Influence of Machining Parameters on Dynamic Errors in a Hexapod Machining Cell

Kanglin Xing
Ilian A. Bonev
Zhaoheng Liu (✉ zhaoheng.liu@etsmtl.ca)

Ecole de technologie superieure  https://orcid.org/0000-0002-8088-7136

Henri Champliaud

Research Article

Keywords: Machining parameters, Dynamic errors, Hexapod machining cell, Telescoping ballbar, Machining-based ballbar test, Unscented Kalman Filter, Particle Swarm Optimization

Posted Date: September 26th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3325111/v1

License: © This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License
Influence of Machining Parameters on Dynamic Errors in a Hexapod Machining Cell

Kanglin Xing\textsuperscript{1}, Ilian A. Bonev\textsuperscript{2}, Zhaoheng Liu\textsuperscript{1,*}, Henri Champliaud\textsuperscript{1}

\textsuperscript{1} Department of Mechanical Engineering, École de technologie supérieure, 1100 Notre-Dame St W, Montreal, Quebec, H3C 1K3, Canada
\textsuperscript{2} Department of Systems Engineering, École de technologie supérieure, 1100 Notre-Dame St W, Montreal, Quebec, H3C 1K3, Canada
\* E-mail: zhaoheng.liu@estmtl.ca

Abstract: Dynamic errors from the robotic machining process can negatively impact the accuracy of manufactured parts. Currently, effectively reducing dynamic errors in robotic machining remains a challenge due to the incomplete understanding of the relationship between machining parameters and dynamic errors, especially for hexapod machining cell. To address this topic, a dynamic error measurement strategy combining a telescoping ballbar, an Unscented Kalman Filter (UKF), and particle swarm optimization (PSO) was utilized in robotic machining. The machining parameters, including spindle speed, cutting depth, and feeding speed, were defined using the Taguchi method. Simultaneously, vibrations during machining were also systematically measured to fully comprehend the nature of dynamic errors. Experimental results indicate that dynamic errors in a hexapod machining cell (HMC) are significantly amplified in machining setups, ranging from 4 to 20 times greater compared to non-machining setups. These errors are particularly influenced by machining parameters, especially for spindle speed. Furthermore, the extracted dynamic errors exhibit comparable frequency distributions, such as spindle frequency and tool passing frequency, to the vibration signals obtained at the chosen sampling rate. This expands the application and enhances the comprehension of dynamic errors for spindle and cutting tool condition recognition.

Keywords: Machining parameters; Dynamic errors; Hexapod machining cell; Telescoping ballbar; Machining-based ballbar test; Unscented Kalman Filter; Particle Swarm Optimization.

Nomenclature

UKF Unsected Kalman filter
PSO Particle swarm optimization
HMC Hexapod machining cell
CD Circular deviation
RD Radial deviation
DE Dynamic error
DTW Dynamic time warping

1. Introduction

Industrial robot arms have enormous potential in various machining processes such as milling, grinding, and polishing due to their universality, flexibility, and affordability compared to conventional CNC machine tools [17]. However, their limited accuracy resulting from the low stiffness of the serial chain restricts their widespread application in robotic machining [14]. To tackle this challenge, a parallel kinematic robots-based machining cell has been developed, consisting of two Fanuc F-200iB hexapod industrial robots [26]. An algorithm was developed to efficiently calculate the inverse kinematics of the hexapod, enabling the planning of optimal trajectories. Additionally, the machining cell’s workspace was meticulously calculated to ensure high precision. The positioning performance of the HMC was thoroughly evaluated using a telescoping ballbar, considering various testing positions, the thermal effect, and several feeding speeds. By understanding the sources of errors in HMC machining, valuable insights can be gained to optimize machining conditions and setups, ultimately enhancing the overall quality of machining.

Three main categories of errors could be found in robotic machining: (1) environment-related errors including mounting errors and thermal effects, (2) robot-related errors, and (3) process-related errors. The robot-related errors are divided into two sources: geometrical errors resulting from the manufacturing or machining accuracy of robot parts and components, and non-geometrical errors arising from structural deformations, wear, nonlinear effects, and other factors in load-transmitting components, links, and energy-transforming devices [31]. Both types of robot-related errors can be greatly compensated through calibration. Process-related errors, namely dynamic errors, are primarily caused by the machining force and are dependent on process parameters such as spindle speed, feeding speed, cutting depth (axial and radial direction), and chip load [30,36]. Hence, a comprehensive understanding of the impact of machining parameters on dynamic errors in
HMC is crucial for achieving high-quality robotic machining in HMC. Current research on robotic machining primarily focuses on investigating the impact of machining parameters on machining quality [25,35], vibration analysis in relation to machining parameters [11], prediction of machining quality based on parameters and vibrations [12], and more [38]. However, there is still a need for further understanding of the relationship between machining parameters and dynamic errors in robotic machining.

