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DEVELOPMENT OF A SUITABLE TECHNIQUE FOR FAULT DETECTION IN INDUSTRIAL ROBOT MANIPULATORS

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ABSTRACT

Fault detection are becoming increasingly important in modern industrial robotic manipulators, particularly for those working in inaccessible & hazardous environments. Robot manipulators are used in a variety of disciplines, including mechanical, electrical, and electronic industries, medical applications, and other fields that demand great accuracy and stability of operation. For this aim, industrial robot manipulators must have a thorough understanding of joint variables and kinematic characteristics. The PUMA 560 robot is considered for the evaluation of the proposed technique. An extended Jacobian technique is used to find out the fault or error value in the PUMA 560 robot. The mathematical model of the PUMA 560 six DOF robot is modelled. Then the DH technique is employed to derive the forward and inverse kinematics of the PUMA 560 robot. Finally the extended Jacobian algorithm is derived to find error function. The derived error function is considered as the objective function for the optimization.

Keywords: Fault Detection, PUMA 560 robot, Robot manipulation, Industrial robot etc.

INTRODUCTION

Robot is an industrial system which has the capacity to carry out various kinds of task in both controlled and automatic manners. Robots are utilized as small machines that perform challenging tasks, which cannot be done by a human. Micro manufacturing is becoming increasingly important for delicate operations such as semiconductors processing, micropart assembly, and precise material handling as contemporary production methods advance. Micro-assembly is the process of attaching components that have a least one dimension smaller than one millimetre and must be put with micrometre precision.

Industrial robots perform self-sufficient and semi-autonomous tasks in an unstructured, dynamic environment. They have several practical applications, such as planetary spac exploration, home use, medical operations, and recovery processes (Yang *et al.*2001).

Robots are typically exceedingly intricate in order to perform these needed duties, which increase their chance of failure. However, if people are regularly sent into these scenarios to repair every component failure in robot, benefits of employing robots soon vanish. The construction of robots that perceive their environment has become a major concern, encompassing condition illustration, identification, and robot activation (Yakey *et al.* 2001).

The application of robot works under organization and unstructured conditions (Xia *et al.* 2001). Robots have become an important part in every aspect of modern human life, which also helps the humans in a discomfort situation.

For the purpose of kinematic analysis, fault detection and fault tolerant PUMA 560 robot is used among the group of industrial robots. PUMA 560 robot, has six joint and links which are connected to each other by joints. The PUMA 560 robot has two types of joints: prismatic joint & revolute joint. The prismatic joint involves linear motion around an axis, whereas the revolute joint involves rotating motion around an axis (Mazhari, 2008). The advantage of this robot is that it has nonlinear features and unpredictable dynamic parameters.

FAULT DETECTION

Fault-tolerant robots are required that can detect & adapt to software (or) hardware failures, allowing the robots to continue functioning until repair can be realistically scheduled. When a component fails, these systems must generally follow four main concepts to fulfill their goals: fault detection, fault isolation, problem identification, and fault recovery. Fault detection & isolation approaches are often based on residual generation & analysis concept. Robot failures are mostly caused by power outages, computer failures, shoulder, elbow, and wrist failures, as well as other mechanical, electrical, electronic, hydraulic, and pneumatic failures.

Internal sensors and motors are key components of robotic systems. Kinematic errors are mostly caused by motors and sensors; internal sensors provide information to the controller about the robot joints' current position and velocity. as a sensor failure is identified and the measured reading exceeds the specified threshold error value in comparison to the expected value, the algorithm stops relying on the failed sensor and instead sends data to the processor from the alternative functional sensors. Electric motors serve an essential role in adjusting the posture of the robot. The controller determines required torque to apply to appropriate motor in order to move robot from its current position to the next expected location. The methods therefore safeguard robot controller from inaccurate sensor data & tolerate sensor failures. Despite the joint failure, the planner can maintain the required robot end-effecter trajectory thanks to kinematic redundancy. A joint's two motors must be able to work together to create a single output. Fault-tolerant control systems can automatically maintain system stability and acceptable performance.

A mathematical model is used to simulate dynamic behaviour of a fault-free system. The difference between model's predicted output and actual output measurements is known as the residual, and when properly analyzed, it provides significant information regarding failures. The motion of a manipulator's separate joints must be precisely coordinated. Robot control typically entails applying a control signal to the robot's joints while specifying the intended trajectory for the end effector. It is critical for controller to offer both position & velocity transformations from Cartesian space to joint space coordinates.

The observer design includes a constrained disturbance term to account for unstructured modelling uncertainties. Technically, an adaptive observer is created using particular regularity assumptions & a persistence excitation condition. The proposed observer error system includes estimation errors for actuator & sensor defects, as well as two auxiliary variables. Multiple variables are produced by filtering the signal of the fault direction vectors.

