Laser Metrology and Performance XII

Identification of machine tools linear axes performance using on-machine embedded inertial measurement units

G.W. Vogl[1], A. Archenti[2], and M.A. Donmez[1]
[1]National Institute of Standards and Technology (NIST), Gaithersburg, Maryland, 20899, USA
[2]KTH Royal Institute of Technology, Brinellvägen 68, 10044, Stockholm, Sweden

Abstract

The current trend in manufacturing industry is from mass production towards adaptive manufacturing systems and cloud manufacturing. Self-learning machines and robot systems can play an essential role in the development of intelligent manufacturing systems and can be deployed to deal with a variety of tasks that can require flexibility and accuracy. However, in order for the machine tool (physical and control system) to deal with the desired task in a cognitive and efficient manner, the system must be "aware" of its capability in order to adjust itself to the desired task. Thus, characterization of machine tool accuracy and capability is necessary to realize this goal.

In this study, data from a machine-embedded inertial measurement unit (IMU), consisting of accelerometers and rate gyroscopes, was used for identification of changes in linear and angular error motions due to changes in operational conditions or component degradation. The IMU-based results were validated against laser-based measurement results, demonstrating that the IMU-based method is capable of detecting micrometer-level and microradian-level degradation of machine tool linear axes. Thus, manufacturers could use the method to efficiently and robustly diagnose the condition of their machine tool linear axes with minimal disruptions to production.

1 Introduction

Precision manufacturing has steadily evolved over the past decades to cope with the complexity of components and the requirements for high quality and low cost production. A typical machine tool has multiple linear axes whose accuracies directly impact the quality of manufactured parts. Yet over a machine tool's lifetime, various faults lead to performance degradation, lowering accuracy and repeatability [1]. Typical sources of errors within linear axes are due to pitting, wear, corrosion, and cracks of the system components such as guideways and recirculating balls [2]. As degradation increases, tool-to-workpiece errors increase, which eventually may result in a loss of production quality and/or a failure [3]. Yet knowledge of degradation is elusive; proper assessment of axis degradation is often a manual, time-consuming, and potentially cost-prohibitive process.

While direct methods for machine tool performance evaluation are well-established [4] and reliable for position-dependent error quantification, such measurements typically interrupt production [5]. An online condition monitoring system for linear axes is needed to help reduce machine downtime, increase productivity and product quality, and improve knowledge about manufacturing processes [6]. Efforts to monitor the condition of linear axes components have utilized various sensors, e.g., built-in rotary encoders [7], current sensors [3], and accelerometers [8, 9]. These attempts at condition monitoring of linear axes have had limited success, partly because of the lack of robustness and defined relationships of signals to axis degradation composed of a wide range of spatial frequencies.

Consequently, efficient quantitative measures are needed to monitor the degradation of linear axes. Recently, accelerometers have been used for dynamic metrology of machine tools [10, 11] and six-degree-of-freedom motion sensors exist within integrated circuit (IC) components [12]. Thus, the use of an inertial measurement unit (IMU) is attractive for on-machine condition monitoring.

2 Methodology

One potential solution for online monitoring of linear axis degradation is the use of an IMU [13]. As seen in the schematic of Figure 1, an IMU is mounted to a moving machine tool component. To diagnose axis degradation, the axis is moved back and forth at various speeds to capture data for different frequency bandwidths. This data is then integrated, filtered, and fused to estimate the changes in the 6-degree-of-freedom (DOF) geometric errors of the axis. Because the linear axes are stacked, coordinate transformations may be used with all 6-DOF errors to estimate the errors at the functional point [4]. Ideally, data would be collected periodically to track axis degradation with minimal disruptions to production. With robust diagnostics and prognostics algorithms, incipient faults may be detected and future failures may be avoided. In essence, IMU data can be used to help optimize maintenance, production planning, and ultimately improve part quality.

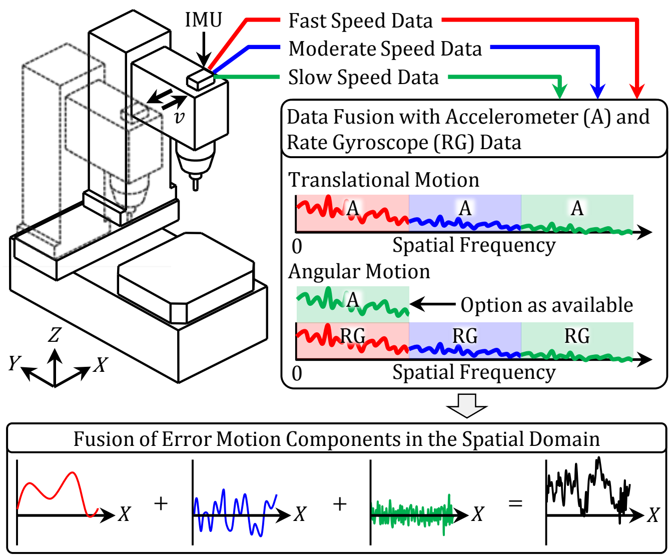

Figure 1. IMU-based method utilizing data fusion for diagnostics of machine tool performance degradation.

