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Diagnostics for geometric performance of machine tool linear axes

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ABSTRACT

Machine tools degrade during operations, yet knowledge of degradation is elusive; accurately detecting degradation of linear axes is typically a manual and time-consuming process. Manufacturers need automated and efficient methods to diagnose the condition of their machine tool linear axes with minimal disruptions to production. A method was developed to use data from an inertial measurement unit (IMU) for identification of changes in the translational and angular errors due to axis degradation. A linear axis testbed, established for the purpose of verification and validation, revealed that the IMU-based method was capable of measuring geometric errors with acceptable test uncertainty ratios.

1. Introduction

Machine tool linear axes move the cutting tool and workpiece to their desired positions for parts production [1]. A typical machine tool has multiple linear axes, and their accuracies directly impact the quality of manufactured parts. However, over a machine tool's lifetime, emerging faults lead to performance degradation, lowering accuracy and repeatability [2]. Typical sources of errors within feed drive systems are due to pitting, wear, corrosion, and cracks of the system components such as guideways and recirculating balls [3]. As degradation increases, tool-to-workpiece errors increase that eventually may result in a failure and/or a loss of production quality [4]. Yet knowledge of degradation is illusive; 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 [5] and reliable for position-dependent error quantification, such measurements typically interrupt production [6]. An online condition monitoring system for linear axes is needed to help achieve decreased machine downtime, higher productivity, higher product quality, and enhanced knowledge about manufacturing processes [7]. Efforts to monitor the condition of linear axes components have utilized various sensors, e.g., built-in rotary encoders [8], current sensors [4], and accelerometers [9,10]. These attempts at condition monitoring of linear axes were limited in success, partly because of the lack of robustness and defined relationships of signals to axis degradation composed of a wide range of spatial frequencies.

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One potential solution for online monitoring of linear axis degradation is the use of an inertial measurement unit (IMU). As seen in Fig. 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 bandwidths. This data is then '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 [5]. Ideally, data would be collected periodically to track axis degradation with minimal disruptions to production. With robust diagnostics and prognostics algorithms, incipient

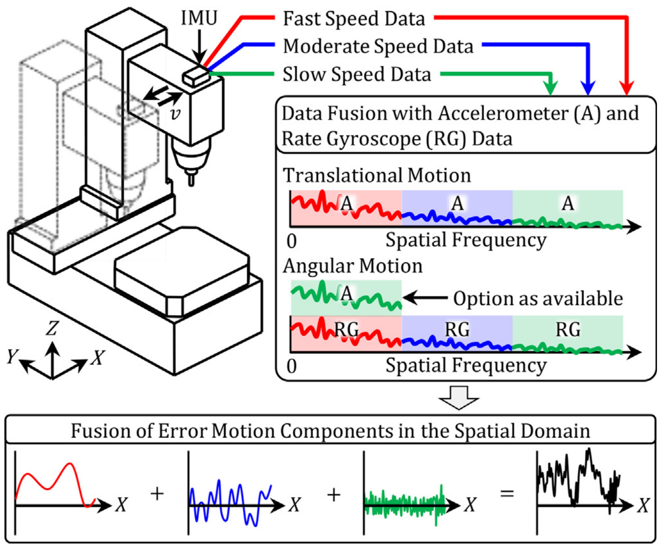

Fig. 1. IMU-based method for diagnostics of machine tool performance degradation.

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 part quality.

Following the approach outlined in Fig. 1, this paper introduces a novel IMU-based method for diagnostics of machine tool linear axes. A linear axis testbed was designed to physically implement the custom IMU and the IMU-based method. Various degradation patterns were experimentally simulated by adjustments of a guideway rail or defects imparted on bearing balls. This paper outlines the major findings of these experiments, revealing the potential of the novel IMU-based approach for diagnostics and prognostics of machine tools.

2. Testbed setup

A testbed was designed for evaluation of the IMU-based method. As seen in Fig. 2(a), the testbed includes a linear axis, the IMU, a commercial laser-based system for measuring the geometric errors of the axis, and a direct current (DC) motor with encoder for motion control. While the metrology system measures the motion of the carriage with respect to the base of the linear axis, the carriage-mounted IMU measures the changes in the inertial motion of the carriage. The commercial metrology system is able to measure straightness and angular error motions over the travel length of 0.32 m with standard uncertainties of 0.7 μm and 3.0 μrad. The laser-based system is used for verification and validation (V&V) of the IMU-based results.

For the detection of both translational and rotational motions, the IMU contains three accelerometers and one triaxial rate gyroscope, as seen in Fig. 2(b). Table 1 outlines key specifications of the IMU sensors. Each sensitive direction is nominally aligned with either the *X*-, *Y*-, or *Z*-axis of the testbed coordinate system. Consequently, these sensors enable the estimation of 6-DOF motion.

