Quick Positional Health Assessment for Industrial Robot Prognostics and Health Management (PHM)

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***Abstract*— Robot calibration and performance will degrade if proper maintenance isn't performed. There have been challenges for manufacturers to optimize the maintenance strategy and minimize unexpected shutdowns. Prognostics and health management (PHM) can be applied to industrial robots through the development of performance metrics, test methods, reference datasets, and supporting tools. A subset of this research involves developing a quick health assessment methodology emphasizing the identification of the positional health (position and orientation accuracy) changes. This methodology enables manufacturers to quickly assess the static/dynamic position and orientation accuracies of their robot systems. In this paper, the National Institute of Standards and Technology's (NIST) effort to develop the measurement science to support this development is presented, including the modeling and algorithm development for the test method, the advanced sensor development to measure 7-D information (time, X, Y, Z, roll, pitch, and yaw), algorithms to analyze the data, and a use case to present the results.**

I. Introduction

As robotic technologies become more integrated with complex manufacturing environments, robot system reliability has become more critical. From the moment a robot system is put into service to enable a manufacturing process, the overall process, its constituent sub-systems, and components begin to degrade. Without maintenance, these degradations will lead to faults and/or failures impacting the process. These faults and/or failures ultimately lead to unexpected downtime and lost production if they are not remedied. Unexpected downtime and lost production are 'pain points' for manufacturers, especially in that they usually translate to financial losses. To minimize these pain points, manufacturers are developing new health monitoring, diagnostic, prognostic, and maintenance (collectively known as prognostics and health management (PHM)) techniques to advance the state-of-the-art in their maintenance strategies.

PHM is an approach to the system life-cycle support that seeks to reduce/eliminate time-based maintenance through accurate monitoring, incipient fault detection, and prediction of impending faults [1]. PHM can be applied in both the component level and system level. Component level PHM is typically focused on monitoring the health of individual components (e.g., gears, engines, and electronic devices) to determine if the health of the monitored component is degraded by taking into account environmental, operational, and performance-related parameters [2, 3]. System level PHM assesses the health of the overall system by taking into account the system architecture, system function, and process-related parameters [4]. System level PHM may delay the need to replace a component that would not immediately affect the operation of the system. In the case of monitoring the system where robot system reconfiguration and re-tasking is necessary (often driven by the market requirement for high design-variation and low-batch), efficient health monitoring should be addressed not only at component level, but also at higher system level since the decision making procedure may rely on the global industrial system state [4]. Many of the existing PHM strategies are adept at handling component PHM; fewer PHM techniques are capable of being integrated into the sometimes volatile nature of the manufacturing process (for example, system process changes and hardware reconfiguration) [5].

A robot system is complex. It contains robot arms, sensors, control systems, end-effectors, process tooling, power supplies, and software all working together to perform a task. To successfully perform a task, the robot system needs to deliver the position and orientation accuracy of the tool center position (TCP), the trajectory of the arm, the correct speed, force, and torque. The robot system's accuracy relies on the actual geometries of components in a robot cell. Tiny changes of the components, such as needed calibration of the robot arm, end-effectors, fixtures, and tooling in the robot cells, can cause inaccuracies of the robot TCP positions used in existing robot programs. In some systems where machine vision is applied to assist localizing the robot to the workpiece with high accuracy, the combined camera/robot system is critical since this drives the accuracy of the process. The degradation of a robot system's positional health (position and orientation accuracy) can lead to a decrease in manufacturing quality and production efficiency. The in-process system level health degradation is difficult to detect compared to a complete system break-down. Given the use of robot systems in many high precision industries (e.g., aerospace, automotive), it is important that robot system's positional health degradations be understood so that maintenance and control strategies can be optimized at the system level.

Enhancing positional health within manufacturing robotic operations would be greatly beneficial to the manufacturing community in terms of improving their efficiency and product quality while reducing scrap. Developing, advancing, and integrating monitoring, diagnostic, and prognostic capabilities will support these enhancements. However, there are numerous technological challenges that must be addressed to increase the capability of PHM, ultimately leading to improved accuracy.

