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ACCURACY DEGRADATION ANALYSIS FOR INDUSTRIAL ROBOT SYSTEMS

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ABSTRACT

As robot systems become increasingly prevalent in manufacturing environments, the need for improved accuracy continues to grow. Recent accuracy improvements have greatly enhanced automotive and aerospace manufacturing capabilities, including high-precision assembly, two-sided drilling and fastening, material removal, automated fiber placement, and in-process inspection. The accuracy requirement of those applications is primarily a function of two main criteria: (1) The pose accuracy (position and orientation accuracy) of a robot system's tool center position (TCP), and (2) the ability of a robot system's TCP to remain in position or on-path when loads are applied. The degradation of a robot system's tool center accuracy can lead to a decrease in manufacturing quality and production efficiency. Given the high output rate of production lines, it is critical to develop technologies to verify and validate robot systems' health assessment techniques, particularly the accuracy degradation. In this paper, the National Institute of Standards and Technology's (NIST) effort to develop the measurement science to support the monitoring, diagnostics, and prognostics (collectively known as prognostics and health management (PHM)) of robot accuracy degradation is presented. This discussion includes 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), and algorithms to analyze the data.

INTRODUCTION

In recent years there is a growing demand within the automotive and aerospace industry for greater robot accuracy [1, 2]. With the accuracy improvement in both position and orientation, the articulated robot arm can be applied to a much broader range of applications that were once limited to custom machines, including high precision assembly, two-sided drilling and fastening, material removal, automated fiber placement, and in-process inspection. Compared to custom machines, the robot's articulated arm can span a relatively large working envelope capable of navigating along highly curved surfaces and into tight spaces. Since the robot's mass is relatively low, the foundation (e.g., supporting structure) requirements of robots are minimal. Robot applications bring manufacturers benefits in both improving flexibility and reducing costs with these noted advantages.

Robot accuracy is defined as the measurement of the deviation between the commanded and attained robot 6-D (six degree-of-freedom) position and orientation [3]. Accuracy can also represent the difference between commanded and actual velocities, accelerations, forces, and torques. Improving accuracy (i.e., lessening the difference between commanded and actual values) allows rapid deployments of industrial robot applications by rapidly transferring or downloading robot programs between two "identical" robot cells. It enables the quick replacement of a robot in a manufacturing system by reducing or eliminating re-teaching processes. High robot accuracy during manufacturing ensures that parts are precisely manufactured with predictable results even after changes are made to the process. High accuracy is also critical in data-driven applications, such as those applications developed using off-line programming methods [4]. High accuracy enables the use of offline programs to minimize the robot downtime (e.g., the time-consuming task to train a robot to drill thousands of holes on an airplane's fuselage). The market requirement for high design-variations and low-batch production has driven users and integrators to look more towards "off-line programming". Using robots for in-process inspection or gauging is another application that calls for high accuracy of a robot's pose because the robot is an influential part of the measurement operations [5, 6]. There are a large number of automotive and aerospace applications that currently utilize and could benefit from the flexibility of robotics with high accuracy to perform metrology on manufactured parts.

High accuracy robots are becoming valuable tools for many of the afore-mentioned processes that lead to substantial cost savings for the manufacturing industry [7].

The degradation of a robot system's pose accuracy can lead to a decrease in manufacturing quality and production efficiency. Robots are used to accurately move, manipulate, and/or perform a process (e.g., welding, drilling, assembling) to certain specifications. The robot system's pose accuracy relies on the actual geometries and positions of components in a robot cell. Tiny changes of link length, tools, and objects (geometric errors) in the workspace can cause inaccuracies of the TCP pose used in existing robot programs. 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. The sag from the link masses and payload can create significant errors at the TCP if there is no compensation. Another aspect unique to robotics is the general use of harmonic gear drives or strain wave gears. These gears use flexible membranes, which can result in a loss of accuracy, particularly with wear over time. The flexible element in these joints can also generate significant backlash error. The backlash error can vary significantly over the range of motion of the joint [8].