The dynamic error is expressed as the difference between the actual displacement of the end-effector and its reference displacement (setpoints) during feed motion [22]. It can be attributed to two sources: internal servo loop errors, resulting from the high bandwidth of setpoints conflicting with the low servo bandwidth of the servo feed system, and external servo loop errors, originating from elastic deformation and vibrations in the mechanical series outside the servo loop, caused by acceleration and jerk of setpoints [22]. The dynamic error of the machining platform is influenced by its feeding system (motion) and feeding rate, with the latter having a greater impact on the dynamic errors [27]. Other factors that contribute to dynamic errors include acceleration, tool path curvature, and trajectory errors [22]. Unlike the low-frequency static errors of industrial robots, dynamic errors encompass the main spectral features of key robot components and are observable in the high frequency domain [7]. In order to accurately measure dynamic error, it is necessary to use the measurement device with a sampling frequency that can capture high-frequency errors. The optimal sampling rates of testing devices for dynamic error measurement in non-machining states were found to be 1000 and 2000 Hz [27,29]. While, in the machining process, large vibrations caused by factors such as machining platforms, machining parameters, cutting tools, and materials can result in significant dynamic errors. The main spectral frequency of vibration can vary and may fall greatly above 500 Hz.

Several techniques have been developed to measure and decompose dynamic-related errors. In one study, a stepped feature workpiece was used to map the relationship between machine tool geometric errors and workpiece features. After machining, the workpiece was measured on the machine and then calibrated with a coordinate measuring machine, allowing for the successful identification and separation of seven geometric and dynamic errors [21]. Another method, the Capball-based approach, is effective for five-axis and multi-axis machine tools, and has been shown to decompose both quasi-static geometric errors and dynamic geometric errors [2]. In addition, Kalman filter-based methods also show potential for accurately estimating error parameters in robot and machine tools. For example, a Kalman filter has been successfully used to reduce vibrations and estimate kinematic parameters of an industrial robot [9]. Moreover, the Kalman filter has proven to be highly effective in extracting periodic forced vibrations and isolating unstable chatter signals by removing them from the raw data [28]. An UKF was also used to model multiple types of machine tool errors, minimizing measuring and modeling errors caused by non-linearity and measurement noise [4]. Compared to the stepped feature workpiece and Capball-based methods, Kalman filter-based techniques can be easily integrated into data processing without additional hardware, making them a promising option for processing dynamic errors in ballbar results. Although the standard Kalman filter is effective for estimating linear systems, real-world systems are often nonlinear, so nonlinear filtering methods such as UKF are commonly used.

Herein, a dynamic error measurement strategy was developed and used by integrating telescoping ballbar, UKF, and PSO for accurate measurement of dynamic errors in robotic machining. The telescope ballbar was seamlessly incorporated into the hexapod machining process through specialized testing conditions and a novel fixture. The raw data obtained from the ballbar was processed using the PSO-tuned UKF for precise dynamic error measurement. A series of meticulously selected machining parameters, determined by the Taguchi method, were employed in conducting the machining tests. Then, these experiments allow us to investigate the impact of machining parameters on dynamic errors during robotic machining.

The remainder of this paper is structured as follows. The next section presents the dynamic error measurement method based on ballbar. Section 3 provides an overview of the ballbar setup for machining operations, as well as the details of the machining tests. The results are analyzed and discussed in Sections 4 and 5, respectively. Finally, the findings are summarized in Section 6.

2. Dynamic errors measured with ballbar under machining operations

The telescoping ballbar serves as an automated and user-friendly tool for identifying errors in machine tools or industrial robots. The ballbar test, aligned with ISO 230-4, Test code for machine tools, offers precise error detection capabilities [1]. By assessing the machine movement along a circular path, the ballbar evaluates circular contouring accuracy, presenting the results in a polar format [10]. Commercial ballbar analysis software (e.g., Renishaw Ballbar 20) can calculate and identify multiple error sources such as backlash, scale-mismatch, and squareness, etc. The ballbar is typically employed in non-machining processes because its end is fixed in the spindle toolholder. When using the ballbar to assess the effects of dynamic errors in HMC, it is essential to carefully consider the following areas: (1) a constant and sufficient sampling rate
for dynamic error measurement; (2) integration of ballbar measurement and machining process; and (3) separation of dynamic errors from the ballbar results measured under machining operations.

The following dynamic error measurement strategy was proposed and used in this research for the measurement of dynamic errors (Fig. 1). Based on the unique structure of HMC, the ballbar can be seamlessly integrated into the robotic machining process through the utilization of two specially designed components, namely A (fixtures) and B (supporting bar), which are depicted within the white square in the diagram. The incorporation of these specific fixtures allows the placement of one of the ballbar end-points on the axis of the spindle. As a result of this configuration, a closed kinematic chain is formed, encompassing the following components in sequential order: spindle - tool - workpiece - hexapod (wall) - frame - supporting bar - ballbar - spindle. The integration of the ballbar into HMC facilitates precise measurement and machining processes, ensuring accurate ballbar measurement during the robotic machining operation. In addition, an efficient ballbar data acquisition strategy by leveraging the Renishaw provided API has been developed. This strategy ensures a consistent sampling rate of 1000 Hz, overcoming the challenges posed by the varying feeding speeds associated with the general commercial ballbar, and it allows us to get a maximum range of dynamic errors during testing.

Within this machining and testing platform, the robotic machining process are subsequently configured. The dynamic errors in the machining process can be influenced by various factors, including machining parameters, cutting tools, workpiece, and cooling systems. Given the relative stability of cutting tools and workpiece during the machining process, this research primarily focuses on analyzing and optimizing the machining parameters. After considering the mechanical structure of the tool holder and the recommended robotic machining cutting depth without cooling [3], a conservative maximum cutting depth of 0.15 mm was chosen to prevent any potential damage to the ballbar and cutting tool.