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II. Challenges of the Quick Positional Health Assessment for Industrial Robots

Robot accuracy is defined as the measurement of the deviation between the commanded and attained robot position and orientation [6]. Accuracy can also represent the difference between commands and actual velocities, accelerations, forces, and torques. Robots are employed to accurately move, manipulate, and/or perform a process (e.g., welding) to certain specifications. The consideration of robot accuracy (static and dynamic) is one of the key elements when assessing the health state of an industrial robot used in the manufacturing process.

There are many challenges for the positional health assessment (position and orientation accuracy) of industrial robots. Challenges include: (1) lack of sensing technology to quickly acquire X, Y, Z, roll, pitch, and yaw information that describes the robot TCP accuracy. Existing 6-D measurement systems include laser tracker-based systems and optical tracking systems [7]. These systems are expensive. The laser tracker-based systems need to maintain line-of-sight between the laser tracker and the target. The optical tracking systems use reflective balls as markers and the near-infrared filter attached to lenses to obtain images which only contain the markers. The optical tracker's near-infrared cameras are "blind" to the environment. There is no redundancy when ambient light influences the reflected light from the targets [8]; (2) lack of test methods that can quickly and efficiently detect key performance metrics without interrupting production lines. For example, TCP accuracy needs to be assessed within a volumetric method because the error magnitudes and directions are different depending on the approach directions of joints. Efficient modeling and algorithms are needed for the test method to identify the health of the robot system; (3) lack of a PHM data taxonomy and architecture to support the interoperability between sensor/data formats and communication modes to capture, share, and analyze data across heterogeneous robot systems; (4) lack of PHM overall structure to enable various PHM technologies for robot systems, to be evaluated in an unbiased manner; and (5) lack of algorithms to analyze the results of the positional health assessment to detect the root cause of failures and the potential remedies to fix the problem.

To address the broad landscape of barriers and challenges, measurement science is needed which includes a collection of performance metrics, use case scenarios, test methods, reference datasets, and software tools to promote unbiased assessment to verify and validate (V&V) position and trajectory accuracy health assessment strategies. One specific area of NIST research is the Prognostics, Health Management, and Control (PHMC) project, which aims to develop the measurement science within several manufacturing domains to promote the advancement of monitoring, diagnostic, prognostic, and maintenance strategies [9]. This work is supported by the development of a robot system test bed.

The key building blocks of the test bed are shown in Fig. 1. The first key building block is the advanced sensing module for PHM (shown in the upper left of Fig. 1). Advanced sensing will be developed to measure and monitor the system's health status and will have three sensing layers: a system layer, a component layer, and an add-on layer. The system layer aims to support the overall system's health assessment, including