It is important that robot system degradations be understood so that maintenance and control strategies can be ideally optimized. Degradation analysis of the TCP accuracy is one of the key elements when assessing the health state of an industrial robot within the manufacturing industry. Health monitoring, diagnostics, prognostics, and maintenance (collectively known as Prognostics and Health Management (PHM)) have gained considerable attention within the robot system domain with respect to the design, implementation, operations (including control), and maintenance phases. Accuracy degradation is difficult to detect when the system is still operational as compared to detecting a complete system break-down. There are many challenges for the TCP health assessment of industrial robots.

- **Lack of sensor technology to quickly acquire 6-D information (X, Y, Z, roll, pitch, and yaw) that describes the robot's TCP accuracy.** Existing 6-D measurement systems include laser tracker-based systems and optical tracking systems [9]. 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[10]. Development is needed for advanced sensing to enable the quickly acquirement of 6-D information. NIST research begins to address this challenge; this effort is presented in the Advanced Sensor Development for System Level Sensing section of this paper.
- **Lack of test methods that can quickly and efficiently capture key TCP accuracy metrics without interrupting production line.** 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.
- **Lack of a PHM data taxonomy and architecture**. There is a lack of interoperability between sensor/data formats and communication modes to capture, share, and analyze data across heterogeneous robot systems. This challenge can be remedied through the creation of 1) a data taxonomy for PHM that covers data formats, storage, semantics, and other pertinent elements and 2) standard data interfaces and communication protocols. Communication protocol standards are already in use by numerous machine tools and a range of relevant sensors yet it would be advantageous to expand this capability to robot systems [11].
- **Lack of PHM overall structure to enable various PHM technologies, as applied to robot systems, to be evaluated in an unbiased manner.** This challenge can be solved through the development of an overarching architecture framework for PHM with standards and key performance indicators (KPIs). This framework would include benchmarking current states, determining key performance indicators, and defining a standard architecture aimed at performance assessment and traceability.
- **Lack of algorithms to analyze the results of the TCP pose health assessment to detect the root cause of failures and the potential remedies to fix the problem.** Solutions are needed to apply remedies to controllers (i.e., improved programmable logic controller (PLC) control strategies, or maintenance recommendations, such as re-calibration or gearbox changes).

To address the broad landscape of barriers and challenges, measurement science is needed which includes a collection of performance metrics, use case scenarios [12], test methods, reference datasets, and software tools to promote unbiased assessment to verify and validate 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 [13]. The PHMC for robotics, as a research thrust, is actively developing measurement science to promote the design, test, verification, and validation (V&V) of PHM technology for industrial robot systems. In this paper, the development of the quick assessment of the robot TCP accuracy degradation is presented as a subset of the robot health performance metrics.

DEGRADATION ANALYSIS LEVELS FOR INDUSTRIAL ROBOT SYSTEMS

A PHMC for Robotics Test Bed is being constructed at NIST to provide a platform for the development, testing, verification, and validation of the planned *Health and Control Management* *of Robot Systems* measurement science output. The test bed will serve as the home to several industrial robot arms and promote the generation of operationally-relevant test methods and datasets [13]. The test bed will support research to address the challenge of the lack of a PHM overall structure to enable various PHM technologies, as applied to robot systems. One of the use cases developed using the test bed is the quick health assessment methodology to identify the health of the robot system, with an emphasis on the subset of the robot health performance metrics – TCP pose accuracy (6-D accuracy of position and orientation, including when loads are applied) and dynamic accuracy (TCP pose accuracy while the arm is in motion). The output of this effort will provide manufacturers with a methodology that will enable them to quickly assess the TCP pose health of their robot systems when environmental conditions change or after the work cell has been reconfigured. This methodology can also allow manufacturers and technology developers to verify and validate their own PHM techniques that monitor robot health in terms of TCP pose accuracy.