Once the setups are complete, the machining based ballbar test can be conducted and the recorded ballbar raw data via Bluetooth will be processed with a self-developed ballbar processing tool for dynamic error calculation (Fig. 1).
2.1 Quantification of dynamic errors

The ballbar raw data was processed using an alternative Matlab program that adheres to the ISO 230-4 2005 standard [1]. The raw data was corrected using the nominal radius (50.0037 mm) to obtain the actual circular path. Then, the least-square fitting method was used to calculate the true center of the circular path and the circular deviation (CD), defined as the difference between the radius of the least-squares circle and the nominal ballbar radius [32]. In addition, the ballbar raw data undergoes processing using the UKF and PSO algorithms. The effectiveness of the UKF heavily relies on its tunable parameters. To ensure optimal performance, the PSO method is employed for automatic tuning of the UKF parameters. The UKF processing retains the frequency components that are relevant to the static error state of the machining platform. The details of UKF and PSO in ballbar data processing will be introduced in sections 2.2 and 2.3.

The filtered data are then processed using the standard ballbar processing program to determine the radial deviation (RD) and CD. The dynamic errors (DEs) on the ballbar are quantified as the disparities in RD/CD before and after applying the UKF processing. Herein, DEs are characterized by the following three parameters: (1) differences in CDs (DE$_1$); (2) peak-to-peak value of differences in RDs (DE$_2$); and (3) the mean absolute value of differences in RDs (DE$_3$). These three are defined as:

\[
\begin{align*}
DE_1 &= CD_1 - CD_2, \\
DE_2 &= \text{Peak2peak} (RD_1 - RD_2), \\
DE_3 &= \text{RMS} (RD_1 - RD_2).
\end{align*}
\]

2.2 Unscented Kalman Filter

The Kalman filter, developed by Rudolf E. Kalman, is used for estimating the state of a dynamic system by analyzing multiple noisy measurements [33]. Despite its limitations, it is widely applied in engineering and economics systems [18]. However, it is only suitable for linear systems with linear relationships between measurements and the system’s state, which is not the case in most real-world engineering problems. To address nonlinearities, extensions of the Kalman filter such as the Extended Kalman Filter, Robust Extended Kalman Filter, and the Unscented Kalman filter (UKF) have been developed [24]. In this research, we employ the UKF as our primary tool for processing ballbar measurements, given its capability to approximate gaussian distributions more effectively than other nonlinear functions [4].

Consider the general ballbar system described by the following equations 4 and 5:

\[
\begin{align*}
X_k &= f(X_{k-1}) + w_{k-1}, \\
Y_k &= f(X_k) + v_k.
\end{align*}
\]

where $W_k$ is the process noise and $V_k$ is the observation noise, both of which are considered as white Gaussian noise processed of covariance matrices $Q_k$ and $P_k$, respectively. Given the state vector at step $k - 1$ and assuming that this has a mean value of $\bar{X}_{k-1}$ and $P_{k-1}$ covariance, the statistics of $x_k$ can be calculated by using the unscented transformation, or in other words by computing the set of sigma points $\chi^\pm_k$ with associated weights $W_i$. The steps of UKF are summarized in Fig. 2. The scaling parameter $\lambda$ reflects the distribution of the sigma points around the mean $\bar{x}$ and is typically set to a value between 0.0001 and 1, with $\alpha^2(L + K) - L$ being its equation [23]. The secondary scaling parameter $K$ is usually set to 0, while $\beta$ is used to incorporate prior knowledge of the distribution of $x$, with $\beta = 2$ being optimal for Gaussian distributions [15].

Based on the above analysis of the UKF, we can find that the parameters including $\lambda$, $K$, and $\beta$ are the main parameters for unscented transformation. Other adjustable parameters such as state covariance, process noise, and measurement noise may also impact UKF’s performance. Herein, they are selected based on the recommended values [15].
2.3 Automatic tuning for UKF using particle swarm optimization

To determine the optimal parameters of UKF for dynamic errors calculation, the PSO was employed. The non-machining based ballbar measurement result is used as the reference, ideally, a good UKF fitting can make the filtered ballbar data have similar curve shape as the ballbar raw data measured at the non-machining process. To check this similarity, Fréchet distance (Eq. 6) [8] and dynamic time warping (DTW) parameter (Eq. 7) [16] were used.

The Fréchet distance stands as a measure quantifying the similarity between two curves. This measure takes into account not only the arrangement of points along the curves but also their positional information. In an ideal scenario, this measure yields a value of zero, signifying perfect equivalence between the two curves. In contrast, the DTW parameter finds its common usage in assessing the similarity of patterns within time series data. It accommodates the possibility of one time series undergoing a "warped" transformation, involving nonlinear stretching or compression along its temporal axis. Essentially, the DTW parameter gauges the extent of likeness between two patterns exhibited by curves. DTW value of 0 is attained when the two curves achieve an exact match. For an in-depth understanding of the DTW concept, refer to [16].