Figure 2 and Figure 3 provide details of the data fusion schemes outlined in Figure 1 for estimation of translational and angular error motions using data corresponding to three speed regimes (the fast speed is 0.5 m/s, the moderate speed is 0.1 m/s, and the slow speed is 0.02 m/s). As seen in Figure 2, the accelerometer data is integrated twice, low- or band-pass filtered, processed, and summed to yield the net translational motions. As seen in Figure 3(b), the rate gyroscope data is integrated once, low- or band-pass filtered, processed, and summed to yield the net angular motions. However, if the measurement axis is nominally orthogonal to the gravitational vector, then the high-speed rate gyroscope data in Figure 3(b) may be replaced by the slow-speed accelerometer data, as shown in Figure 3(a). The schemes in Figure 2 and Figure 3 rely upon the matching of spatial cutoff frequencies and the exclusion of significant modal excitations.

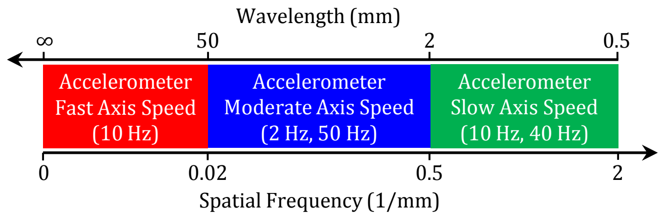

Figure 2. Data fusion scheme for translational motions via use of accelerometer data. Filter cutoff frequencies are shown in parentheses.

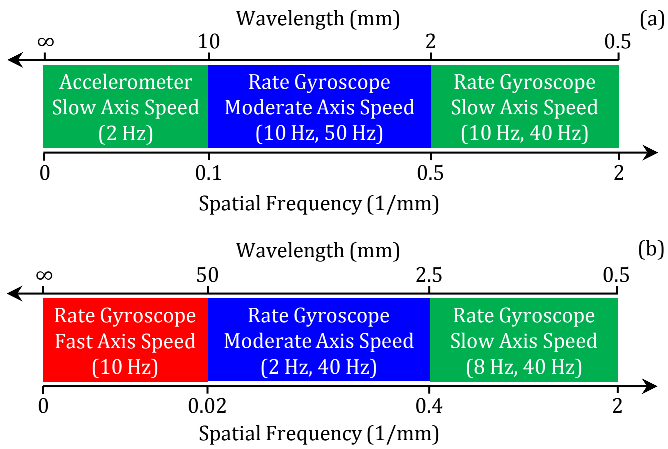

Figure 3. Data fusion scheme for angular motions via use of (a) accelerometer and rate gyroscope data or (b) rate gyroscope data only. Filter cutoff frequencies are shown in parentheses. Wavelengths and frequencies correspond to 1 m of travel for 0.5 m/s (fast speed), 0.1 m/s (moderate speed), and 0.02 m/s (slow speed).

3 IMU for Industrial Application

For industrial application, an IMU should be physically small and economical while still satisfying the measurement needs. Consequently, for application on machine tools, an ‘industrial IMU’ was created that is about 73% smaller than the ‘testbed IMU’ used within a linear axis testbed at NIST [14]. As seen in Figure 4, the industrial IMU is about 9 cm long and contains a triaxial rate gyroscope and a triaxial accelerometer. The bandwidths and noise properties of these sensors are seen in Table 1.

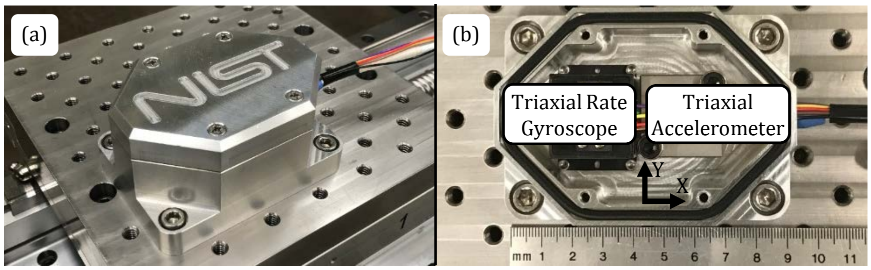

Figure 4. (a) Isometric view of industrial IMU and (b) top view of industrial IMU without its lid.