Advanced sensing provides important input for this research to monitor, diagnose, and predict the system's health status to avoid the condition where a robot would malfunction (with degraded accuracy) or unexpectedly halt/shutdown. For the industrial robot TCP pose accuracy degradation, there are four levels of degradation analysis. These levels are shown in Fig. 1: the controller level sensing and analysis, the environmental level sensing and analysis, the add-on level sensing and analysis, and the system level sensing and analysis. From the system level to the controller level, information is becoming more granular by sensing information in more focused ways on specific elements of the system.

System level sensing and analysis aims to actively assess the health of the overall system by taking into account the system architecture, system function, and process-related parameters [14]. For system level accuracy degradation analysis, integrated sensors are needed to efficiently assess the TCP's pose accuracy degradation. The reason to avoid using multiple 1-D (one dimensional) or 2-D (two dimensional) sensors is that the setup is complex and introduces error stacking. To resolve the challenges described in the previous section where there has been a lack of sensor technology that can quickly acquire the 6-D information of TCP accuracy, a 7-D (seven dimensional) measurement system (time, X, Y, Z, roll, pitch, and yaw) is developing at NIST to directly measure and assess the TCP pose

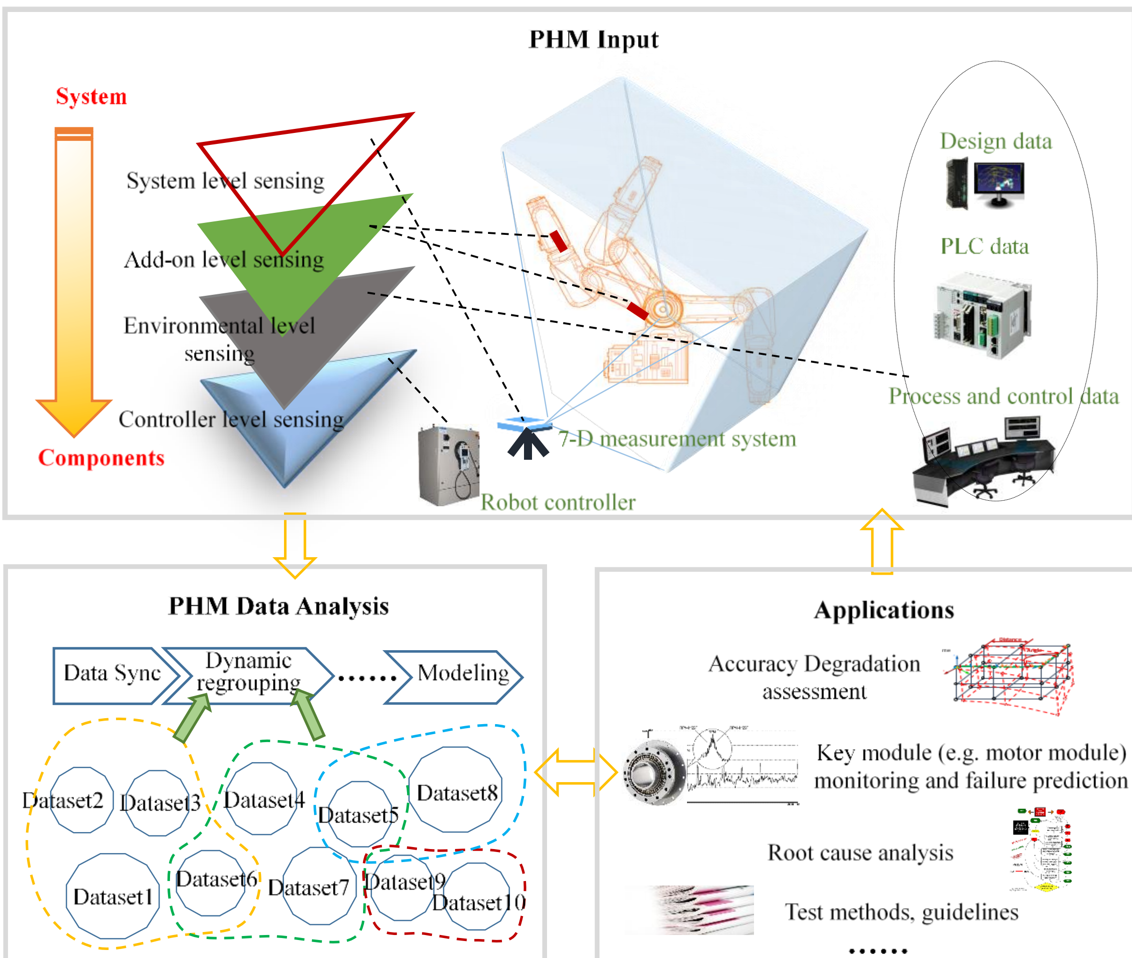


Figure 1. Four levels of degradation analysis for industrial robot accuracy degradation

accuracy degradation of the robot's TCP. A test method is also developed to analyze the TCP accuracy degradation in a volumetric way (evaluate TCP errors from different direction in 3D space) because the error magnitudes and directions are different depending on the approach of joints. The 7-D information is captured with a time synchronization feature. Data synchronization is important for fusion of this data with data from other levels to support root cause analysis [15-17]. NIST's work at this level emphasizes the development of advanced sensing (the 7-D measurement system) and the test method (including model and analysis algorithm) that can quickly and efficiently assess the TCP accuracy degradation.

The add-on level sensing and analysis are developed to collect pre-designed features from the targeted sub-systems. The add-on sensing promotes the inclusion of additional sensors to provide information that the controller and system layers may be neglecting. NIST's research at this level emphasizes the key subsystem/module (e.g., motor module) identification and suitable sensing methodology selection. The design of the add-on system needs to be easily integrated in the system's controller(s) without complex interface and wiring.

