Proceedings 2018 ASME International Manufacturing Science and Engineering Conference
MSEC2018
June 18-22, Texas A&M University, USA

MSEC2018-6603

MONITORING, DIAGNOSTICS, AND PROGNOSTICS FOR ROBOT TOOL CENTER ACCURACY DEGRADATION

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KEYWORDS

Condition Monitoring, Diagnostics, Prognostics Maintenance, Manufacturing Processes, Robot Systems, Robot Performance Degradation

ABSTRACT

Over time, robots degrade because of age and wear, leading to decreased reliability and increased the potential for faults and failures. The effect of faults and failures impacts robot availability. Economic factors motivate facilities and factories to improve maintenance techniques and operations to monitor robot degradation and detect faults, especially to eliminate unexpected shutdowns. Since robot systems are complex, with sub-systems and components, it is challenging to determine these constituent elements' specific influences on the overall system performance. The development of monitoring, diagnostic, and prognostic technologies, which is collectively known as Prognostics and Health Management (PHM), can aid manufacturers in maintaining the performance of robot systems by providing intelligence to enhance maintenance and control strategies. This paper presents the strategy of integrating top level and component level PHM to detect robot performance degradation (including robot tool center accuracy degradation), supported by the development of four-layer sensing and analysis structure. The top level PHM can quickly detect robot tool center accuracy degradation through the advanced sensing and test methods developed at the National Institute of Standards and Technology (NIST). The component level PHM supports the deep data analysis for root cause diagnostics and prognostics. A reference data set is collected and analyzed using the integration of top level PHM and component level PHM to understand the influence of temperature, speed, and payload on robot's accuracy degradation.

INTRODUCTION

Robot systems play important roles in many manufacturing environments including automotive, electronics, consumer packaged goods, and aerospace manufacturing [1, 2]. The applications of robots in manufacturing systems bring benefits through both improving flexibility and reducing costs [3-5]. Robot work cells have become more complex, especially when considering robot-robot and human-robot operations [6-9]. More complexity leads to more sources of faults and failures, which can compromise the efficiency, quality, and productivity of a manufacturing system. Moreover, new innovative technologies are making robot work cells more accurate and intelligent, enabling them to be applied to some new applications [4, 10, 11]. New applications include material removal, high precision assembly, two-side drilling and fastening, in-process inspection, and three-dimensional (3D) composite material layout. New technologies often introduce new types of challenges that may not be fully understood. The afore-mentioned applications require high accuracy in both robot position and path. The degradation of robot tool center accuracy can lead to a decrease in manufacturing quality and production efficiency. It is important to understand robot accuracy degradation so that maintenance and control strategies can be optimized.

There are many challenges in developing monitoring, diagnostics, and prognostics for robot tool center accuracy degradation. First, robot tool center accuracy degradation may be difficult to detect, in a timely manner, because the robot may still be operating without any obvious signs of degradation, e.g., the robot being frozen or performing an undesirable activity. Second, with more diverse systems, sub-systems, and components integrated to increase robot work cell capabilities, further challenges are introduced in determining an element's specific influence(s) on the overall system performance [12, 13]. Third, continuous changes to an existing system give rise to new relationships that may lead to greater complexity. This complexity may include, dynamic robotic configurations (e.g., reconfiguration of the instrument layout and production processes), working parameters (e.g., program changes, temperature, payload, speed, part/grasp changes which causes force and torque changing), controller changes (e.g., control strategy, proportional–integral–derivative (PID) tuning), and worn parts [14]. To address these barriers and challenges, measurement science is needed, including performance metrics, use case scenarios, test methods, reference datasets, and software tools, to promote unbiased assessment of robot system accuracy degradation and to verify and validate health assessment strategies. Health monitoring, diagnostics, prognostics, and maintenance, which is collectively known as Prognostics and Health Management (PHM), have gained more and more attention within the robot system domain. The objective of PHM for robotics is to maintain the performance of robot systems by providing intelligence to enhance maintenance and control strategies. Robot systems within manufacturing environments can benefit from PHM where PHM technologies can reduce unscheduled downtime and costs.

Degradation monitoring, diagnosis, and prognosis at a system's highest level are defined as top level PHM. The same efforts at the component level are defined as component level PHM [15]. The top level PHM is difficult due to the great complexity and from the interactions among multiple sub-systems and components that comprise the system. A considerable body of knowledge has been accumulated on component level PHM. Researches are conducted in the development of reasoning algorithms and in establishing failure precursors for components [15-18]. Research approaches for solving PHM problems (for both top level PHM and component level PHM) are typically either physics-based or data-driven; while a hybrid combination also exists, it is but usually dominated by one of them [8, 19]. Physics-based approaches typically involve building technically comprehensive mathematical models to describe the physics of a system and its failure modes. For most industrial applications, physics-based approaches might not be the most practical solutions, especially for component level PHM, since the fault type in question is often unique from one component to another. It might also be hard to identify the fault without interrupting operations (e.g., needing special instruments to measure a component's performance or health that may interrupt the production operations) [20]. Data-driven approaches attempt to derive models directly from routinely-collected condition monitoring data instead of building models based on comprehensive system physics and human expertise. They are built using historical information and produce prediction outputs directly in terms of condition monitoring (CM) data [21]. Data-driven approaches may be the more available solution in many practical cases since it is easier to gather data than to build accurate system physics models [20]. However, data-driven approaches raise the questions of what data to collect, when to collect, how to collect (what sensors to use), and how to quantify the impact of degradation on the output of the robot work cell (process or final products).