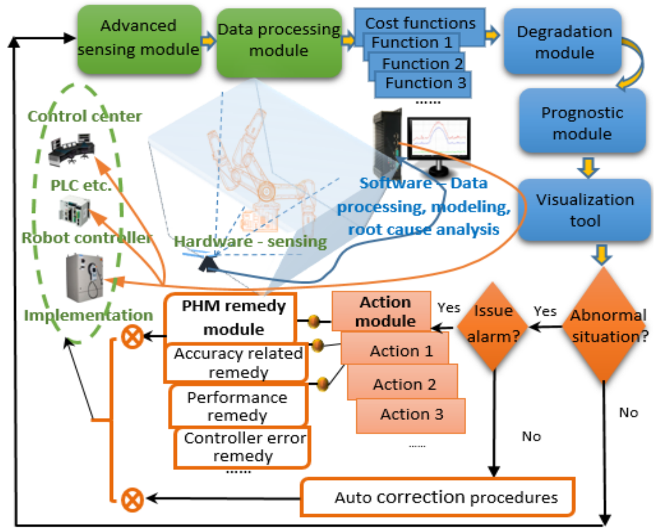


Figure 1. Key building blocks of the PHMC for Robotics structure

repeatability, accuracy, velocity, force, and torque; the component layer extracts data from the robots' controllers and/or embedded sensors to perform the on-line monitoring; the add-on layer promotes the inclusion of additional sensors to provide information that the component and system layers may be neglecting. The second key building block is the data processing module (shown as the data collection module in Fig. 1). This module will focus on the development of reference algorithms to fuse data captured from multiple sensors employed in the advanced sensing module. The data processing module will offer greater analysis capability through targeted data collection on top of complex and/or reconfigurable robotic applications. The third key building block is the development of algorithms for robot system health assessment and PHM V&V methods (collectively shown in the cost function module, degradation module, prognostic module, and visualization tools module in Fig. 1). As the fourth key building block, the closed-loop implementation (shown as the action module and the PHM remedy module in Fig. 1) of PHM solution within the control structure is reviewed. This structure serves as the back bone of use case development. The development and expansion of each module will further address elements of the measurement science. It also serves as the platform for reference dataset collection.

III. Quick Positional Health Assessment Methodology

Use cases are created within the overall test bed. The first use case is the development of a robot system quick positional health assessment methodology based on the increasing demand on industrial robot accuracy. This methodology contains the development of test methods, sensors used to take measurements, reference algorithms for data processing and health assessments, and V&V of PHM techniques. We will focus on the first three developments in this paper.

The robot system's positional health includes the robot arm's accuracy and the accuracy of any system interacting with the robot arm (e.g., a conveyor moving products within the range of the robot arm). By checking the position and orientation accuracy of the TCP and the part conveyors, users can get a quick health evaluation of the combined conveyor/robot system since this drives the accuracy of the process. To assess the robot arm's positional health, a test method with a fixed loop motion is developed by extending the existing standard methods for robot performance, as described in [5]. This fixed loop motion of the robot arm is designed such that the test method can be executed periodically and in a relatively short amount of time. While the TCP is moving to these pre-determined positions, X, Y, Z, roll, pitch, yaw, and time (7-D information) data are being captured from a 7-D measurement system. All measurements will be taken under a global coordinate system which is defined on the 7-D measurement system. Analyzed position, time, and orientation data will provide a measure of the positional health of the robot system when compared to original specifications and prior measurements. Ideally, periodic data would be collected to track accuracy degradation with minimal disruptions to production. This accuracy degradation data would offer insight into the robot system's health.

A. Modeling and Algorithm Development for the Test Method

When developing the test method model for the robot positional health assessment, the model should reflect error sources of the robot system. Thus, after the positional health assessment, this model can be further used for the root cause analysis to find the problematic individual joints. Traditional modeling methods assume that joint motion is ideal, and the geometric relationships between the joints are constant. Yet there are also non-geometric errors, such as the non-ideal motion of joints, and deflections of the structure and joints due to external loading or gravity, backlash, etc. Those errors are position dependent. It means that the errors are not constant with respect to joint motion, but a model with parameters that depend on the pose of the robot. Furthermore, since each TCP pose (position and orientation) in the Cartesian space could have multiple inverse kinematic solutions, the error magnitude and direction changes by choosing different solutions. This makes the assessment of the TCP accuracy very difficult since it's hard to measure the accuracy from all directions. Given a measurement system that can capture the TCP's poses, a user can implement a simple strategy to run a working program and measure the robot's TCP movements. Deviations can be calculated from the measured positions to the nominal positions. The shortcoming of this strategy is that it cannot represent the overall positional health condition of the robot. The robot might be programmed to work in the "sweet zone" in the volume with the optimal approaching direction. If another program is called, this process would need to be performed again. There needs an efficient model/algorithm to support the test method that can calculate the robot's overall positional health results through its working volume using limited measurements. Moreover, there is challenge of how to decouple the measurement instruments' uncertainty from the actual robot errors. The presented modeling and algorithm development for the test method will solve these challenges.