The environmental level sensing and analysis are developed to collect information about environmental conditions and settings while 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 PLC data. The environmental level sensing and analysis can help to clarify the operational settings of the robot (e.g., speed of the robot, temperature changes, or payload changes) when an anomaly is detected (by the system level 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 level data with the controller level data and the add-on level data for deeper data analysis.

Controller level sensing and analysis extracts data from the robot controllers and/or embedded sensors. Collected information includes actual joint position, commanded joint position, actual joint speed, joint current, joint voltage, motor temperature, etc. The controller level sensing is not the direct measurement of the TCP's accuracy degradation, but can highlight issues in the system through data analysis. Robot original equipment manufacturers (OEMs) and integrators have started the effort of extracting data from controllers. So far, most of the data collection tools are built based on the OEMs' own proprietary controller system. Standard data interfaces and communication protocols that can be applied among different robots are still missing. NIST's work at this level is to address the challenge of the lack of a PHM data taxonomy and architecture for robot applications, and moreover, develop methods and algorithms to analyze the data, including root cause analysis.

Using the four levels of degradation analysis, the robot system's TCP accuracy degradation can be quickly assessed by the system level sensing and analysis. Once accuracy degradations are detected from the system level sensing, data from other levels are added to the data analysis (as shown in the PHM data analysis module in Fig. 1). Datasets can be dynamically regrouped for different focuses. The controller level sensing and analysis provides detailed component information about abnormal issues that may influence the robot's TCP accuracy. The environmental level sensing and analysis provides the operational settings when an issue occurs. Combining data (from different sensing levels) supports deep data analysis, including root cause analysis. Dedicated applications can be developed to monitor the key modules, constantly update the key modules' health status, and link the key modules' health status with the system health status, ultimately helping to optimize the maintenance strategy.

As the first step of the accuracy degradation analysis, the 7-D sensor development and the test method development for the system level sensing and analysis are discussed in the next two sections. This discussion will include the algorithm that will calculate the robot's TCP pose health results through its working volume using limited measurements.