LITERATURE REVIEW

Henten et al. (2010) investigated a 7-link robot gripper for cucumber pick operation utilizing analytical and computational algorithm-based methodologies. The robot manipulator's inverse kinematic solution is solved using a typical DH algorithm. Drawbacks are that the analytical method is used with a quantitative analysis-based methodology to obtain the best answer for the robot manipulation.

Muller et al. (2011) proposed common properties of kinematic mapping for manipulator. The system's stability with slight geometric modifications may alter the robot setup and raise concerns about singularity analysis. A straightforward explanation of motion spaces for each joint and kinematic map classes is provided. Limitations are redundant components are present this makes the robot geometry changes.

Al-Khedher et al. (2012) proposed neural network-based controller of SCARA manipulator and associated with the PD controller and Denavit Hartenberg algorithm for the calculation of the inverse kinematic of the robot manipulator. A serial-parallel configuration neural network is used for location control of all joint variables. The number of hidden layers is more to reach good result. Drawbacks are neural network are not capable of approximating a non-linear static function to arbitrary desired accuracy.

Zhang et al. (2013) presented the connection and correlation between speed level and quickening level tedious movement by means of PA10 robot arm. This paper was mainly focused on the movement of the robot in desired position while performing the desired task. Drawbacks include the difficulty of developing appropriate inverse kinematic strategies for serial robots using the most widely utilized algebraic, linear, or numerical methods.

Li-Xin et al. (2014) have presented the analysis or procedure that is used to compute the joint coordinates of a given set of end effector coordinates is called inverse kinematics. The calculations are, in common for nonlinear and complex. Inverse kinematics refers to the technique of estimating joint characteristics in order to get a quantified location of an end effector. An inverse kinematic issue involves transforming a kinematic chain's end effector point to the joint coordinate region. Drawbacks of parallel singularities, taking into mind the robot's physical size.

Baghernezhad et al. (2015) proposed a fault detection & isolation by using adaptive threshold generation schemes. The residuals for checking fault detection. Initially local thresholds are determined separately for each neuron, it provides a maximum contribution to the overall output estimation. The second technique involves error modelling in combination with RBF neural networks as well. The drawbacks of this approach are that the gain is adjusted using a set of data for training, resulting in a narrow range of operating circumstances and low noise levels. The possibility of error occurrence is high while fault tolerance.

Arrouk et al.(2016) proposed geometric and kinematic analysis of 3-degree planar parallel robotic manipulator using CAD based graphical programming which gives high resolution. Drawbacks of this approach are it doesn"t work for spatial and spherical 3DOF parallel robotic manipulators. The work space analysis and trajectory planning is not defined for 3 DOF.

Arian et al. (2017) presented the mathematical modelling of kinematics for 3-degrees of freedom Gantry – Tau manipulator. Inverse dynamics equation model was obtained through 2 different methods, Virtual work & Newton -Euler. Limitations are computational complexity is more and time consuming. Internal force moments are required for Newton- Euler method analysis.

A. Freddi et al. (2018) present a Fault Tolerant Control (FTC) strategy for manipulating robots with actuator defects. The actuator defect is characterized by an unknown partial joint torque drop, resulting in the loss of desired end-effector motion. The FTC approach incorporates a Fault Detection and Diagnostic (FDD) system that uses a first-order sliding mode observer to identify and assess joint torque faults. The estimated fault ismapped into a kinematic deviation of the motion of the end effector from the desired one, and compensated at the level of the kinematic controller. Simulation results demonstrate the effectiveness of the proposed scheme for a planar manipulator affected by two types of actuator faults, namely bias fault and partial torque fault.

According to Janmenjoy Nayak et al. (2020), FA and its modifications have been used to solve several complicated problems. Taking these details into account, this work provides the first in-depth investigation of the varieties, relevance, uses, and upgrades of FA in BME and HC. The primary goal of this research is to encourage academics to enhance and invent new solutions to multidimensional challenges in healthcare and biomedical engineering utilizing FA.

Adil Yousif et al. (2022) assessed various sizes of real grid computing workload traces, beginning with lightweight traces with just 500 tasks, progressing to typical with 3000 to 7000 jobs, and ultimately heavy load with 8000 to 10,000 jobs. The experiment findings demonstrated that the greedy firefly algorithm could not considerably lower the makespan and execution durations of the IoT grid scheduling process when compared to other tested scheduling approaches. Furthermore, the proposed greedy firefly method converges on vast search spaces more quickly, making it appropriate for large-scale IoT grid scenarios.

Shishir Kumar Shandilya et al. (2023) paper proposes a modified version of firefly optimization algorithm to effectively monitor the network by introducing a novel health function for the early detection of suspicious nodes. We implement event management schemes based on the proposed algorithm and optimize the observation priority list based on a genetic evolution algorithm for real-time events in the network. The simulation results indicate the suggested algorithm's efficacy in a variety of assault situations. Furthermore, the findings show that the suggested strategy decreases the number of suspect nodes by around 60-80% while increasing turnaround time by just about 1-2%. The suggested solution is also focused on accurate network health monitoring in order to defend the network proactive.