PSO represents a population-based stochastic optimization method originally inspired by the collective behavior of bird flocks [37]. This technique, now generally used in optimization, boasts ease of implementation and widespread application across diverse domains such as parameter adjustment, function optimization, feature extraction, multi-objective optimization, and constraint handling [37]. Its utility extends to fine-tuning covariance matrices in the context of the Extended Kalman Filter (EKF) for predicting lithium-ion battery performance [19]. Moreover, PSO finds application in refining process noise covariance matrices and measurement noise covariance matrices within the UKF for the purpose of ballistic target tracking [13]. To delve into the mathematical intricacies of PSO, refer to [37]. In this specific study, the Matlab function “particleswarm” was employed to autonomously fine-tune the UKF.

PSO operates by considering a candidate solution represented as a vector of real numbers, often corresponding to tuning targets. This vector undergoes evaluation within the fitness function, yielding a single real number that reflects its fitness value. The ultimate objective of this process is to uncover the global minimum of fitness function. The utilization of PSO in UKF implementation involves two primary steps. Initially, the focus lies on formulating the fitness function, denoted as \( f(x_1, x_2, \ldots, x_n) \), which serves as the foundation of the optimization endeavor. The inputs and outputs pertaining to this fitness function can be expressed through the subsequent equations. In this context, \( BF_n \) represents the UKF-filtered ballbar raw data acquired during machining operations, \( B_n \) symbolizes the ballbar raw data obtained under similar machining conditions, while \( RB_n \) corresponds to the reference ballbar raw data collected in non-machining operations and \( x_1, x_2, \ldots, x_n \) denote the tunable parameters for UKF. We have

\[
\delta_P(BF_n, RB_n) = \max\{\max\{\min d(a, b)\}, \max\{\min d(a, b)\}\} \quad \text{where} \ a \in BF_n \text{ and } b \in RB_n, \tag{6}
\]
\[ DTW(BF_n, RB_n) = \sqrt{\sum_{(i,j) \in \pi} (BF_n - RB_n)^2}. \] (7)

\[ BF_n = f_{UKF}(B_n, x_1, x_2, \ldots). \] (8)

\[ f(x_1, x_2, \ldots, x_n) = DTW(BF_n, RB_n) + \delta_F(BF_n, RB_n). \] (9)

Subsequently, the PSO algorithm involves selecting crucial parameters including the number of tuning targets and its range values (lower bound and upper bound), self-adjusted weight and social adjusted weight, etc., to facilitate its functioning. The entire workflow of using PSO for tuning of UKF is visually depicted in Fig. 3.

Fig. 3. Flowchart for tuning UKF using PSO method.

In this research, most tunable parameters were selected based on the references, except for the scaling parameter \( \lambda \). This approach facilitates the identification of optimal UKF parameters tailored to each ballbar data processing instance. The utilization of the PSO method further expands the potential for discovering alternative parameter sets conducive to UKF. Notwithstanding potential influences on UKF performance, real-world applications consistently demonstrate the capacity to attain pragmatic and satisfactory outcomes.

3 Experimental setups

3.1 Ballbar setup for machining operations

A ballbar measurement was performed on a HMC comprised of two FANUC F-200i hexapods, an electrical spindle, a bench clamp, and a mechanical frame. The CD of the floor-mounted hexapod was assessed using a Renishaw QC20-W telescopic ballbar with accuracy of 0.1 \( \mu \)m (at 20°C) and a measuring range of \( \pm 1.0 \) mm. When using the Renishaw ballbar software, the sampling rate of the ballbar is influenced by the feeding speed, resulting in a rate lower than the maximum 1000 Hz. In contrast, an alternative approach was adopted, employing a bespoke ballbar data acquisition strategy to capture measurements at the maximum sampling rate of 1000 Hz.

The machining-based ballbar test utilized two custom fixtures (A and B in Fig. 4, d) attached to the back of the electrical spindle and frame bar of the HMC (more details are available in [26,34]). During the measurement, the floor-mounted hexapod moved in the YZ plane while the wall-mounted hexapod moved along the X-axis to allow the workpiece to make contact with the cutting tool for a fixed-depth circular cut. The cutting was performed in the CCW direction and with a 90-degree angular overshoot (double sides), as depicted in Fig. 4.
3.2 Machining tests

Ballbar tests for machining were designed by considering three key factors: spindle speed, feeding speed, and cutting depth. The Taguchi experiment design method was chosen to maximize cost savings, reduce experimentation time, and determine the primary factor contributing to dynamic errors in ballbar results. Each factor was assigned two levels, resulting in an L8 ($2^3$) plan of eight experiments. The specific machining parameter settings are outlined in Section 4, Table 1.