In this use case development, the robot platform is the Universal Robot UR3 with CB3 controller. The UR3's serial kinematic structure with coordinate frames is shown in Fig. 2. Any error of the joint axes will be reflected in the TCP errors through the kinematic chain. Similar to machine tools, the errors of a joint axis (either a linear or a rotary axis) can be

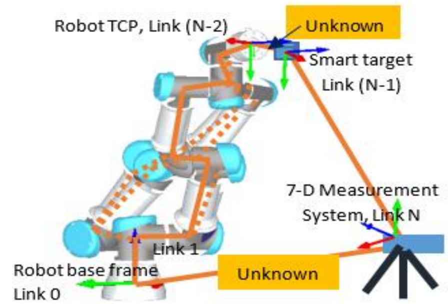


Figure 2. Robot system kinematic chain

described as geometric errors that are functions of joint positions. Each of the six robot joint axes contains six errors of the axis: three displacements of the axis (in x, y, and z direction) and three rotation errors of the axis (roll, pitch, and yaw errors). Fig. 3 shows a rotary axis (we refer to it as the

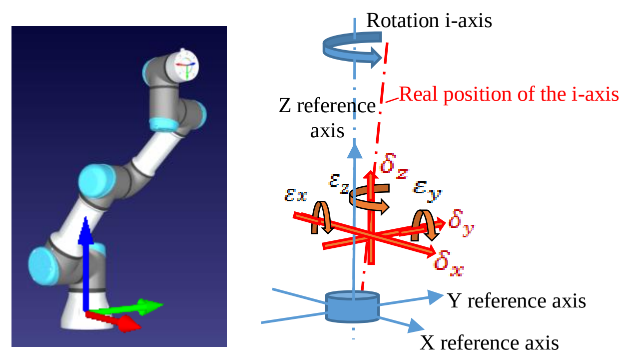


Figure 3. Six errors of a rotation axis

"i-axis" as the representation of a general situation), which represents the i^{th} joint of a robot. In Fig. 3, the real axis has deviated from its designed position. The reason for the deviation could be from the errors in robot geometry, axis motion, robot gear box degradation, backlash, thermal environment changes, or external loading/gravity. The errors of this axis are represented as: (1) δ_x - radial error motion of i-axis in X direction; (2) δ_y - radial error motion of i-axis in Y direction; (3) δ_z - axial error motion of i-axis in Z direction; (4) ε_x - tilt error motion around X of i-axis; (5) ε_y - tilt error motion around Y of i-axis; and (6) ε_z - angular positioning error (also called scale error of the rotation axis). The error model of the joint is described as:

$$E_{(i-1)i}(\theta) = \begin{bmatrix} 1 & -\varepsilon_z(\theta) & \varepsilon_y(\theta) & \delta_x(\theta) \\ \varepsilon_z(\theta) & 1 & -\varepsilon_x(\theta) & \delta_y(\theta) \\ -\varepsilon_y(\theta) & \varepsilon_x(\theta) & 1 & \delta_z(\theta) \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

Where $E_{(i-1)i}$ is the transformation from frame i-1 to frame i and θ is the i^{th} joint angle variable.

Different from the traditional error model, the $\delta(\theta)$ and $\varepsilon(\theta)$ are not constant values, but are functions of axis locations which we refer to as a higher order model [10]. That means the error model can model not only the position-independent geometry errors, but also the position-dependent axis motion errors. Another challenge for the traditional error model is the lack of handling of the measurement noise. The uncertainties coming from measurements are usually treated as joint errors. In that case, the parameter estimates may be biased. In our model, an implicit loop method is adapted to address this issue. In the implicit loop method, the mechanism is treated as having a closed loop from the first link out to the tool tip, and then back to the first link via a measuring device. The displacements around a closed loop sum to zero (or Identity matrix). With this convention, the measurement instrument is included in the loop. The measurement instrument's uncertainty is modeled inside the model equation using a weight. Joint and end-effector measurements are on equal footing, with weights assigned according to the accuracy of each joint. As shown in Fig. 2, the 7-D measurement system is included in the loop of the kinematic chain. The kinematic model of the robot is:

$$I = E_0 A_{01} E_{01} A_{12} E_{12} \ldots A_{(N-1)N} E_{(N-1)N} A_{N0} E_{N0} \qquad (2)$$