Table 1. Properties of sensors in industrial IMU

Sensor	Bandwidth[a]	Noise
Accelerometer	0 Hz to 400 Hz	69 (μm/s²)/√Hz
Rate Gyroscope	0 Hz to 200 Hz	35 (μrad/s)/√Hz

[a] frequencies correspond to half-power points, also known as 3 dB points

4 Experimentation

4.1 Setup

The industrial IMU shown in Figure 4 was designed for industrial application. Accordingly, repeated testing of the IMU on machine is required for acceptance testing, to determine how well the IMU-based methodology can detect various types of degradation.

Accordingly, Figure 5 shows an experimental setup of the IMU on a vertical milling machine at NIST. For each dataset, the IMU is attached to the worktable at one of three different locations (A, B, or C) and the Y-axis travels between Y = 0 m and Y = 0.5 m. Hence, IMU data was collected for 50 runs sequentially at each location with motion back and forth along the Y axis, according to the method outlined in Figure 1. The three speeds for data collection are 0.5 m/s (fast speed), 0.1 m/s (moderate speed), and 0.02 m/s (slow speed).

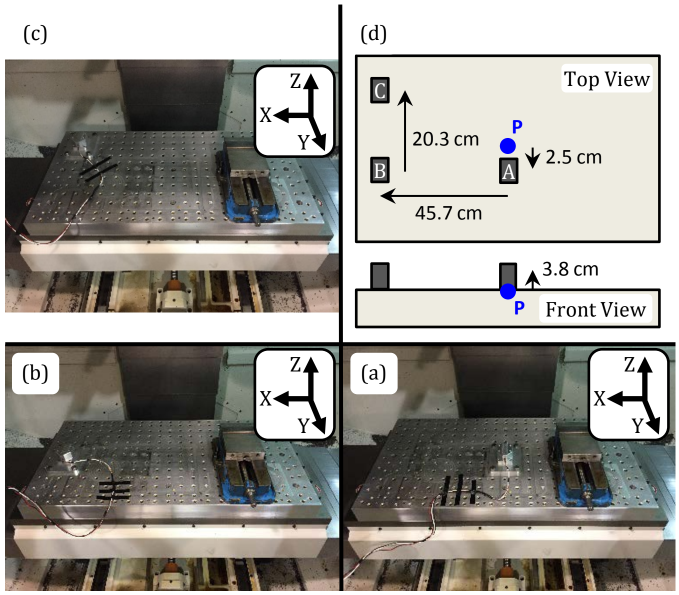

Figure 5. Experimental setup of IMU on machine tool worktable: Pictures of IMU at (a) Location A, (b) Location B, and (c) Location C and (d) schematic of three IMU locations relative to center point P of worktable.

Furthermore, data was collected with a commercial laser-based system ('Reference' system) for measuring the geometric errors of the axis at the three worktable locations. The laser-based system is used for verification and validation (V&V) of the IMU-based results. However, while the Reference system measures the motion of the worktable with respect to the base of the machine tool, the worktable-mounted IMU measures the changes in the inertial motion of the worktable.

4.2 Results

The IMU data was processed to yield the estimated translational and angular error motions at the three worktable locations (A, B, and C). In order to estimate the translational error motions (E_{XY}, E_{YY}, and E_{ZY}) at the three locations, the IMU data was processed according to Figure 2. The linear term of the positioning error motion (E_{YY}) was determined based on an additional process, not shown in this paper for the sake of brevity, that utilizes only the slow-speed data. Also, the IMU data was processed according to Figure 3(a) or Figure 3(b) to estimate two angular error motions (E_{AY} and E_{BY}) or the third angular error motion (E_{CY}), respectively.

Assuming that the worktable is sufficiently rigid, the estimated error motions are translated via homogeneous transformations from each of the three worktable locations (A, B, and C) to the center point P of the worktable. In theory, the estimated error motions at the center point P should be independent of which of the three sets is used for the homogeneous transformation. Figure 6 shows the translational errors estimated at the center point P of the worktable, based on data collected at three locations (A, B, and C). The data from the Reference system is also shown in the figures (as thinner lines) for comparison purposes. At each worktable location, Reference data was collected for five runs, which were averaged to produce the curves seen in Figure 6. The standard deviations of each set of five runs was also used to produce the shaded 95 %-confidence zones in Figure 6. Thus, the shaded zones represent a contribution towards, but not the total of, the measurement uncertainty.