One research effort at NIST is the Prognostics, Health Management, and Control (PHMC) project, which is developing the measurement science to promote advanced monitoring, diagnostic, and prognostic strategies within the manufacturing domain [22]. Part of the research effort for robot system PHM, from the PHMC project, is presented in this paper. The *Research Background and Approach* section presents the development of the PHMC for robot systems structure and its four-layer data sensing. The *Integration of Top Level and Component level PHM* section presents the development of using top level PHM to directly detect tool center accuracy degradation, and using component level PHM for deep data analysis (including root cause analysis) and PHM solution development. The *Reference Data Collection and Analysis* section presents the data sets collected on a Universal Robot [1] (UR5) to measure the degradation of the robot tool center position accuracy. The Conclusion wraps up the paper and highlights future work.

RESEARCH BACKGROUND AND APPROACH

PHMC for robot systems research is being conducted at NIST. The efforts include the development of performance metrics, test methods, reference datasets, and supporting tools to help the manufacturing community enhancing their PHM capabilities [12]. The research effort includes: 1) identifying data and information needed to make an informed decision with respect to robot systems setting and updating control points; 2) determining appropriate structure, organization, and analysis of data to gain actionable intelligence for robot systems; 3) enabling feedback of intelligence through the robot system to update control for optimal production; and 4) developing use cases to implement PHMC for robot systems in industrial applications. The goal is to deliver vendor-neutral approaches and plug-and-play solutions to improve decision-making support and automation [13].

Structure for the Robot Performance Degradation PHM

As a subset of the research, a structure and the key building elements are developed for robot performance degradation PHM (including robot tool center accuracy degradation) as shown in Fig. 1. The first key building element is an advanced sensing module shown in the upper left of Fig. 1. PHM efforts cannot be performed without proper sensing to understand the status of the system and components. The advanced sensing module provides important inputs for the research to promote monitoring, diagnosing, and predicting the system's health. This module has four layers of sensing that will be detailed in the next subsection. The second key building element is the data processing module as shown in the second upper left of Fig. 1. This module centers on reference algorithms development to fuse data. Data are captured from multiple sensors that are employed in the advanced sensing module. The third key building element is the development of algorithms for robot system health assessment, which is collectively shown in the cost function, degradation, prognostic, and visualization tools modules in Fig. 1. The purpose is to develop algorithms for robot system health assessment. The cost function works on solving robot error model to identify the possible root causes of faults and failures.

[1] https://www.universal-robots.com/

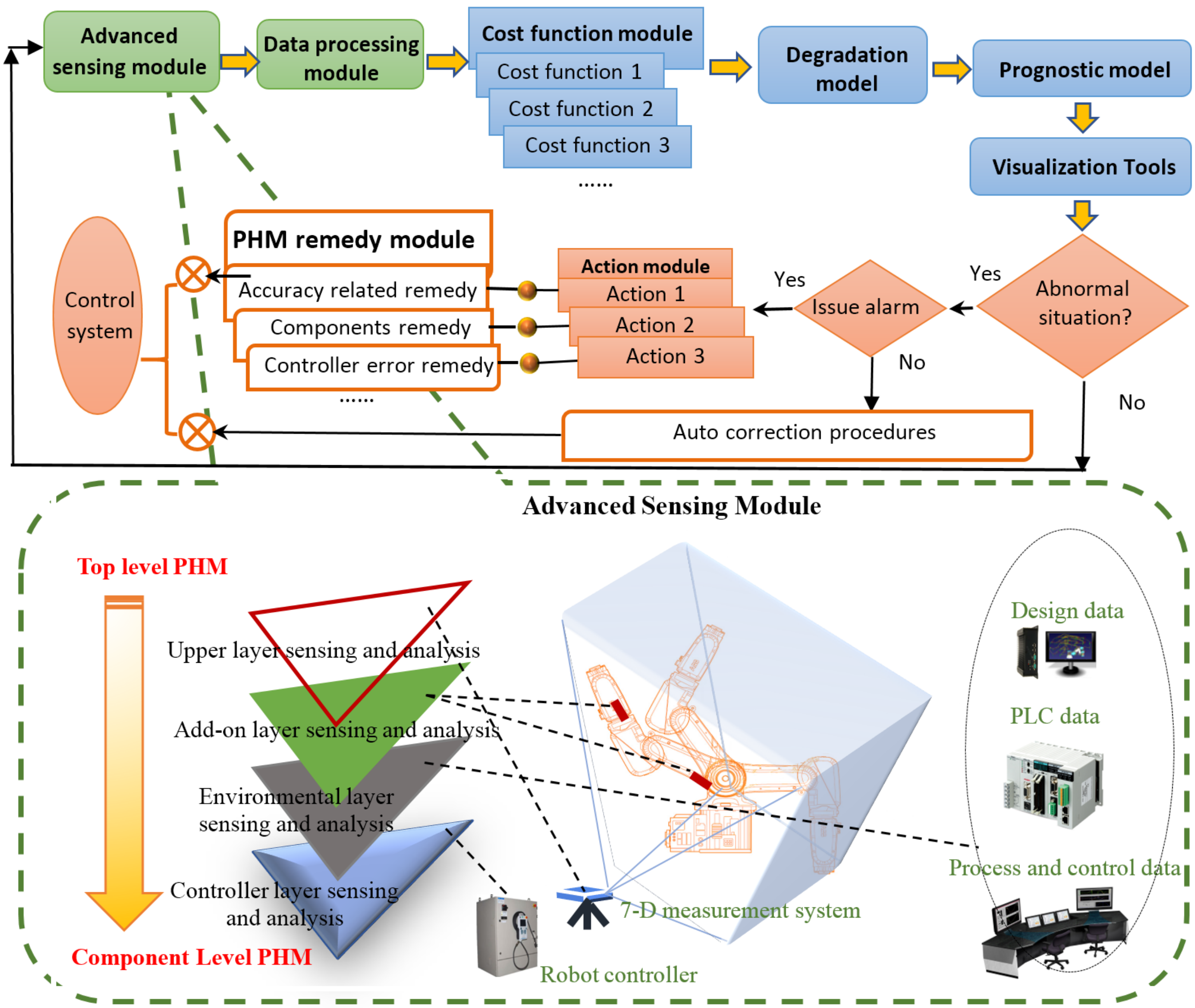

Figure 1. Structure and the key building elements for robot performance degradation PHM

The fourth key building element presents a closed-loop implementation of the PHM solution within the control, which is shown as the action module and the PHM remedy module in Fig. 1.