Where A is the nominal axis motion, A_{01} is the nominal transformation from joint 0 to joint 1, E is the error of the joint, E_0 is the setup error of the robot base, and E_{01} is the transformation error from joint 0 to joint 1. Each E follows the definition shown in Equation (1). The δ(θ) and ε(θ) are high order Chebyshev polynomials with unknown polynomial coefficients to be solved by analysis algorithms.

B. *Method of Analysis*

Before calculating and deriving the error model from this kinematic model, there are two unknown transformations in the kinematic chain in Fig. 2. One is the $A_{(N-2)(N-1)}$ transformation that is from the TCP (link (N-2)) to the smart target (link (N-1)). The smart target is mounted on the robot end effector that is tasked by the measurement system to determine time, x, y, z, roll, pitch, and yaw information. Since, for different robots, it may need different adaptors, the transformation from the TCP to the smart target coordinate frame often requires calibration. The calibration needs to identify the six constant parameters of the $A_{(N-2)(N-1)}$ (three translations and three rotations). The other unknown transformation is the A_{N0} that is from the 7-D measurement system (link N) to the robot base frame (link 0). To avoid calibration processes as part of the setup overhead, these constant parameters are put in the error model to be identified together with the other high order parameters. This technology eliminates the time-consuming calibration and setup procedures, which are hurdles of new technologies' implementation in practical industrial applications.

Placing all measurements (joint and measuring device) in a single measurement vector x, Equation (2) becomes:

$$f(x, p) = 0 \qquad f : R^k \times R^n \rightarrow R^m \qquad (3)$$

$$x \in R^k,\ p \in R^n,\ f \in R^m$$

where x is a vector of motion variables and k is the number of measurements taken for each pose. The vector x may include joint and end-effector displacements being measured, as well as backlashes or other small unknown displacements. p is the vector of parameters in the error model to be estimated and n is the unknown number of parameters. m is the number of constraints or loops. We require k ≥ m and evaluate $(\partial f / \partial x)$ = m to guarantee that the loop can always be closed. The robot will be sent to various poses (a designed fixed loop motion), and a measurement of x for each pose will be obtained. For a particular pose i, let's assume the true value of the measurement vector is x_i, which we would record as measurement $\bar{x}_i$ with unknown measurement error $\hat{x}_i$, so that $x_i = \bar{x}_i + \hat{x}_i$. Throughout all of the sample poses, the parameters should be constant, but our initial estimates of $\bar{p}$ parameters may be in error by $\hat{p}$, that is $p = \bar{p} + \hat{p}$. For example, $\bar{p}$ might be the blueprint value of a link length and $\hat{p}$ would then be the error incurred in manufacturing the part.

$$f(x_i, p) = f(\bar{x}_i + \hat{x}_i, \bar{p} + \hat{p}) = 0, \qquad i=1, \ldots, N \qquad (4)$$

where N is the number of sample positions.

The χ^2 error function is derived as:

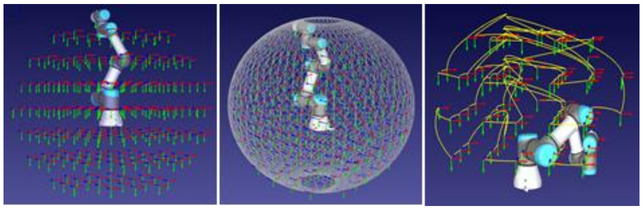
$$\chi^2 = \sum_{i=1}^{N} \hat{x}_i^T \Sigma_x^{-1} \hat{x}_i + \hat{p}^T \Sigma_p^{-1} \hat{p} \qquad (5)$$