ADVANCED SENSOR DEVELOPMENT FOR SYSTEM LEVEL SENSING

The robot system's TCP accuracy 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 health evaluation of the combined conveyor/robot system since this drives the accuracy of the process. Advanced sensing development is an important part of the PHMC for robotics structure to quickly acquire the 6-D information (X, Y, Z, roll, pitch, and yaw) that describes the robot TCP accuracy.

Existing measurement systems that can measure 3-D or 6-D information are shown in Fig. 2. The measurement systems 1-3 are laser trackers from different manufacturers. Laser trackers

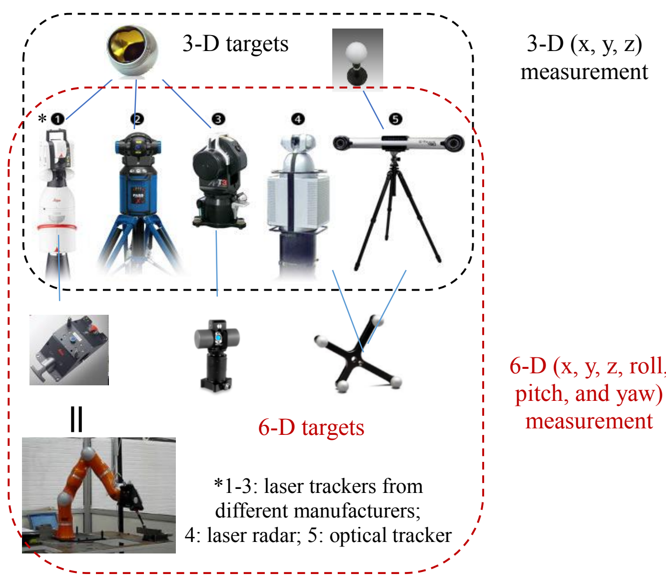


Figure 2. Existing 3-D and 6-D measurement systems

are instruments that can measure 3-D coordinates by tracking a laser beam to a retro-reflective target held in contact with the object of interest [18]. Light reflected off the target retraces its path, re-entering the tracker at the same position it originated. This provides distance information. A laser tracker also contains two angular encoders. Encoders measure the angular orientation of the tracker's two mechanical axes: the azimuth axis and the elevation axis. The angles from the encoders and the distance from the laser are sufficient to precisely calculate the center (x, y, z) of the retro-reflective targets. Retro-reflective targets are considered 3-D targets since only x, y, and z information are measured from target types. 6-D targets are designed to capture the extra orientation information. For laser trackers, a 6-D target has retro-reflector(s) mounted on the target to track the laser beam and get the x, y, and z position information. The extra orientation information is measured by embedding other sensors in the target, or adding a camera system on the tracking head to capture the features that define the coordinate frame on the 6-D target (e.g., multiple light-emitting diodes (LEDs) on the target that define a coordinate frame). Tracker systems are expensive. These measurement systems required line-of-sight to be maintained between the laser tracker and the target. This means that the tracker will ultimately lose its view of the target when observing the target on a robot rotating to an angle. In this case, the robot's TCP rotation has to be limited. The 6-D target should be mounted on the robot's TCP. Mounting the target typically requires the production line to be stopped to change the setup or work tools.

The fourth measurement system is the laser radar which is also shown in Fig. 2 [18]. Laser radar scans the workspace and outputs measurement data as 3-D point clouds. Laser radar can measure a 6-D target (e.g., with multiple reflective spheres that define a coordinate frame as shown in Fig. 2). Getting the 6-D information may take multiple steps of software operations (e.g., segmentation of the 6-D target point cloud is needed from the surrounding objects; removing outliers; best-fit of spherical centers). The best-fit accuracy varies depending on the quality of the point cloud and the quality of segmentation. Laser radar is expensive and not an efficient measurement system for the robot 6-D information acquirement.