Expanded from the first key building element, the advanced sensing module consists of four layers of data sensing and analysis as shown in the callout picture at the bottom of Fig. 1. These layers are: the controller layer sensing and analysis, the environmental layer sensing and analysis, the add-on layer sensing and analysis, and the upper layer sensing and analysis. From the upper layer to the controller layer, information is becoming more granular by detailing sensing information in specific elements of the system.

Details for the Advance Sensing Module

Upper layer sensing and analysis aim to actively assess the health of the overall system by taking into account the system architecture, system functions, and process-related parameters [23]. For upper layer accuracy degradation analysis, integrated sensors are needed to efficiently assess the overall system's health degradation. Using multiple 1-D (one dimensional) or 2-D (two dimensional) sensors should be avoided since the setup is complex and will introduce error stacking. The research approach at this layer emphasizes the development of advanced sensing and test methods (including models and analysis algorithms) that can quickly and efficiently assess the tool center accuracy degradation.

Add-on layer sensing and analysis are developed to collect pre-designed features, e.g., using force and torque sensors to understand the influence of payload and the unbalanced tool mounting, from the targeted sub-systems. The add-on sensing promotes the involvement of additional sensors for additional information that the controller and upper layers may not provide. The research at this layer emphasizes the key subsystem/module (e.g., motor within a robot arm) identification and suitable sensing methodology selection. The design of the add-on system needs to be easily integrated into the system's controller(s) without complex interfaces or wirings.

The environmental layer sensing and analysis are developed to collect information about environmental conditions and settings when a robot is performing a task. Information includes design data (e.g., the program that a robot is running), process data, system integration control data, and external programmable logic controller (PLC) data. The environmental layer sensing and analysis can help to clarify the operational settings of the robot (e.g., speed of the robot, payload changes, etc.) when an anomaly is detected (by the upper layer sensing and analysis), or the parameters of an on-going robot operation when a dataset is collected from a controller. There are still challenges of how to integrate and align the environmental layer data with the controller layer data and the add-on layer data for deeper data analysis.

Controller layer sensing and analysis extracts data, for example, commanded and actual joint positions, commanded and actual speed, joint current, etc., from the robot controllers and/or embedded sensors. The controller layer sensing is not the direct measurement of the tool center accuracy degradation, but can highlight issues in the system through data analysis. NIST's research at this layer is to develop methods and algorithms for deep data analysis, including root cause analysis.

After the four-layer sensing and analysis are structured, a strategy is developed to use the structure to support the monitoring, diagnostics, and prognostics for robot tool center accuracy degradation. The next section will present the idea of integrating the top level PHM and the component level PHM by utilizing the four-layer sensing and analysis.

INTEGRATION OF TOP LEVEL AND COMPONENT LEVEL PHM

The integration of the top level PHM and the component level PHM is adopted for this robot tool center accuracy monitoring, diagnostic, and prognostic research. Instead of using stacks of data from components to quantify the robot tool center accuracy degradation, which may miss some influencing components since the measurements are indirect, the tool center accuracy degradation is directly measured from the upper layer sensing and analysis. The measured deviation errors can be directly used as a comparison against the robot's task specification and tolerance to aid in the prediction of faults and failures. Top level PHM can quickly detect problems and give the robot tool center a quick health assessment if the condition of environmental conditions changes, or reconfigurations occur for the work cell, or manufacturers need to make sure the robot has not experienced a degradation when an important part is put in the work cell. At the same time, the component level PHM is needed because once a problem is detected from the top level PHM, the root cause needs to be found, and remedies can be applied to the problematic components by understanding the components' health status, e.g., a calibration needs to be performed (components are in good condition, but the mechanical relationship between them needs to be recalibrated) or a gearbox needs to be changed (components have some failure).

To support the integration of top level PHM and the component level PHM, the four-layer sensing and analysis have the following functionalities:

- Upper layer sensing and analysis: perform quick health assessment
- Add-on layer sensing and analysis: provide extra information that is missing from other layers of sensing
- Environmental layer sensing and analysis: identify key environmental information needed for PHM purpose
- Controller layer sensing and analysis: collect/monitor robot controller data.

Top Level PHM - the Quick Health Assessment Methodology Supported by Upper Layer Sensing and Analysis

The upper layer sensing and analysis support the top level PHM through the development of the quick health assessment methodology [24]. The quick health assessment methodology assesses the robot tool center position and orientation accuracy degradation. Developments of the quick health assessment include: 1) advanced sensing to measure the tool center position and orientation; 2) test methods and model to assess the health status of the full robot working volume using limited measurements; and 3) algorithms to solve the test method model, which handles the geometric and non-geometric robot errors, and the uncertainties of the measurement system [24].