The implicit loop based maximum-likelihood estimation is used [10] to solve this error model and minimize the error by fitting the parameters in Equation (1). There are two outputs from this modeling method. The first one is the derived errors from the calculation of the position and orientation accuracy of the robot. The advantage of this method is that the uncertainties of the measurements are decoupled from the true errors and won't bias the analysis result. The second output is to find the maximum likelihood estimation of $\hat{p}$ to minimize the error function. Because $\hat{p}$ represents the unknown coefficients of the polynomials of the error terms in each of the E matrix, that result can be used to detect the root cause of axis errors. Moreover, compensation can be calculated to improve the accuracy of the kinematic model, which can be used in the future system remedy and prognostic algorithm development. To solve the implicit loop based maximum-likelihood estimation, one needs an innovative optimization algorithm because it's a combinatorial problem which has no concept of a derivative or gradient for algorithm converging. Traditional Quasi-Newton methods won't work on this problem. The optimization algorithms will be detailed in future publications.

C. *Fixed Loop Motion Design*

An important feature of the model (for the test method) is that it requires the measurements be evenly distributed in both joint space and Cartesian space. The even distribution in joint space prevents any errors from being missed or from being too heavily weighted. The even distribution of measurements in Cartesian space covers an entire workspace range of robot arm poses, including some that are near, far, high, and low, to evaluate arm accuracy and rigidity when the arm is both fully and minimally extended. A fixed loop motion needs to be designed to satisfy those requirements.

Fig. 4 shows the designed fixed loop motion of the UR3 robot created for the use case. The robot workspace is a spherical volume with a cylindrical dead zone in the center of the sphere. To generate this fixed loop motion, the following procedure is created: (1) in Cartesian space, a grid of poses is generated inside the robot workspace as the target poses (as shown in Fig.4 (a) and (b)); (2) inverse kinematic calculations are performed to check if the target positions are reachable by any configuration (if not, the target is skipped); (3) a linear motion path is planned between each pose. This means that each joint performs complicated motions to keep the TCP/tool on a straight line path; and (4) calculations are performed to check if the robot linear motion is possible. In the meantime, collision checking is also performed. If the linear motion is impossible, the algorithm will change the current joint configuration to a different configuration, then redo the check



(a) (b) (c)

Figure 4. Robot fixed loop motion for test method

in step 4. For example, a pose of the UR3 robot in its workspace is represented by a 4×4 Linear Homogenous Transformations matrix (transforming from the robot base).

$$\begin{bmatrix} -1.000000 & -0.000227 & 0.000070 & 412.500000 \\ -0.000070 & -0.000000 & -1.000000 & 0.000000 \\ 0.000227 & -1.000000 & 0.000000 & 340.00000 \\ 0.000000 & 0.000000 & 0.000000 & 1.000000 \end{bmatrix}$$

Each pose in the space has multiple inverse kinematics solutions to convert it into joint angles. The number of solutions varies depending on the pose of the robot arm. In this example, this TCP has 20 possible options, as shown in Table 1 (using degree as the unit). J0 could vary from -182.9 to 176.1. J4 could vary from -176.1 to 333.5. In Step 4 of the procedure, when different configurations are needed, a search from all possible configurations is performed to select the satisfactory configuration for the even joint distribution requirement. If none of the configurations are possible, a curved motion path is attempted; if a curved motion path is not possible either (because there is a collision), this target pose is skipped. Otherwise, this pose is saved as one of the target positions in the fixed loop. This procedure is repeated until all of the poses in Fig. 4 (a) are evaluated. The final poses and paths are shown in Fig. 4 (c). In this particular example, because the robot is mounted on an optical table, only poses above the table surface clear the check procedures. After these initial procedures, a fixed loop of robot positions is saved that will be executed periodically. The reason for preferring linear motion paths is that extra analysis can be performed, such as errors from the best fit of the linear lines and square angles between the linear lines. While the TCP is moving to these pre-determined positions, the X, Y, Z, roll, pitch, yaw, and time data are being captured from a 7-D measurement system.