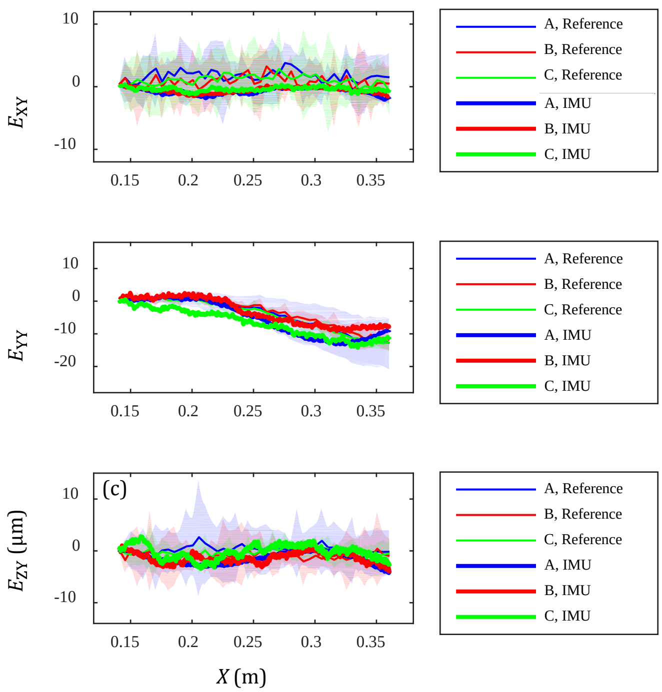

Figure 6. Translational errors (a) E_{XY}, (a) E_{YY}, and (a) E_{ZY} estimated at center point P of worktable based on data collected at three locations (A, B, and C) with the IMU and a commercial Reference system. The Reference data has shaded areas representing measurement expanded uncertainties (k = 2) at 95 % confidence based on 5 runs.

As seen in Figure 6, the estimated translational errors from the IMU data match each other respectively to within 5 µm for the three worktable locations (A, B, and C). Also, the estimated error motions from the IMU match those from the reference system to within about 5 µm. The slight differences may be due to differences in error type (inertial for IMU, while relative for the Reference system) as well as to sources of uncertainty.

4.3 Factors affecting measurement uncertainty

For any type of measurement analysis, it is required that uncertainty and/or factors affecting uncertainty are identified and specified. Measurement uncertainty is a combination of uncertainties due to instrumentation, application of the instrument (e.g., erroneous alignment), environmental influences (e.g., floor vibration), and the object (e.g., repeatability of machine tool).

The most significant contributors to the measurement uncertainty u [15] in this study are the IMU, the reference laser system (u_{laser} = 0.7 µm or 3.0 µrad), and the environmental conditions of the measurement runs. The IMU box was rigidly attached to the machine tool table and the condition of the machine tool operation was such that results are repeatable. The laser-based measurement device was applied for five runs according to manufacturer instructions, in order to compute the standard deviation and indicate repeatable results, as seen by the shaded 95 % confidence intervals in Figure 6. Furthermore, environmental conditions were within normal shop conditions (temperature range, floor vibration limit, etc.).

According to simulations of the data fusion process, the accelerometer used in the industrial IMU will result in uncertainties that could be sufficiently low for machine tool purposes. As seen in Figure 7, an accelerometer noise of 69 ($\mu m/s^2$)/$\sqrt{Hz}$ (for the industrial IMU) should result in a straightness uncertainty of about 5 µm when the results of ten runs are averaged.

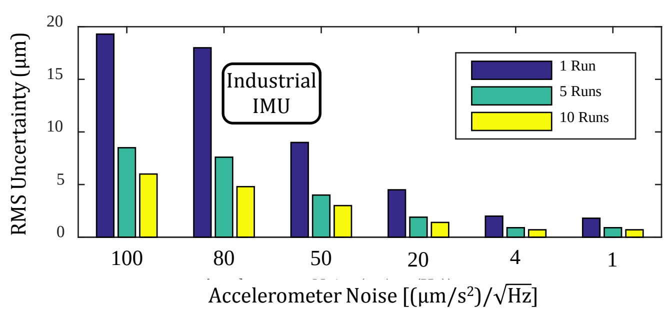

Figure 7. Simulated uncertainty for straightness error motions due to only data fusion process with uncertainty sources of accelerometer noise, data acquisition noise, and number of runs used for averaging.

These simulations include only influences from accelerometer noise, data acquisition noise, and the method itself, while excluding uncertainties from other sources such as sensor misalignment, crosstalk, and system vibrations. Figure 7 shows that as the accelerometer noise decreases, the uncertainty decreases to a limit caused by noise of the data acquisition equipment. Thus, smaller uncertainties are possible with a more expensive and accurate IMU [14].