The advanced sensing developed at NIST is a 7-D (seven dimensional - time, X, Y, Z, roll, pitch, and yaw) measurement system, which includes a vision-based measurement instrument and a special target (under consideration for a patent). The developed advanced sensing system can quickly acquire the position and orientation information of a robot tool center accuracy [24]. Existing position and orientation measurement technologies include laser tracker systems and optical tracking systems [10, 25]. These systems are expensive. The laser tracking systems need to keep the line-of-sight of its laser beam. Otherwise, the loss-and-reconnect beam processes significantly slow down the measurement speed. The beam may be easy to break if a target is mounted on the robot's end effector when the robot arm rotates. As for the condition of the optical tracking systems, optical tracking uses infrared (IR) technology. The accuracy and efficiency are influenced by ambient lights. Since objects that need to be tracked are equipped with retro-reflective markers, the images of the optical tracker's IR image sensor can only contain the markers. They cannot see the measurement objects or an environment. When ambient lights exist, the reflected lights from ambient objects or targets will be treated as real targets. There is no redundancy when applications are used under a complex industrial environment. The 7-D measurement system developed at NIST is a vision-based system. The 7-D measurement instrument uses two high-speed color cameras. The reasons to use vision-based design are because: (1) a vision-based system can measure position and orientation information simultaneously; (2) novel camera technologies enable the achievement of camera sub-pixel accuracy. The sub-pixel accuracy converts to the measurement system's high degree of accuracy after optical triangulations; and (3) camera technology is getting mature. A vision-based system is relatively cost-effective to integrate [26]. The 7-D measurement system doesn't use infrared cameras, but selected high-speed color cameras. Redundant information from color images and advanced color image processing technologies are utilized to get more accurate target detection results. A high-performance computer will be used to perform the image processing. A special target is designed to work with the measurement instrument to measure the robot position and orientation information. Software tools are developed to perform the measurements. The 7-D information is captured with a time synchronization feature. Data synchronization is important for fusion of this data with the data from other layers to support root cause analysis [27-29].

Test methods and algorithms are developed to analyze the tool center accuracy degradation in a volumetric way (i.e., evaluate tool center errors from different directions in 3D space) because the error magnitudes and directions are different depending on the specific joint movements to achieve the desired tool center. A robot arm fixed loop motion is designed. The fixed loop motion needs to be evenly distributed in both joint space and Cartesian space within the robot working volume [24]. The even distribution in joint spaces prevents any errors from being missed or from being too heavily weighted. The even distribution in Cartesian spaces enables the evaluation of the arm accuracy and rigidity throughout the robot working volume, including near positions or fully extended positions. While the tool center is moving to these pre-programmed positions, the 7-D measurement system captures the position and orientation information of the robot tool center. Ideally, periodic data would be collected to track accuracy degradation with minimal disruptions to production. Analyzed time, position, and orientation data will be used to measure the robot tool center accuracy degradation when compared to original specifications and prior measurements.

Detail Data Analysis – Integration of Component level PHM

Once accuracy degradations are detected at the top level PHM, data from other layers are added to the analysis. The environmental layer, add-on layer, and controller layer sensing and analysis support the integration of the component level PHM to top level PHM, for deep data analysis (including root cause analysis) and proposed solutions. The environmental and add-on layer sensing and analysis provide the operational settings and system setups when an issue occurs (the environmental and add-on layer sensing are not the focus of this paper, so they are minimally discussed). The controller layer sensing and analysis provide detailed component information about abnormal issues that may influence the robot's tool center accuracy. When the robot is performing the fixed loop motion for top level PHM, the controller layer data are also collected, including joint positions, joint velocities, joint current, joint temperature, etc. The controller layer sensing and analysis will focus on the section of data where the degradation conditions are detected (by the top level PHM). With known quantified deviation detected by the top level PHM, multiple problematic conditions are analyzed to find the abnormal components to identify the factors that influence the system performance (for diagnostic purposes). These analyses can be used to build the knowledge for quantifying precursors used for the PHM prognostics purpose. During the occurrence of a fault or a failure, the combination of abnormal component features (for example, a particular pose, speed, and payload) is captured. When historical data exist, searches can be aimed using the condition under which the specific fault or failure occurred. It is more efficient for the targeted condition search, comparing with the general search of abnormal changes in the historical data, which is usually difficult without clear precursors.

Historical data can be collected before and after maintenance is performed on a robot. The top level PHM can measure and record the robot's performance changes before and after maintenance. Component level PHM data can capture the components' performance changes, thereby understanding the influences from maintenance activities (e.g., a gearbox changes). This approach can help to develop the link of the top level PHM and component level PHM to automatically capture failure precursors that can be used for prognostic analysis.

Data synchronization is important for the integration of top level PHM and component level PHM. Data are collected from different layers using different frequencies. It takes substantial effort to align unsynchronized data. A global timer is used to time-stamp all the data. In dynamic motion-related analyses, data synchronization has strict latency requirements. When robots are moving at fast speeds, the data may shift a lot even with a small amount of delay time. Controller layer data is collected at the highest allowable speed (e.g., 125 Hz for the robot used in this research). Both static and dynamic errors are captured, along with the transition errors (following error, gear cyclic errors, etc.). These data can provide insights of what from the robot's controller is influencing the robot's degradation.

A test was conducted at NIST to provide an example and create reference data sets for the robot tool center accuracy degradation monitoring, diagnostics, and prognostics using the integration of top level PHM and component level PHM.