The machining-based ballbar test was conducted using a hexapod equipped with a 3.3 kW TMPE 4 ER25 electrical spindle from Elte Srl. A solid carbide finishing end-mill cutter with a diameter of 10.6 mm and four flutes was used for cutting. The workpiece was a 316L stainless steel plate mounted on the wall-mounted hexapod. The selection of the three machining parameters was based on the following findings:

1. Previous tests indicated that minimal differences in circular deviations in both the CCW and CW directions occurred when the feeding speed was between 1200 and 3000 mm/min. To minimize the impact of vibration on ballbar measurement, a feeding speed of 1200 mm/min was selected.
2. The mechanical structure of the tool holder and recommended robotic machining cutting depth without cooling prompted the selection of a maximum cutting depth of 0.15 mm to avoid potential damage to the ballbar and cutting tool.
3. Given the 316L stainless steel material, spindle speeds of 2000 and 12,000 RPM were randomly selected after determining the feeding speed and cutting depth.
Prior to and following the machining-based ballbar test, a single non-machining based ballbar test was performed (T0 and T9) at the same measurement position with a feeding speed of 1200 mm/min. The sequence of machining-based tests is displayed in Table 1 of Section 4, ranging from T1 to T8. Results were analyzed using MiniTab 19 software for variance analysis.

4. Results and analysis

4.1 Dynamic errors extracted from ballbar results

The ballbar outcomes achieved across diverse machining conditions underwent processing via UKF, leveraging optimally scaling parameter ($\lambda$) derived from PSO technique. The PSO automatically discovers the local and global minimum of the objective function $f(\lambda)$, enabling the calculation of CD following UKF processing. As an illustration, consider T1 (Fig. 6) where $\lambda$ spanned from $10^{-5}$ to 1. Using PSO, a local minimum at 0.00034 corresponding to a CD value of 22.8 $\mu$m was identified. Employing the same data processing approach, the CD and DE values for the other tests can be similarly computed.

![Fig. 6. CDs and values of the target function, $f(\lambda)$, of T1 calculated with UKF and PSO.](image)

As seen in Fig. 7, compared to the non-machining based ballbar measurement results (T0 and T9, T9 is omitted as it yields similar results as T0), more dynamic effects (vibrations) can be observed in each machining condition, particularly for tests T1, T3, T5, and T7. Despite the presence of these effects, the shapes of the measured radial deviation curves were largely preserved under the selected machining conditions (Fig. 7), suggesting that the static kinematic error remains the primary contributor to the radial deviation at each angular position of the arc path. The proposed UKF can effectively eliminate the dynamic effects from the machining process contained in the radial deviation curve.

Before filtering, the CDs of the HMC in the machining process ranged from 30.5 to 92.9 $\mu$m and were higher (1 to 63.4 $\mu$m) than the T0 and T9 measurements taken at non-machining-based counterparts (Fig. 8, a). This highlights the importance of properly selecting machining parameters to maintain the hexapod's positioning performance and optimize machining tolerance and surface roughness. When using UKF, the CDs of the HMC in the machining process decreased. Furthermore, after UKF filtering, the CDs were closer to the results obtained from the non-machining based ballbar test, although there were small differences with a maximum of 3 $\mu$m. Better filtering for dynamic errors can be achieved when the dynamic errors present in the machining process are smaller or closer to the CD measured in the non-machining based ballbar measurement (Fig. 8, b). As an example, when the value of $DE_1$ is smaller than the reference value (mean value of T0 and T9 taken at non-machining states), the shape of the radial deviation curve after filtering is closer to that of T0. However, for T1, T3, T5, and T7, even after UKF filtering, the CD may be close to the relevant value of T0, but the shape of the radial deviation curve still shows levels of vibrations. Although the DE values may differ, the UKF consistently demonstrates a similar relative change trend in experimental machining conditions (Fig. 8, b to d).
Test 0 (1200 mm/min, 0 RPM, 0 mm)
Test 1 (600 mm/min, 2000 RPM, 0.05 mm)
Test 2 (600 mm/min, 12000 RPM, 0.05 mm)
Test 3 (600 mm/min, 2000 RPM, 0.15 mm)
Test 4 (600 mm/min, 12000 RPM, 0.15 mm)
Test 5 (1200 mm/min, 2000 RPM, 0.05 mm)
Test 6 (1200 mm/min, 12000 RPM, 0.05 mm)
Test 7 (1200 mm/min, 2000 RPM, 0.15 mm)
Test 8 (1200 mm/min, 12000 RPM, 0.15 mm)

Fig. 7. Radial deviation curve patterns of ballbar results under different machining conditions.

(a) CDs before and after UKF filtering
(b) $D_{E_1}$ calculated with UKF
The accuracy of DE in evaluating dynamic errors’ impact on ballbar results was confirmed by examining the relationship between DE and tool torque (as depicted in Fig. 9). The cutting force, which directly affects dynamic errors, was taken into account during the machining process by calculating the tool torque using G-Wizard Speeds and Feeds Calculator. To better illustrate the relationship, a linear model \( \text{val}(x) = p1*x + p2 \) was used to fit the DE values calculated using UKF with the tool torque. Using the same linear model, \( DE_1 \) (UKF) had \( p1 = 0.0078 \), \( p2 = -0.08 \), and RMSE of 0.0734. \( DE_2 \) (UKF) had \( p1 = 0.0616 \), \( p2 = -0.1388 \), and RMSE of 0.0765. \( DE_3 \) (UKF) had \( p1 = 0.04332 \), \( p2 = -0.094 \), and RMSE of 0.0686. The small RMSE values in the fitting process and clear linear fit suggest that the UKF has a superior performance in exploring dynamic errors on ballbar results [5]. This conclusion is further supported by the consistency of the fitting results and the Ref value.