TABLE I. MUTLIPLE SOLUTIONS OF ROBOT INVERSE KINEMATICS

#	J0	J1	J2	J3	J4	J5	#	J0	J1	J2	J3	J4	J5
1	-183.9	-0.1	-40.2	-139.6	183.9	0	**11**	176.1	-0.1	-40.2	-139.6	183.9	0
2	176.1	-37.6	40.2	177.3	-176.1	0	**12**	176.1	-37.6	40.2	177.3	183.9	0
3	26.5	-142.4	-40.2	2.7	-26.5	0	**13**	26.5	-142.4	-40.2	2.7	333.5	0
4	26.5	-179.9	40.2	-40.4	-26.5	0	**14**	26.5	-179.9	40.2	-40.4	333.5	0
5	-183.9	-0.1	-40.2	-139.6	-176.1	0	**15**	-183.9	-37.6	40.2	177.3	183.9	0
6	-183.9	-37.6	40.2	177.3	-176.1	0	**16**	176.1	-0.1	-40.2	-139.6	-176.1	0
7	-333.5	-142.4	-40.2	2.7	-26.5	0	**17**	-333.5	-142.4	-40.2	2.7	333.5	0
8	-333.5	-179.9	40.2	-40.4	-26.5	0	**18**	-333.5	-179.9	40.2	-40.4	333.5	0
9	176.1	-37.6	40.2	-182.7	-176.1	0	**19**	176.1	-37.6	40.2	-182.7	183.9	0
10	-183.9	-37.6	40.2	-182.7	-176.1	0	**20**	-183.9	-37.6	40.2	-182.7	183.9	0

D. Advanced Sensing Development (a 7-D Measurement System)

Advanced sensing development is an important part of the PHMC for robotics structure to quickly acquire the 6D information (X, Y, Z, roll, pitch, and yaw) that describes the robot TCP accuracy. Existing 6D measurement systems include laser tracker-based systems and optical tracking systems [7]. These systems are expensive. The laser tracker-based system needs to maintain line-of-sight between the laser tracker and the target. The target mounting usually requires changing setups or work tools. The optical tracking system uses reflective balls as markers and the near-infrared filter attached to lenses to obtain images which only contain the markers. The optical tracker's near-infrared cameras are "blind" to the environment. There is no redundancy when ambient light influences the reflection light from the targets. The advanced sensor used to capture the 7-D information on the TCP needs to be a relatively low-cost solution for industrial implementation. The measurement system needs to be designed such that its integration and use does not interfere with the robot system's normal operations. Considering the measurement requirements for the positional health assessment test method, a 7-D measurement system is being developed by NIST to support this research effort. A vision-based design is selected because: (1) vision-based systems can obtain position and orientation information simultaneously; (2) camera technology can deliver sub-pixel accuracy. After optical triangulation, the sub-pixel accuracy provides the measurement system with a higher degree of accuracy than was previously available; and (3) vision systems are relatively easy to integrate [11]. Instead of using near-infrared cameras, high speed color cameras were selected. With new, advanced color image stereo technology, target detection can be more accurate by utilizing redundant information from color images. The 7-D measurement system consists of two high-speed color cameras, a high performance image processing control box (computer), special targets, and software tools.

Innovative target design is an important part of this work. Specific targets are designed as adaptors to mount on the robot arm's end-effector with known offsets from the TCP. The purpose of designing innovative target fixtures is to avoid tool changes during measurement which would require a brief interruption of the production. The specific target design is currently under consideration for a patent. Differing from and exceeding the performance of traditional stereo technology, the 7-D measurement system is designed and embedded with a time synchronization feature, which is important for analysis when fusing with other sensors for robot system health analysis. Also, a self-calibration method is created by utilizing the designed features on the specific target to avoid the condition where a camera-based measurement system needs to frequently self-calibrate. Moreover, the advanced color sensor processing technology is utilized which uses redundant information from the environment conditions for more accurate target detection. Design of the 7-D measurement system and the target will be detailed in future publications.