REFERENCE DATA COLLECTION AND ANALYSIS

A data set was collected from the UR5 robot to measure the degradation of robot tool center position accuracy. For this test, a precision checkerboard (20 µm accuracy) was mounted on the robot arm's tool flange as shown in Fig. 2. The 7-D measurement system (shown in Fig 2. with two cameras mounted on a tripod) developed at NIST, was placed in front of the robot to detect and measure the center of the checkerboard. The tool center accuracy is described using six degrees of freedom (6DOF), containing position accuracy (3DOF - x, y, z) and orientation accuracy (anther 3DOF - yaw, pitch, and roll). For this test, only the tool center's accuracy (x, y, and z) was measured using the checkerboard target by the 7-D measurement system. For the orientation accuracy (yaw, pitch, and roll), extra information need to be taken. A special target was developed (under consideration for a patent) to measure both position and orientation information (this will be presented in a future publication). For this test, the tool center accuracy degradation

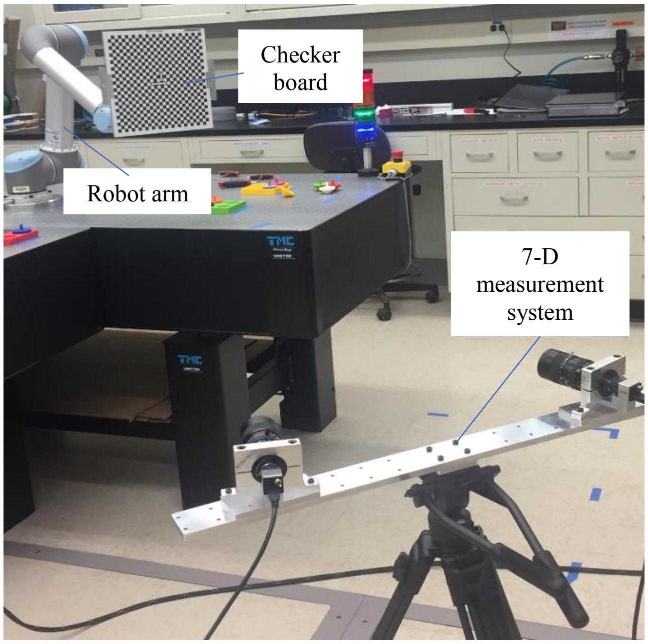

Figure 2. Setup of the test in robot work cell

can indicate a degradation in the robot's accuracy health. Most of the robot operations in manufacturing need to guarantee the position accuracy (x, y, z). When position accuracy degrades, there is a possibility that some problems may exist in the orientation accuracy too.

A motion path for the robot was preprogrammed using a simulator and offline programming software. A script program was generated from the offline programming software and later copied to the robot, which can run from the robot teach pendant. A software tool was developed to communicate with the robot controller. The 7-D measurement system software and the communication software tool used the same global time stamp allowing the tool center measurement and the controller data to be automatically aligned. When the script program started running, the robot moved along the preprogrammed path. At the same time, the controller data was captured at 125 Hz and saved to a file at the conclusion of the robot's motion. A software tool was developed to use the collected, actual joint data from the controller to playback the robot motion in the simulator software. The change of joint angles was monitored within this software tool. When a joint angle change was bigger than one degree (e.g., user-defined criteria), a new "teach point" in the simulator was created. All of the teaching points created the playback path of the robot motion (as shown in Fig.3). Other factors (e.g., time), can also be used as the criteria to create "teach points." For example, a "teach point" was created every 0.2 seconds. This kind of playback drew 3D paths of the robot's real physical motion (as shown in Fig. 3). The playback can be saved and re-played like a simulation program, but it reflects the real robot motions in its actual condition. Different from a video recording, the playback can be viewed from different angles and can call out detailed position and orientation information. The playback

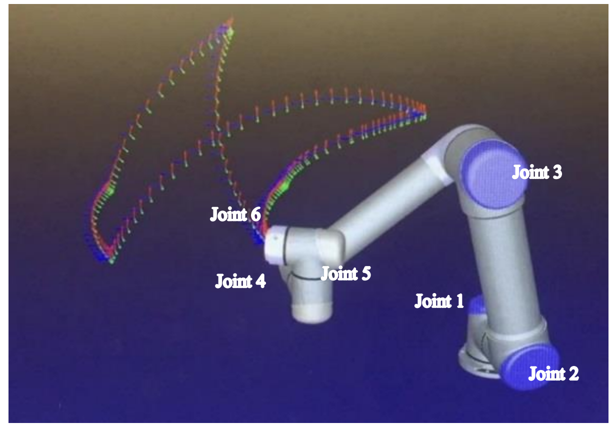

Figure 3. Playback of robot motion

can be used as a user-friendly tool to help users understand the robot pre-programmed motion. Being user-friendly was an important requirement of the PHM tools developed at NIST to transfer the technology to the manufacturing community.

In this test, the 7-D system measured the tool center's x, y, and z positions using the checkerboard target. Measurements were taken when the robot arrives at a waypoint and remains stationary (dynamic measurements will be performed using the special target in future work). Deviations were calculated from the measured positions to the nominal positions. At the same time, controller data was collected. The controller data contained time information (the time elapsed since the controller was started - a global timestamp replaces the controller time when data collection starts), target joint positions, actual joint positions, target joint velocities, actual joint velocities, etc. Details are shown in Table 1.