Previous studies have shown that the spindle speed has a substantial impact on ballbar measurement results in machining, while feeding speed and cutting depth have no significant impact [34]. The difference in ballbar measurement results between machining and non-machining setups is primarily due to dynamic error-related effects. Since the ballbar results measured in the non-machining setup are relatively stable, these dynamic error-related effects should also be greatly influenced by the spindle. By confirming the impact of machining parameters on dynamic errors, the accuracy of these DEs can be indirectly verified. Table 1 presents the results of a range analysis for an orthogonal experiment. Further details of the range analysis can be found in [20]. S1 and S2 are the average DEs in the two factors of experiments, and range is the difference between S1 and S2 for each factor. The comparison of range values reveals that the impact of machining parameters on DEs can be ranked as follows: Spindle speed > Cutting depth > Feeding speed. Table 2 illustrates the variance results of the orthogonal experiment. A factor is considered significant when its P-Value is less than 0.05. The results show a significant effect of spindle speed on DE1, while feeding speed and cutting depth have no significant impact. Similar conclusions can be drawn for DE2 and DE3. These results align with the findings of [34], thereby validating the proposed UKF-based method for exploring the effect of dynamic errors from ballbar measurements.
Table 1. The range analysis result of the orthogonal design experiment. Herein, T0 and T9, related to non-machining based ballbar tests, were not included.

<table>
<thead>
<tr>
<th>No.</th>
<th>Feeding speed [mm/min]</th>
<th>Cutting depth [mm]</th>
<th>Spindle speed [RPM]</th>
<th>DE1 [µm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>600</td>
<td>0.05</td>
<td>2000</td>
<td>34.2</td>
</tr>
<tr>
<td>T2</td>
<td>600</td>
<td>0.05</td>
<td>12000</td>
<td>18.5</td>
</tr>
<tr>
<td>T3</td>
<td>600</td>
<td>0.15</td>
<td>2000</td>
<td>48.9</td>
</tr>
<tr>
<td>T4</td>
<td>600</td>
<td>0.15</td>
<td>12000</td>
<td>14.9</td>
</tr>
<tr>
<td>T5</td>
<td>1200</td>
<td>0.05</td>
<td>2000</td>
<td>28.0</td>
</tr>
<tr>
<td>T6</td>
<td>1200</td>
<td>0.05</td>
<td>12000</td>
<td>13.1</td>
</tr>
<tr>
<td>T7</td>
<td>1200</td>
<td>0.15</td>
<td>2000</td>
<td>63.7</td>
</tr>
<tr>
<td>T8</td>
<td>1200</td>
<td>0.15</td>
<td>12000</td>
<td>9.6</td>
</tr>
<tr>
<td>S1</td>
<td>29.15</td>
<td>23.45</td>
<td>43.69</td>
<td></td>
</tr>
<tr>
<td>S2</td>
<td>28.59</td>
<td>34.29</td>
<td>14.05</td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>0.55</td>
<td>10.85</td>
<td>29.64</td>
<td></td>
</tr>
<tr>
<td>Rank</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Variance analysis of the orthogonal experiment

<table>
<thead>
<tr>
<th>Source</th>
<th>Degree of freedom</th>
<th>Square Sum</th>
<th>Mean Square</th>
<th>F-Value</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feeding speed</td>
<td>1</td>
<td>1</td>
<td>0.55</td>
<td>0.004</td>
<td>0.953</td>
</tr>
<tr>
<td>Cutting depth</td>
<td>1</td>
<td>1</td>
<td>234.4</td>
<td>1.644</td>
<td>0.269</td>
</tr>
<tr>
<td>Spindle speed</td>
<td>1</td>
<td>1</td>
<td>1761.2</td>
<td>12.36</td>
<td>0.025</td>
</tr>
<tr>
<td>Error</td>
<td>4</td>
<td>4</td>
<td>142.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>7</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.2 Relationship between machining parameters and dynamic errors

Fig. 10 illustrates the relationship between machining parameters and dynamic error indicators (DE1, DE2, and DE3). This relationship holds true for all dynamic error indicators examined. Within the experimental setup, the impact of spindle speed on dynamic errors is evident across DE1, DE2, and DE3. Increased spindle speeds consistently result in diminished dynamic errors. Notably, distinct scenarios arise: when investigating the influence of cutting depth and feeding speed on dynamic errors, DE2 demonstrates proximity in values in certain instances. However, such parallels are not mirrored in DE1 and DE3. In this case, DE1 and DE3 can perform better than DE2 on exploring the relationship between machining parameters and dynamic errors.
Fig. 10. Relationship between different machining parameters and dynamic errors expressed with different indicators $DE_1$ (a), $DE_2$ (b) and $DE_3$ (c), where FS stands for the feeding speed, SS stands for the spindle speed and Cud stands for the cutting depth.