The fifth measurement system shown in Fig. 2 is the optical tracker. The optical tracker is a 3-D localization technology based on monitoring a defined measurement space using two or more cameras. Each camera is equipped with an infrared (IR) pass filter in front of the lens, and a ring of IR LEDs around the lens to periodically illuminate the measurement space with IR light. Objects that need to be tracked are equipped with retro-reflective markers (e.g., reflective spheres). The 3-D position can be measured by using a single marker in the measurement space. Multiple markers are placed on each object to measure the orientation of an object or to track multiple objects simultaneously. There are limitations of this measurement system. It is difficult to ensure multiple markers can be seen from each angle. Also, the images of the near-infrared cameras only contain the markers. They are "blind" to the environment. There is no redundancy when ambient light influences the reflected light from the targets [9].

Besides the need to avoid the limitations of the existing measurement systems, several features are required by the robot TCP pose accuracy measurement:

- The measurement system should be 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. This includes avoiding the scenario where a robot system's end-effector needs to be removed or adjusted to accommodate a target sensor.
- The measurement system needs to be robust for industrial environments. For example, target(s) should be resistant to industrial dust, oil, etc.
- The measurement system should provide robust measurements also in ambient light conditions.

To address the challenges of advanced sensing, 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 in feature calculation (after optical triangulation, the sub-pixel accuracy provides the measurement system with a higher degree of accuracy than was previously available); (3) vision systems are becoming relatively low-cost and easy to integrate given their recent advancement and maturation [19].

The 7-D measurement system is designed as shown in Fig. 3. It consists of two high-speed color cameras, a high

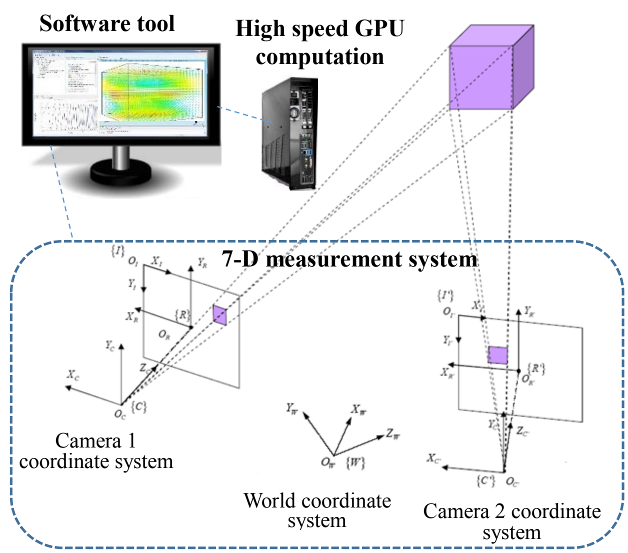


Figure 3. 7-D measurement system

performance image processing control box (operating on a personal computer), special targets, and software tools. Instead of using near-infrared cameras, high speed color cameras were selected to address the negative influence of the ambient light.

New, advanced color image stereo technology promotes more accurate target detection by utilizing redundant information from color images. An advanced image-distortion-correction algorithm is applied. High density differential technologies are developed to help with the removal of the background noises. Parallel calculation and hardware acceleration are used for fast image processing. The graphics processing unit (GPU) programming is utilized to enable the implementation of complex image processing algorithms. Differing from and exceeding the performance of traditional stereo technology, the 7-D measurement system is designed and embedded with a time synchronization feature. Time synchronization is important for the analysis when fusing this data with other sensor data for deep robot system health analysis. Additionally, a self-calibration method is created to avoid the condition where a camera-based measurement system needs to frequently self-calibrate.

Innovative target design is an important part of this work. The customized target is designed to address three specific challenges: (1) Maintaining line-of-sight between the 7-D measurement system and the target; (2) Maintaining the same measurement uncertainty when the target rotates at different angles; and (3) Low-cost and easy to mount on the robot arm's tool with known offsets from the TCP. This target design supports avoiding tool changes during measurement which would require some interruption of the production. Specific target design is not discussed in this publication; this design is currently under consideration for a patent.