Table 1 Controller data sets

Meaning	Type	Number	Size in	Notes
ROBOT_TIME	double	1	8	Time elapsed since the controller was started
ROBOT_TARGET_JOINT_POSITIONS	double	6	48	Target joint positions
ROBOT_ACTUAL_JOINT_POSITIONS	double	6	48	Actual joint positions
ROBOT_TARGET_JOINT_VELOCITIES	double	6	48	Target joint velocities
ROBOT_ACTUAL_JOINT_VELOCITIES	double	6	48	Actual joint velocities
ROBOT_TARGET_JOINT_CURRENT	double	6	48	Target joint currents
ROBOT_ACTUAL_JOINT_CURRENT	double	6	48	Actual joint currents
ROBOT_TARGET_JOINT_ACCELERATIONS	double	6	48	Target joint accelerations
ROBOT_TARGET_JOINT_TORQUES	double	6	48	Target joint torques
ROBOT_JOINT_CONTROL_CURRENT	double	6	48	Joint control currents
ROBOT_CARTESIAN_COORD_TOOL	double	6	48	Actual Cartesian coordinates of the tool: (x,y,z,rx,ry,rz), where rx, ry and rz is a rotation vector representation of the tool orientation
ROBOT_TCP_FORCE	double	6	48	Generalised forces in the TCP
ROBOT_JOINT_TEMP	double	6	48	Temperature of each joint in degrees celsius

For the test, the same program ran with different conditions to understand the influences of position degradation from temperature, speed, and payload. A one-second motion halt was added to the script program at the waypoint positions. Since the controller retrieved data at 125 Hz, the one-second motion halt contained the continuous data stream of 125 samples. It is important to observe how soon the robot arm could stop completely at a waypoint. The 125 data-sample during this time showed the dynamic performance of the joint motor, especially under the influences from different speeds, temperatures, payloads, and the tool mounting configurations. Fig. 4 shows the tool center position deviation (combined changes of x, y, and z as distance deviation) calculated from the target joint position and the actual joint position during the motion halt status (all joint speeds are zero). Each cluster is one second worth of data (125 points). The x-axis of Fig. 4 is the number of points measured. The vertical axis shows the distance deviation in mm. The 7-D measurement system measured the static positions at the middle of motion halt as shown in Fig. 4 (the red dots labeled with 7-D measurement data). The deviations that the 7-D system measured are larger than the calculation error from joint kinematics (actual joint positions minus target joint positions). One reason is that the joint kinematics calculations didn't include the imperfection of joints, links, and deformations. Another reason is that the arm is still not fully settled when the 7-D system began taking measurements. For this test, the robot works at the condition of cold start, full speed (1m/s), and payload of 2 kg (maximum designed load of this platform is 5 kg). Fig. 4 shows that there are significant fluctuations of the position deviation (from 80 µm to 180 µm) and overshoots when the robot stops at waypoints. To understand why the big deviations of tool center positions occurred, speed vs. joint deviation data were studied. Fig. 5 shows the joint's deviation at the cold start, half of the full speed (the full speed is 1 m/s), and 2 kg payload condition.

The target joint positions and the actual joint positions retrieved from the controller were used to calculate the change in joint positions (as shown in the primary y-axis on the left side of Fig. 5). This reflects the condition when a robot is programmed to move to a position; the arm actually moves to a position that is slightly deviated from the commanded position. The smaller the deviation, the more accurate the robot joint moved. A small joint angle error can result in a large tool center position, and orientation deviation since the effect is enlarged with the kinematic chain of arm length. Velocity may also influence the deviation. The velocity is drawn on the secondary y-axis on the right side of Fig. 5 to show the relationship with

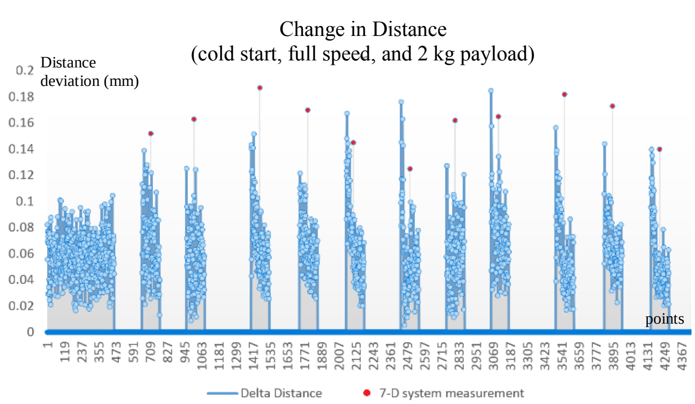

Figure 4. Tool center position deviation

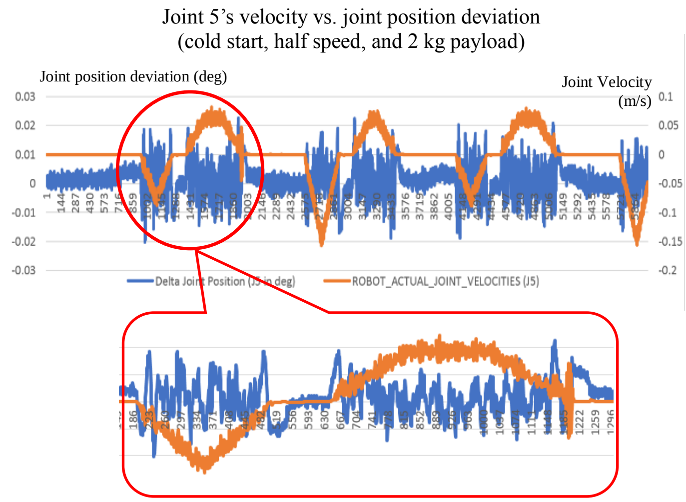

Figure 5. Joint's velocity vs. joint position deviation

joint position deviations. The x-axis presents the number of the point measured. Among the six joints of the test robot, the fifth joint (as shown in Fig. 3) shows large vibration patterns (as shown in Fig. 5 in the ROBOT_ACTUAL_JOINT_VELOCITIES data). The correlation of the velocity and joint position deviation shows that when the robot is moving, the deviation is about four times larger as compared to when the robot is stationary (the fluctuation range is ~0.04 degrees while moving compared to ~0.01 degrees while static). Therefore, the tool center accuracy will be influenced by the fluctuation. If a robot is moving to perform material removal or a composite additive layout, any tool center position degradations will impact the part quality. Accuracy degradation during dynamic operations needs to be carefully monitored for these applications that require relatively high-precision motion. To understand the payload influences, the same test and analysis were performed after removing the payload. The phenomenon still existed. It was determined that payload was not the cause of joint vibration in this test.

