to address the challenges posed by residual noise in dynamic vibration signals. All these studies demonstrate the potential of KF , EKF and UKF in applications of vibration sensors in precision manufacturing.

5. Conclusion

This study investigates adaptive filtering techniques to mitigate residual errors, focusing on non-stationary vibration signals typically encountered in machine tool environments. Several methods, including Savitzky-Golay (SG), Wiener filtering, Wavelet denoising, Adaptive Recursive Least Squares (RLS), and Kalman Filtering (KF), were evaluated using a simulated dynamic noisy vibration signal from an industrial CNC machine. The evaluation criteria included Signal-to-Noise Ratio (SNR) improvement, Mean Squared Error (MSE), and convergence time, ensuring real-time applicability. Extensive Monte Carlo simulations were conducted to compare the effectiveness of these techniques in reducing noise and improving signal estimation accuracy. Significant differences were observed in their ability to handle the non-linear and non-stationary characteristics of machine tool vibrations.

The results demonstrate that Kalman Filtering (KF) is the most effective technique for residual error compensation, achieving an SNR of 36.18 dB, a 1074.68% improvement over the raw noisy signal. Wiener Filtering achieved an SNR of 18.17 dB (489.94% improvement), and RLS demonstrated a substantial reduction in MSE to 0.0014, outperforming other methods. RLS and Kalman filters also exhibited fast convergence times, making them suitable for real-time industrial applications.

These findings emphasize the importance of adaptive filtering, particularly KF and its extensions (Extended Kalman Filtering, EKF, and Unscented Kalman Filtering, UKF), in enhancing vibration sensor accuracy. Both RLS and Kalman filters proved highly suitable for time-sensitive industrial applications, a critical factor for predictive maintenance and quality control in the context of Industry 4.0. The research contributes to advancing sensor calibration and monitoring techniques, optimizing machine tool performance, reducing downtime, and improving the reliability of condition monitoring systems.

This study fills a gap in the literature by offering a comprehensive comparison of multiple filtering techniques and providing valuable insights into their practical application in machine tool metrology. It lays the foundation for future advancements in sensor technology, real-time monitoring, and industrial optimization. As IIoT and smart manufacturing technologies evolve, adaptive filtering will play a key role in enhancing the accuracy and reliability of vibration sensors, enabling more efficient, data-driven industrial operations.

Future research should explore the integration of these filtering methods with emerging sensor technologies, real-time data analytics platforms, and advanced machine learning algorithms to further optimize manufacturing processes and predictive maintenance strategies.

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References

[1] D'Emilia G, Gaspari A, Natale E, Adduce G, and Vecchiarelli S 2021 *IEEE Instrumentation & Measurement Magazine* **24** 30-37

[2] Mohd Ghazali M H and Rahiman W 2021 *Shock and Vibration* **2021** 9469318

[3] Iqbal A, Mian N, Longstaff A, and Fletcher S 2023 *15th International Conference and Exhibition on Laser Metrology, Coordinate Measuring Machine and Machine Tool Performance*. 103-113 euspen

[4] Iqbal A, Mian N, Longstaff A, and Fletcher S 2022 *International Journal of Automation Technology*

[5] Iqbal A, Mian N, Longstaff A, and Fletcher S 2021 *14th International Conference and Exhibition on Laser Metrology, Coordinate Measuring Machine and Machine Tool Performance*. 78-87 euspen

[6] D'Emilia G, Gaspari A, and Natale E 2016 *Measurement* **77** 95-104

[7] Hernández W 2001 *Sensors and Actuators A: Physical* **88** 198-208

[8] Liu Y, Dang B, Li Y, Lin H, and Ma H 2015 *Acta Geophysica* **64**

[9] Widrow B, Glover J R, McCool J M, Kaunitz J, Williams C S, Hearn R H, Zeidler J R, Dong J E, and Goodlin R C 1975 *Proceedings of the IEEE* **63** 1692-1716

[10] Raya M A D and Sison L G 2002 *Proceedings of the Second Joint 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society] [Engineering in Medicine and Biology* **2**. 1756-1757 vol.2

[11] van Ophem S and Berkhoff A P 2013 *The Journal of the Acoustical Society of America* **133** 2105-2115

[12] Brandt A 2011 *Noise and vibration analysis: signal analysis and experimental procedures*.(John Wiley & Sons).

[13] Huang M, Liu Z, and Tao Y 2020 *Simulation Modelling Practice and Theory* **102** 101981

[14] Dorst T, Ludwig B, Eichstädt S, Schneider T, and Schütze A 2019 *2019 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. 1-5 IEEE

[15] Iqbal A, Mian N, Longstaff A, and Fletcher S 2024 Metrological evaluation of Integrated Electronics Piezo-Electric Accelerometer measurement chains in industrial applications: Modelling and characterisation of noise Proceedings of EUSPEN 24th International Conference & Exhibition, 2024/6/14 2024.

[16] Miao F, Zhao R, and Wang X 2020 *Shock and Vibration* **2020** 7587840

[17] Zheng R, Chen G, and Chen H 2021 *Chinese Journal of Aeronautics* **34** 350-363

[18] Antoni J and Randall R B 2004 *Mechanical Systems and Signal Processing* **18** 89-101

[19] Abbasi-Kesbi R and Nikfarjam A 2017 Denoising MEMS accelerometer sensors based on L2-norm total variation algorithm *Electronics Letters* vol. 53 no. 5 pp. 322-324

[20] Haykin S 2014 *Adaptive filter theory: International edition*.(Pearson).

[21] Moreau D, Cazzolato B, Zander A, and Petersen C 2008 *Algorithms* **1** 69-99

[22] Kaur H and Talwar R 2013 *2013 International Conference on Emerging Trends in Communication, Control, Signal Processing and Computing Applications (C2SPCA)*. 1-5 IEEE

[23] Auger F, Hilairet M, Guerrero J M, Monmasson E, Orlowska-Kowalska T, and Katsura S 2013 *IEEE Transactions on Industrial Electronics* **60** 5458-5471