IV. USE CASE ANALYSIS, RESULTS, AND DISCUSSION

A use case analysis (under the existing robot platform) was performed using the simulated measurements with known robot joint errors and measurement uncertainty. In this use case, each axis's nominal forward kinematics ("A" matrix in Equation (2)) was constructed using the robot's Denavit-Hartenbert (DH) parameters. The robot's DH table is omitted here for brevity. Simulated joint errors of J0 and J1 were added into the robot error model "E", following the definition in Equation (1). As shown in Fig. 5, the $\delta(\theta)$ and $\varepsilon(\theta)$ are not constant values but Chebyshev polynomials,

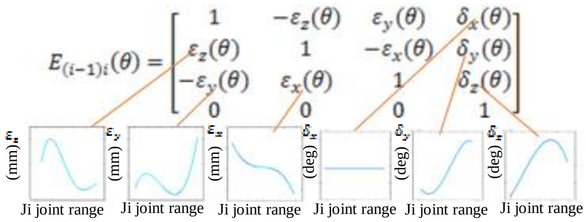


Figure 5. The joint Ji's simulated axis motion errors

which are used to represent the general position-dependent axis errors in industrial robots. The advantages of using Chebyshev polynomials are for the benefit of error model identification and scale invariance because of their two properties: (1) they are orthogonal over an interval; and (2) they have a similar scale over the same interval. Various measurement poses were generated as the fixed loop motion shown in Fig. 4 (c). Measurement noises with known uncertainty were added into simulated measurement results to simulate the environmental noise and instrument noise.

The error function χ^2 is derived in the form of Equation (5). Two outputs come out from the analysis. The first one is the derived errors from the calculation of the robot position and orientation accuracy. The second output is the maximum likelihood estimation of $\hat{p}$ to minimize the error function, which is not the main focus of this paper. For the calculation of the robot position and orientation accuracy, the analysis is not a simple deviation calculation from commanded poses to measured poses, but an identification of the error model to solve the χ^2 error function. The advantage of this method is that the uncertainties of the measurements are decoupled from the true errors and won't bias the analysis result. Also position-dependent errors are calculated more accurately because the advanced modeling method can model not only the motion error of all of the joints (both translation and rotation), but also the geometry error between the joints. Results of the position-dependent error distribution are shown in Fig. 6, with respect to X, Y, Z axis and 3D space under the

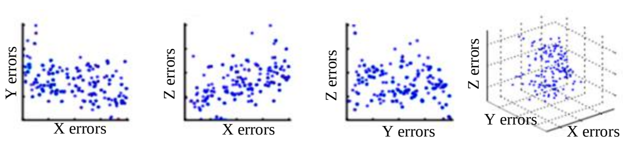


Figure 6. Error distribution on X, Y, Z, and 3D

world coordinates. The position-dependent error distribution can help to track the change of error distribution, provide a comparison of different robot systems' positional health, and establish a baseline of a robot system's positional health condition. Statistical results are also generated including average error, standard deviation of the error, and maximum error. The statistical results are more accurate because they are derived from the error model instead of directly calculating from the limited size of sample measurements.

In summary, this use case demonstrates the utilization of the quick health assessment methodology by using the advanced sensing system (a 7-D measurement system), the designed test method with the robot fixed loop motion, and the advanced error modeling and analysis technique. With this technology, users can assess the robot positional health faster, cheaper, and with higher accuracy. This can help to quickly detect and decrease the manufacturing quality degradation to reduce scrap. This methodology can be applied when environmental conditions change, after the work cell has been reconfigured, or whenever a manufacturer wants to determine if they have experienced a degradation.

V. Conclusion

NIST's development of measurement science to support the PHM for robotics technique is presented. A test bed is being constructed to provide a platform for the development. An advanced methodology of quick health assessment is developed to identify the health of the robot system, which can lead to reduce unexpected downtime, and ultimately improve a robot system's productivity, efficiency, and quality. NIST is seeking to develop additional industrial use cases for further applications. Future efforts are also under way to add more complexity to the environment, such as including conveyors, end-effectors, and tooling.

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