Fig. 6 shows the analysis when the system was allowed a two-hour warm-up where joint 5's (J5) temperature increases by 10 degrees Celsius. Under this temperature condition, Fig. 6 shows when the robot is stationary, the deviation curve remains relatively "flat"; when the robot is moving, J5's position deviation range increases to 0.06 degrees. The higher operating

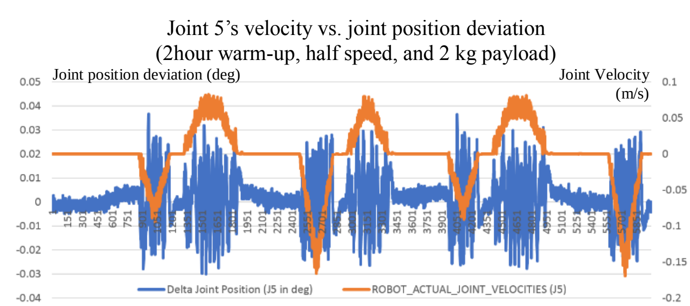

Figure 6. Temperature influence on delta joint position

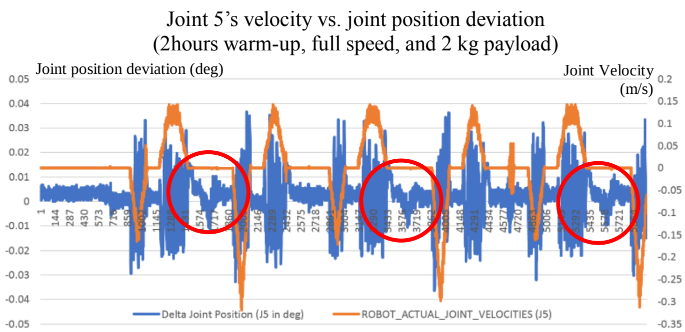

Figure 7. Velocity influence on joint position deviation

temperature made the joint position degradation worse, especially when the robot was in motion. Fig. 7 presents the data when the joint's velocity is at full speed. Under the full speed condition, J5's position deviation range increased to 0.07 degrees; when the robot is stationary, the deviation curve shows "bumps" as highlighted in the red circle in Fig. 7. These "bumps" can cause tool center position jitter. This jitter would need to be eliminated if the robot were to support some high accuracy applications.

The above datasets show that a robot's tool center position errors can be enlarged by various settings. When wear and tear exist, the change and degradation become more complex. On the factory floor, debugging and making parameter adjustment for robot programming/teaching is time-consuming, especially when new tasks are being programmed or changes are made to existing programs. Some task failures of low reliability (unexpected failures occur, although for most of the time the robot works fine) are due to the robot motion being influenced by the combinations of changes (speed, payload, unbalance tool mounting, etc.). In addition, robots of different models and from different manufacturers may have different levels of reliability.

CONCLUSION

Accuracy degradation impacts a robot's performance. In this paper, the NIST's development of measurement science to support the PHM for robot system performance degradation is presented. PHM outputs are expected to reduce unexpected downtime, improve productivity, efficiency, quality, and optimize maintenance strategy. The robot performance degradation PHM structure and its four-layer data sensing were constructed. Innovative approaches for advanced sensing (the 7-D measurement system and special target), test methods, and the fusion of multiple layers' sensing analysis were used. The integration of the top level PHM and the component level PHM was promoted. Data sets are collected to provide an example for robot degradation PHM. The next steps will continue the efforts of developing and the implementing the special target (used by the 7-D measurement system) to measure both position and orientation degradation in static or dynamic robot's conditions. Additional use cases will be developed for further applications. Additionally, datasets will explore what can be accomplished in terms of generating actionable diagnostic and prognostic intelligence.

NIST DISCLAIMER

REFERENCES

[1] J. S. Manyika, R. Dobbs, G. Strube, "Manufacturing the future: The next era of global growth and innovation," McKinsey Global Institute, 2012.

[2] J. Rossmann, "eRobotics meets the Internet of Things Modern Tools for Today's Challenges in Robotics and Automation," in *Proceedings 2015 International Conference on Developments in Esystems Engineering Dese 2015*, ed, 2015, pp. 318-323.

[3] R. DeVlieg, "Expanding the use of robotics in airframe assembly via accurate robot technology," *SAE Int. J. Aerospace,* vol. 3, pp. 198-203, 2010.

[4] T. M. Anandan, "Aerospace Manufacturing on Board with Robots," in https://www.robotics.org/content-detail.cfm/Industrial-Robotics-Industry-Insights/Aerospace-Manufacturing-on-Board-with-Robots/content_id/5960, ed: RIA, 2016.

[5] A. Murphy, "Industrial: Robotics Outlook 2025," in http://loupventures.com/industrial-robotics-outlook-2025/, ed: Loup ventures, June 2017.

[6] L. Lin, Y. Song, Y. Yang, H. Feng, Y. Cheng, and H. Pan, "Computer vision system R&D for EAST Articulated Maintenance Arm robot," *Fusion Engineering and Design,* vol. 100, pp. 254-259, 2015.