5 Conclusions

An ‘industrial IMU’ was developed to test the effectiveness of a new IMU-based method for on-machine application. The industrial IMU includes a triaxial accelerometer and a triaxial rate gyroscope. An experiment was conducted in which data was collected from the IMU at three different locations on a worktable for the same Y-axis motion.

The IMU-based results were validated through comparison with the laser-based measurement results, showing that the IMU could perhaps be used to track the changes of error motions due to linear axis degradation. The IMU-based method is capable of detecting micrometer-level and microradian-level degradation of linear axes. Although the results are promising, the IMU-based method must be improved for robustness due to sensor drift. Concerning the uncertainty of the IMU-based method, further investigations are also needed to fully certify the system for online measurement. Nonetheless, verified and validated data from an ‘industrial IMU’ could provide manufacturers and machine tool operators with near-real-time equipment health, diagnostic, and prognostic intelligence to significantly enhance asset availability and minimize unscheduled maintenance.

Acknowledgements

The authors thank Brian Pries, Travis Shatzley, Dan Falvey, and Jay Brandenburg of the Fabrication Technology Group (NIST) for their outstanding contributions with the experimental setup.

References

[1] Li Y, Wang X, Lin J, Shi S (2014) A Wavelet Bicoherence-Based Quadratic Nonlinearity Feature for Translational Axis Condition Monitoring. *Sensors* 14(2):2071-2088.

[2] Zhou Y, Mei X, Zhang Y, Jiang G, Sun N (2009) Current-Based Feed Axis Condition Monitoring and Fault Diagnosis. *4th IEEE Conference on Industrial Electronics and Applications, ICIEA 2009*, 1191-1195.
[3] Uhlmann E, Geisert C, Hohwieler E (2008) Monitoring of Slowly Progressing Deterioration of Computer Numerical Control Machine Axes. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 222(10):1213-1219.
[4] International Organization for Standardization (2012) ISO 230-1 - Test Code for Machine Tools – Part 1: Geometric Accuracy of Machines Operating under No-Load or Quasi-Static Conditions.
[5] Khan AW, Chen W (2009) Calibration of CNC Milling Machine by Direct Method. *2008 International Conference on Optical Instruments and Technology: Optoelectronic Measurement Technology and Applications*, 7160:716010.
[6] Teti R, Jemielniak K, O'Donnell G, Dornfeld D (2010) Advanced Monitoring of Machining Operations. *CIRP Annals - Manufacturing Technology* 59(2):717-739.
[7] Verl A, Heisel U, Walther M, Maier D (2009) Sensorless Automated Condition Monitoring for the Control of the Predictive Maintenance of Machine Tools. *CIRP Annals - Manufacturing Technology* 58(1):375-378.
[8] Liao L, Lee J (2009) A Novel Method for Machine Performance Degradation Assessment Based on Fixed Cycle Features Test. *Journal of Sound and Vibration* 326(3–5):894-908.
[9] Spiewak S, Zaiss C, Ludwick SJ (2013) High Accuracy, Low-Invasive Displacement Sensor (Halids). *ASME 2013 International Mechanical Engineering Congress and Exposition, IMECE 2013*, 2A:V02AT02A077.
[10] Smith KS, Hocken RJ, 2013, Dynamic Metrology Methods and Systems. United States Patent and Trademark Office: US8401691 B2.
[11] Sato R, Nagaoka K, Sato T, 2015, Machine Motion Trajectory Measuring Device, Numerically Controlled Machine Tool, and Machine Motion Trajectory Measuring Method. United States Patent and Trademark Office: US20110246132 A1.
[12] InvenSense Incorporated, 2016, MPU-6050 Six-Axis (Gyro + Accelerometer) MEMS MotionTracking™ Device, https://www.invensense.com/products/motion-tracking/6-axis/mpu-6050/.
[13] Vogl GW, Weiss BA, Donmez MA, 2015, A Sensor-Based Method for Diagnostics of Machine Tool Linear Axes, Annual Conference of the Prognostics and Health Management Society 2015. Coronado, CA: PHM Society, p. 10.
[14] Vogl GW, Donmez MA, Archenti A (2016) Diagnostics for Geometric Performance of Machine Tool Linear Axes. *CIRP Annals - Manufacturing Technology* 65(1):377-380.
[15] Knapp W (2002) Measurement Uncertainty and Machine Tool Testing. *CIRP Annals - Manufacturing Technology* 51(1):459-462.