4.3 Analysis of dynamic errors and accelerometer results in time domain

While performing machining-based ballbar tests, concurrent vibration measurements were carried out using an accelerometer with the sampling rate of 2048 Hz. Acceleration features were extracted from Y-axis (ballbar test was conducted at the YZ plane) using peak-to-peak parameter. Given the ballbar’s 1000 Hz sampling rate, acquired acceleration raw data also underwent processing through a 1000 Hz low-pass filter. Similar pattern could be found by all DEs. For the given experimental results, the dynamic errors generally increased with vibration (Fig. 11, a and b, the green area). Nevertheless, in cases of minor vibration amplitudes, an unforeseen outcome was observed with T4, which posed a challenge to the established overarching pattern we had identified. Comparable findings were apparent even when employing the fitted acceleration data (at 1000 Hz, Fig. 11, b). This underscores that the high-frequency elements ($\geq 1000$ Hz) of the collected acceleration data had minimal impact on the fluctuations observed in the DEs. As a result, the simultaneous escalation of dynamic errors and acceleration can be considered dependable solely when the vibration magnitude surpasses a certain threshold.

Fig. 11. The correlation between DEs and acceleration magnitudes, determined through peak-to-peak parameter, is depicted as follows: (a) acceleration magnitudes are computed using acceleration data sampled at 2048 Hz; (b) acceleration magnitudes are derived from acceleration data filtered through a standard low-pass filter operating at a 1000 Hz cut-off frequency. The use of a green rectangle effectively highlights the evident upward trend in the experimental results.

4.4 Analysis of dynamic errors and accelerometer results in the frequency domain

Given the significant correlation between vibration and dynamic errors, it is essential for the data acquired from the accelerometer and ballbar system to exhibit comparable frequency content during circular tests performed under machining
conditions, provided that the ballbar system setup is reasonable. The recorded raw data from the accelerometer and ballbar system were processed using the fast fourier transform method and compared in the frequency domain. Fig. 12 reveals the analysis results of two general measurements (T1 and T2) with ballbar and accelerometer in the frequency domain. To compare the results well, the scale of accelerometer in X axis of Fig. 12 was adjusted to 500 Hz.

![FFT analysis of T1](image1)

![FFT analysis of T2](image2)

(a) FFT analysis of T1, $f_S = 32.8$ Hz and $f_T = 131.2$ Hz

(b) FFT analysis of T2, $f_S = 200$ Hz and $f_T = 800$ Hz

Fig. 12. Analysis of the ballbar and accelerometer results measured from T1 and T2 in the frequency domain. $f_S$ and $f_T$ represent the frequencies of the spindle speed and cutting tool, respectively.

The spindle speeds for T1 and T2 are 2000 RPM and 12000 RPM, resulting in $f_S$ values of 32.8 Hz and 200 Hz, respectively. Considering the cutting tool’s four flutes, the corresponding tool frequencies, $f_T$, are 131.2 Hz and 800 Hz. Based on Fig. 12, the spindle frequency and its harmonics for both T1 and T2, the tool frequency and its harmonics for T1 can be well observed. However, the tool frequency of T2 (800 Hz) is more accurately represented by the accelerometer rather than the ballbar owing to the small sampling range of ballbar (Fig. 13). Furthermore, the frequency of 84 Hz (which was not investigated in this research) is clearly displayed in Fig. 12, b, using both ballbar and accelerometer. It is worth noting that a 60 Hz signal detected by the accelerometer indicates that it was influenced by the electrical system. Compared with Fig. 12, b and Fig. 13, a greater number of harmonics of the spindle and tool can be observed within the 500 to 1024 Hz range. This suggests that the ballbar system, due to its relatively small sampling rate, is unable to capture the complete vibration information, particularly in the high frequency domain. Consequently, in this study, the dynamic effect of the ballbar system primarily arises from vibrations within the 0 to 500 Hz range during the machining process. It's important to note that this dynamic effect does not precisely represent the dynamic error inherent in the robotic machining process. Nonetheless, the ballbar system functions equivalently to an accelerometer in exploring the state of the spindle or cutting tool in the selected frequency range.

![FFT of accelerometer of T2](image3)

Fig. 13. FFT of accelerometer of T2 with full scale of frequency (from 0 Hz to 1024 Hz).

13
5. Discussion

The relationship between dynamic errors and machining parameters was systematically investigated through a combination of the Taguchi method and an innovative approach employing machining-based ballbar tests, the UKF, and PSO techniques. The effectiveness of UKF in dynamic error calculation can be influenced by its configuration parameters. Typically, these parameters can be chosen according to recommended values. To enhance this selection process, PSO method was employed. In this study, our attention centered on streamlining the scaling factors, particularly $\lambda$. Yet, it’s worth clarifying that PSO is equally capable of optimizing multiple setup parameters for UKF. This can be achieved with ease by utilizing the “particleswarm” function within Matlab. Leveraging the advantages of this sub-technology, the employed methodology enables the calculation of dynamic errors from the machining based ballbar tests, facilitated by automatically optimized UKF parameters. The corroborative evidence lies in the congruent patterns of radial error curves and consistent CD values before and after PSO-UKF processing. Furthermore, the filtered ballbar data yielded akin outcomes to non-machining condition tests, offering valuable insights into both dynamic and static conditions of the tested subject. Consequently, a single machining-based ballbar test offers a more comprehensive insight than traditional non-machining-based tests.

The robustness of this dynamic error calculation method empowers an exploration of dynamic error performance in both time and frequency domains across various machining scenarios. In the time domain, non-machining setups exhibited DEs ranging from under 3 $\mu$m to 12 $\mu$m. Conversely, machining setups revealed significantly higher DEs (4 to 20 times greater), which varied with machining parameters. In the frequency domain, analogous frequency components were observed in dynamic errors and acceleration results within the effective 0 to 500 Hz analysis range. The synchronization of spindle and tool passing frequencies within dynamic errors and acceleration outcomes unveils a fresh perspective on dynamic errors within the machining process.