[7] Z. Pan, J. Polden, N. Larkin, S. Van Duin, and J. Norrish, "Recent progress on programming methods for industrial robots," *Robotics and Computer-Integrated Manufacturing,* vol. 28, pp. 87-94, 2012.

[8] K. L. Tsui, N. Chen, Q. Zhou, Y. Hai, and W. Wang, "Prognostics and Health Management: A Review on Data-Driven Approaches," *Mathematical Problems in Engineering,* vol. 2015, pp. 1-17, 2015.

[9] J. A. Marvel, J. Falco, and I. Marstio, "Characterizing Task-Based Human-Robot Collaboration Safety in Manufacturing," *IEEE Transactions on Systems Man Cybernetics-Systems,* vol. 45, pp. 260-275, Feb 2015.

[10] B. Greenway, "Robot accuracy," *Industrial Robot,* vol. 27, pp. 257-265, 2000.

[11] C. Feng, Y. Xiao, A. Willette, W. McGee, and V. R. Kamat, "Vision guided autonomous robotic assembly and as-built scanning on unstructured construction sites," *Automation in Construction,* vol. 59, pp. 128-138, 2015.

[12] G. Qiao and B. A. Weiss, "Advancing Measurement Science to Assess Monitoring, Diagnostics, and Prognostics for Manufacturing Robotics " *International Journal of Prognostics and Health Management,* vol. 7, 2016.

[13] B. A. Weiss and G. Qiao, "Hierarchical Decomposition of a Manufacturing Work Cell to Promote Monitoring, Diagnostics, and Prognostics," in *ASME 2017 12th International Manufacturing Science and Engineering Conference*, Los Angeles, CA, USA, 2017.

[14] B. A. Weiss, M. M. Helu, G. W. Vogl, and G. Qiao, "Use Case Development to Advance Monitoring, Diagnostics, and Prognostics in Manufacturing Operations " *Intelligent Manufacturing Systems,* vol. Austin, TX, December 5-7, 2016

[15] V. Sathish, S. D. Sudarsan, and S. Ramaswamy, "Event Based Robot Prognostics using Principal Component Analysis," *2014 IEEE International Symposium on Software Reliability Engineering Workshops,* pp. 14-17, 2014.

[16] F. Massi, N. Bouscharain, S. Milana, G. Le Jeune, Y. Maheo, and Y. Berthier, "Degradation of high loaded oscillating bearings: Numerical analysis and comparison with experimental observations," *Wear,* vol. 317, pp. 141-152, Sep 2014.

[17] J. H. Shin and J. J. Lee, "Fault detection and robust fault recovery control for robot manipulators with actuator failures," *Proceedings 1999 IEEE International Conference on Robotics and Automation 1999,* Detroit, Michigan, pp. 861-866.

[18] G. J. Liu and A. A. Goldenberg, "Uncertainty decomposition-based robust control of robot manipulators," *IEEE Transactions on Control Systems Technology,* vol. 4, pp. 384-393, Jul 1996.

[19] Y. Peng, M. Dong, and M. J. Zuo, "Current status of machine prognostics in condition-based maintenance: a review," *International Journal of Advanced Manufacturing Technology,* vol. 50, pp. 297-313, Sep 2010.

[20] A. Heng, S. Zhang, A. C. C. Tan, and J. Mathew, "Rotating machinery prognostics: State of the art, challenges and opportunities," *Mechanical Systems and Signal Processing,* vol. 23, pp. 724-739, 2009/04/01/ 2009.

[21] K. Javed, "A Robust & Reliable Data-driven Prognostics Approach Based on Extreme Learning Machine and Fuzzy Clustering," *Thesis,* 2014.

[22] B. A. Weiss, G. W. Vogl, M. Helu, G. Qiao, J. Pellegrino, M. Justiniano*, et al.*, "Measurement Science for Prognostics and Health Management for Smart Manufacturing Systems: Key Findings from a Roadmapping Workshop," presented at the Annual Conference of the Prognostics and Health Management Society 2015, Coronado, CA, 2015.

[23] B. Abichou, A. Voisin, and B. Iung, "Bottom-up capacities inference for health indicator fusion within multi-level industrial systems," *IEEE Conference on Prognostics and Health Management (PHM),* pp. 1-7, 18-21 June 2012.

[24] G. Qiao, C. Schlenoff, and B. Weiss, "Quick Positional Health Assessment for Industrial Robot Prognostics and Health Management (PHM)," in *International Conference on Robotics and Automation (ICRA)* Singapore, 2017, pp. 1815-1820.

[25] R. Mautz, "Overview of current indoor positioning systems," *Geodesy and Cartography,* vol. 35, pp. 18-22, 2009.

[26] M. Švaco, B. Šekoranja, F. Šuligoj, and B. Jerbić, "Calibration of an Industrial Robot Using a Stereo Vision System," *Procedia Engineering,* vol. 69, pp. 459-463, 2014.

[27] D. Mahto and A. Kumar, "Application of root cause analysis in improvement of product quality and productivity," *Journal of Industrial Engineering and Management,* vol. 1, pp. 16-53, 2008.

[28] S. De, A. Das, and A. Sureka, "Product failure root cause analysis during warranty analysis for integrated product design and quality improvement for early results in downturn economy," *International Journal of Product Development,* vol. 12, pp. 235-253, 2010.

[29] M. H. C. Li, A. Al-Refaie, and C.-Y. Yang, "DMAIC approach to improve the capability of SMT solder printing process," *IEEE Transactions on Electronics Packaging Manufacturing,* vol. 31, pp. 126-133, 2008.