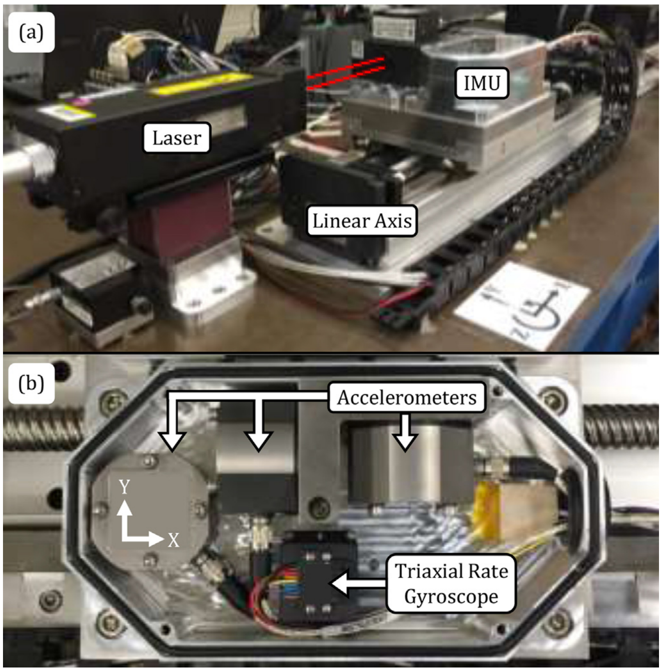

Fig. 2. (a) Linear axis testbed and (b) top view of IMU without its lid.

Table 1
Specified properties of sensors used in the IMU.

Sensor	Bandwidth[a]	Noise
Accelerometer	0–1800 Hz	4.0 (μm/s^2)/$\sqrt{}$Hz from 0 Hz to 100 Hz
Rate gyroscope	0–200 Hz	35 (μrad/s)/$\sqrt{}$Hz

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

3. IMU-based method

As outlined in Fig. 1, the IMU-based method relies on sensor data collected during a fixed-cycle test, in which an axis is programmed to move unloaded at three constant speeds: Fast speed ($v_1 = 0.5$ m/s), moderate speed ($v_2 = 0.1$ m/s), and slow speed ($v_3 = 0.02$ m/s). Constant speeds allow for simple correlation of error motions with axis position while minimizing transient dynamic effects. The different speeds allow for sensing of repeatable error motions, composed of low to high spatial frequencies, within different temporal bandwidths. Such a process takes advantage of the enhanced signal-to-noise and lower sensor drift at faster speeds, while taking advantage of the detection of higher spatial frequencies at slower speeds without violating sensor bandwidths. As seen in Fig. 1, matching the spatial cutoff frequencies enables the data fusion, while filtering allows for the attenuation of significant modal excitations, especially resulting from the initial and final accelerations during the fast speed cycle.

For the linear axis testbed, data is collected while the carriage moves back and forth sequentially at each of three speeds for 50 runs. Data collection for multiple runs allows averaging for convergence purposes. Once data is collected, data fusion follows.

3.1. Angular motions

Data fusion for estimation of angular motions is represented in Fig. 3. Rate gyroscope data for three speeds is integrated once, low- or band-pass filtered, processed, and summed to yield the total angular motions following the scheme in Fig. 3(a).

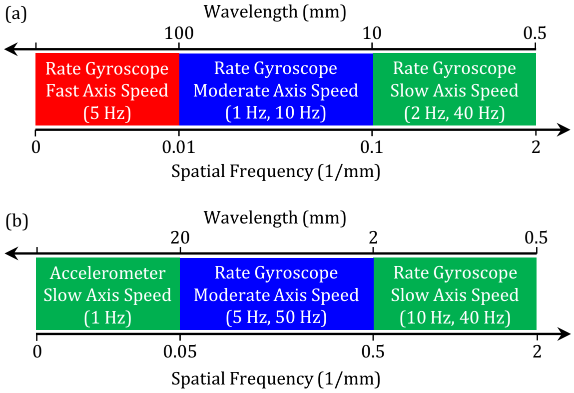

Fig. 3. Data fusion scheme for angular motions via use of (a) rate gyroscope data or (b) accelerometer and rate gyroscope data. Filter cutoff frequencies are shown in parentheses.

In contrast, the scheme in Fig. 3(b) may also be used to estimate the angular motions about the *X*- and *Y*-directions. Measuring down to 0 Hz (see Table 1), the three accelerometer signals (A_X, A_Y and A_Z) for the *X*-, *Y*-, and *Z*-directions relate to the inclination angles (θ_X and θ_Y) as approximately [11]

$$A_X = a_X - g\theta_Y \tag{1a}$$

$$A_Y = a_Y + g\theta_X \tag{1b}$$

$$A_Z = a_Z - \frac{1}{2} g\left(\theta_X^2 + \theta_Y^2\right) \tag{1c}$$

where g is the magnitude of acceleration due to gravity. Thus, Eqs. (1a) and (1b) yield the respective inclinations, θ_Y and θ_X, when the accelerations (a_X and a_Y) are negligible. However, the data fusion scheme in Fig. 3(b) may not be applied for the *Z*-axis, for which no 'inclinometer' exists.