Regarding the relationship between dynamic errors and machining parameters, DE analysis unveiled a noteworthy impact of spindle speeds on dynamic errors. In contrast, the influence of feed speed and cutting depth was found to be less pronounced. This observation could potentially be attributed to the restricted range of cutting depth selections, which were more suitable to non-cooling robotic machining considerations. Furthermore, the efficacy of $DE_2$ in discerning the correlation between machining parameters and dynamic errors is comparatively lower than that of $DE_1$ and $DE_3$. This discrepancy arises due to the identification of similar values across diverse machining configurations. Therefore, $DE_1$ and $DE_3$ are recommended for expressing the DE thanks to their good robustness. Gaining insights into the influence of machining parameters on dynamic errors provides a rational basis for choosing appropriate parameters in hexapod-based robotic machining. The pursuit of minimal dynamic errors holds great significance in robotic machining. With spindle speed as a guiding parameter, the choice of other parameters becomes more focused and can be validated through the application of machining-based ballbar tests.

Technically, the effectiveness of the suggested approach for dynamic error calculation could potentially be influenced by the sampling rate of the ballbar. Presently, renowned manufacturers like Renishaw, API, and Chottest offer commercial ballbar systems with a peak sampling rate of 1000 Hz. While this rate is the maximum at present, it might not encompass the complete range of dynamic errors arising from different machining states. However, through an examination of the correlation between dynamic errors and acceleration, it was found that the dynamic error escalates once the vibration magnitude exceeds a specific threshold. Furthermore, it’s noteworthy that the impact of high-frequency vibration components on the dynamic error-acceleration relationship is negligible. Since similar change tendencies of DE and acceleration in the time and frequency domains could be found at the sampling rate of 1000 Hz. Therefore, the current application of machining based ballbar tests may still have good reliability. Interestingly, the Etalon X-AX LASERBAR showcases an enhanced sampling rate, holding great promise as an optimized measurement tool for future research works.

6. Conclusion

In this study, we conducted a comprehensive experimental evaluation of the influence of machining parameters on dynamic errors. To achieve this, we employed machining-based ballbar tests alongside the advanced techniques of UKF and PSO. The dynamic errors were quantified using distinct indicators-$DE_1$, $DE_2$, and $DE_3$-derived from the ballbar tests conducted under various machining parameters selected through the Taguchi method. The ensuing analysis led to the following conclusions:

1) Within the testing platform-HMC, dynamic errors (DE) spanning under 3 $\mu$m to 12 $\mu$m emerged during non-machining operations. However, higher DE (4 to 20 times higher) were found at different machining states.
2) In examining the relationship between dynamic errors and machining parameters, the analysis of DE revealed a significant correlation between spindle speeds and dynamic errors. Conversely, the influence of feed speed and cutting depth were less prominent. The relationships were well validated by DE_1 and DE_3. While DE_2’s performance falls slightly behind that of DE_1 and DE_3, this is attributed to its similar values calculated from different machining states. Consequently, DE_1 and DE_3 emerge as ideal indicators for highlighting the performance of DE.

3) In the frequency range of 0 to 500 Hz, similar frequency components such as spindle frequency and tool passing frequency were observed in both dynamic errors and acceleration. This novel insight advances our comprehension of dynamic errors in robotic machining. Furthermore, the DE exhibits a synchronized increase in response to vibration when it exceeds a certain threshold. Notably, the impact of high-frequency vibration components on the dynamic error-acceleration relationship remains minimal.

Acknowledgments
The authors acknowledge the financial support from the Fonds de recherche du Québec – Nature et technologies (FRQNT) postdoctoral research scholarship and the Natural Sciences and Engineering Research Council of Canada (NSERC). They express their gratitude to Mr. Mario Corbin, Mr. Joël Grignon, and Dr. Xavier Rimpault for their technical assistance in preparing and manufacturing hardware and fixtures for this study.

Declarations
a. This research is supported by FRQNT (Fonds de recherche du Québec – Nature et technologies) through a postdoctoral scholarship awarded to the first author and by NSERC (Natural Sciences and Engineering Research Council of Canada) through research grants awarded to the last three authors.

b. The authors declare that there is no conflict of interest regarding this research.

c. Authors’ contributions: Kanglin Xing: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original Draft. Ilian Bonev: Conceptualization, Investigation, Resources, Writing - Review & Editing, Supervision, Project administration, Funding acquisition. Zhaoheng Liu: Conceptualization, Investigation, Resources, Writing - Review & Editing, Supervision, Project administration, Funding acquisition. Henri Champliaud: Conceptualization, Investigation, Resources, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

References


5. Chai T, Draxler R (2014) Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. Geosci Model Dev 7 (3):1247-1250. doi:https://doi.org/10.5194/gmd-7-1247-2014


27. Qian D, Bi Q (2018) A dynamic machine tool circle test calibration method by R-test. MATEC Web of Conferences 249:02004. doi: https://doi.org/10.1051/matecconf/201824902004