The 7-D measurement system will be mounted on the floor or table to measure TCP positions. No alignment is needed from the 7-D system to the robot, so the 7-D system can be moved to other stations without the need for time-consuming set up procedures. Outputs from the 7-D measurement system are points (time, X, Y, Z, pitch, yaw, and roll) under the fixed instrument coordinate system.

TEST METHOD AND ALOGRITHM DEVELOPMENT FOR SYSTEM LEVEL DEGRADATION ANALYSIS

Given a measurement system (e.g., the 7-D measurement system) that can capture TCP pose (position and orientation), 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 TCP pose health condition of the robot. Since each TCP pose in the Cartesian space could have multiple inverse kinematic solutions, as a result, the error magnitude and direction changes by choosing different solutions. This makes the assessment of the TCP accuracy degradation very difficult since it is hard to measure the accuracy from all directions. The robot might be programmed to work in the "sweet spot" in the volume with the optimal approaching direction(s). If another program is called, this testing process would need to be performed again. Similar to the existing robot standards (e.g., ISO 9283), most standard methods are designed more to assess repeatability, but not for accuracy [9]. Moreover, the practical application of the test method requires it to be performed in industrial environments with minimal setup. System setup increases the overhead because of the cost of shutting down a production line, especially when a system contains hundreds of robots working together. There needs to be an efficient model and algorithm to support the test method that can calculate the robot's overall TCP pose health results through its working volume using limited measurements.

When developing the model for the test method, the model should reflect error sources of the robot system. Thus, after the TCP pose health assessment, this model can be further used for the root cause analysis to find the problematic individual joints. An example of a robot's serial kinematic structure with coordinate frames is shown in Fig. 4. 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 described as geometric errors that are

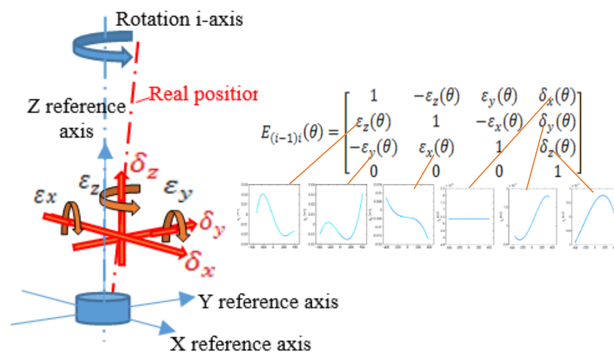


Figure 4. Six errors of a rotation axis

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. 4 shows a rotary axis (we refer to it as the "i-axis" as the representation of a general situation), which represents the i^{th} joint of a robot. In Fig. 4, 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 in Equation (1):

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

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

$$T_0(x) = 1$$
$$T_1(x) = x$$
$$T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x)$$

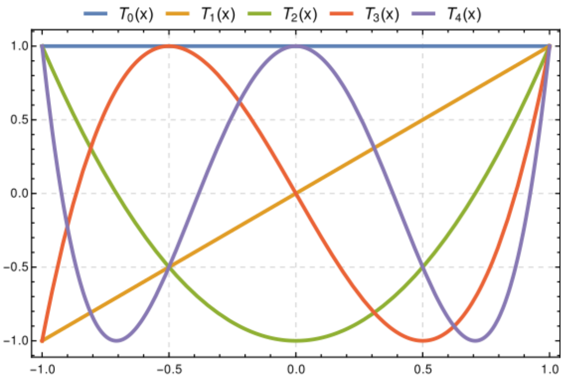


Figure 5. Plot of the first five Chebyshev polynomials

Different from the traditional error model, the δ(θ) and ε(θ) are not constant values. They are functions of axis locations which we refer to as a higher order model (compared to the zero order model) [20], which means the model can handle non-geometric errors, such as the non-ideal motion of joints, deflections of the structure and joints due to external loading or gravity, backlash, etc. As shown in Fig. 4, the error model of the "i-axis" contains six errors ($\varepsilon_x(\theta)$,$\varepsilon_y(\theta)$,$\varepsilon_z(\theta)$,$\delta_x(\theta)$,$\delta_y(\theta)$,$\delta_z(\theta)$). Each is represented as a high order Chebyshev polynomial with unknown polynomial coefficients to be solved [20]. In this way the error model can represent not only the position-independent geometry errors, but also the position-dependent axis motion errors. The reasons to use Chebyshev polynomials are that (1) they are orthogonal to each other over an interval; and (2) they all have a similar scale over the same interval. The first five Chebyshev polynomials are plotted in Fig. 5. Chebyshev polynomials are orthogonal from [-1, 1], and have all n roots and n+1 extremum in [-1, 1]. These properties make them particularly useful as approximating basis polynomials. A simple linear mapping function is used to map the negative axis travel limit to -1 and the positive travel limit to 1.

Another challenge for the traditional error model is the lack of handling measurement noises. 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 equally weighted, with weights assigned according to the accuracy of each joint. As shown in Fig. 3, the 7-D measurement system is included in the loop of the kinematic chain. The kinematic model of the robot is represented in Equation (2):

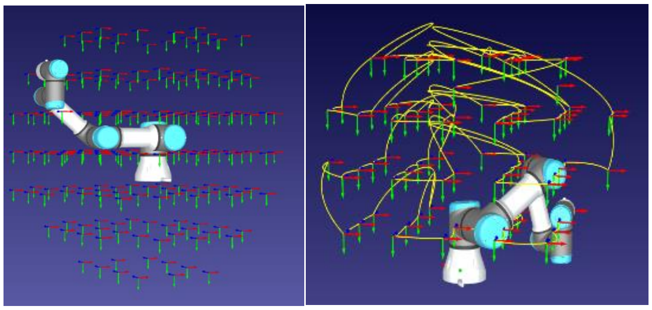
$$I = E_0 A_{01} E_{01} A_{12} E_{12} \dots A_{(N-1)N} E_{(N-1)N} A_{N0} E_{N0} \qquad (2)$$

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. Our complete parameter list is the unknown coefficients of the polynomials of the error terms in each of the E matrices. The order of polynomial should be large enough (e.g., 6-8 for most of the robotic systems) to capture all of the dominant error characteristics, but not too large as to over fit the data. Now it remains to identify the constant coefficients describing the Chebyshev polynomials that describe the joint dependent errors.

After the test method model is developed, a test method with a fixed loop motion is developed by extending the existing standard methods for robot performance, as described in [21]. 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, the X, Y, Z, roll, pitch, yaw, and time data (7-D information) 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 TCP pose accuracy 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.

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. 6 shows the designed fixed loop motion created at NIST for a demo robot. 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 performed: (1) in Cartesian space, a grid of poses is generated inside the robot workspace as the target poses (as shown in Fig.6 (a)); (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)



(a) (b)

Figure 6. Robot fixed loop motion for test method

calculations are performed to check if the robot linear motion is possible. In the meantime, collision avoidance 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 in step 4. 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. 6 (a) are evaluated. The final poses and paths are shown in Fig. 6 (b). 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.

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

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

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

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.

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

where N is the number of sample positions.

The χ^2 error function is derived as:

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

The implicit loop based maximum-likelihood estimation [20] is used to solve this error model and minimize the error by fitting the parameters in Equation (1). 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 [22]. The optimization algorithms will be detailed in future publications. There are two outputs from this modeling method. The first one is the derived errors from the calculation of the TCP pose 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.

CONCLUSION

This paper presents the NIST's development of the robot TCP pose 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 TCP pose health faster, cheaper, and with higher accuracy. This can help to quickly detect and decrease the manufacturing quality degradation to reduce scrap, and ultimately improve a robot system's productivity, efficiency, and quality. 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. Since the methodology has been successfully developed, NIST personnel are constructing use cases within the NIST robotic system test bed. NIST is also seeking to develop additional industrial use cases for further applications.

NIST DISCLAIMER

the best available for the purpose.

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