Xin-She Yang et al.'s (2024) research aims to offer a full explanation of a novel Firefly Algorithm (FA) for multifunctional optimization applications. We will compare the proposed firefly approach to various metaheuristic algorithms, including particle swarm optimization (PSO). Simulations and results demonstrate that the proposed firefly method outperforms existing metaheuristic algorithms in many respects. Finally, we will examine its uses and the implications for future study.

In the study of Heng Yang et al. (2025), an adaptive operator failure compensation control strategy is suggested for visual servoing of an eye-to-hand robotic operator with redundant actuators at joints, without the need for accurate camera calibration. In addition, control design takes into account both stuck-type and time-varying actuator failures. Furthermore, a proportional-actuation technique to handle the duplicate actuators' varying output capabilities is newly designed. Furthermore, a decoupling approach is given, which allows the unknown actuator failure characteristics and camera parameters to be approximated separately. Furthermore, a unique stability analysis approach is presented, allowing us to demonstrate the convergence of picture errors and the boundless potential of all closed-loop signals. Finally, simulation results demonstrate the usefulness of our strategy.

OBJECTIVES OF THE STUDY

The main objective of this study is to develop a suitable technique for fault detection in industrial robot manipulators

JACOBIAN FAULT DETECTION IN INDUSTRIAL ROBOT

Diagnosis and resolution of faults are critical in any industrial robot manipulator in order to maximize benefits in industries. It is necessary to identify a fault detection trail that can be used to a dynamic robot system. The process of developing such checks, or residuals from a for general systems by the use of quantitative multiplicity.

$$|q_{desired} - q_{sensor}| \leq threshold\ value$$

To account for sensor and robot models errors, thresholds must be introduced to calculations to establish an appropriate range of sensor readings around predicted values before converting them into a verification check.

$$\|\ddot{q}_c - \ddot{q}_t| \leq (tachometer - acceleration - threshold)$$

$$|q_d - q_e| \leq (encoder - position - threshold)$$

$$|q_e - q_t| \leq (encoder - tachometer - threshold)$$

Where, q_d = desired position,
q_e= the encoder reading,
q_t= the position derived from the tachometer

FAULT DETECTION METHODS

Robots must have defect detection and tolerance capabilities. Unfortunately, there are several possible causes of failure in robotic systems (skeletal, electrical, electronic, hydraulics, thereby and gas), and fault detection methods are based on residual production and assessment. A mathematical model is utilized to calculate fault-free system's dynamic performance. The disparity b/w model's anticipated output & actual output measurements is known as residuals, and when properly examined, it provides significant information regarding failures. The decision-making system might discover faults in the manipulator using soft computing techniques.

The entire, architecturally based fault types are employed as a databank within the expected framework, receiving failure information from detection algorithms, pruning types as needed, & eventually alerting operator. Based on the fault assessment, the fault recognition algorithms developed in this work are designed to promptly detect faults in sensors or drives and allow the robot to survive them. Because mathematical representations for complicated systems such as a robot manipulator are difficult to generate, model-free techniques based on Artificial Intelligence (AI) or statistical methodology have become popular alternatives. Following the development of the residuals, it is necessary to determine whether the system has a fault or not. This is done by the change detector, which may be divided into three categories: single model, dual model, and multi-model method.

SINGLE MODEL APPROACH

The robot manipulator data is fed to the filtered residual generator εt as an input to a distance measure st (computed from the fault values). A halting rule determines and filters whether the change is meaningful or not. Figure 1 depicts a single-model method to fault detection schematic diagram.

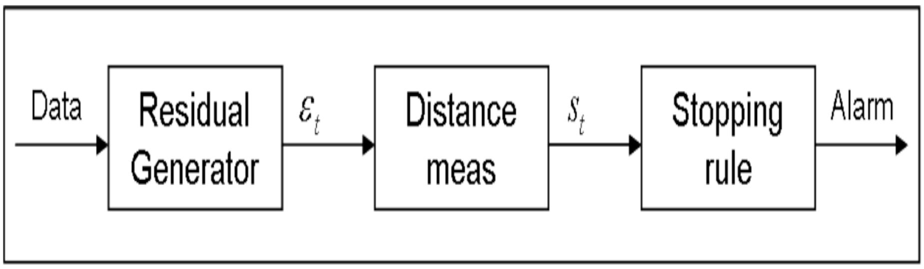

FIGURE 1: SINGLE MODEL APPROACH FOR FAULT DETECTION

DUEL MODEL APPROACH FOR FAULT DETECTION

In the dual model technique, residuals are generated by two filters: the first is slower with a large data window or the entire data, and the second is faster with a narrow data window that is compared; figure 2 depicts the operation. If the model based on the smaller data window produces bigger residuals, then a change has been detected.

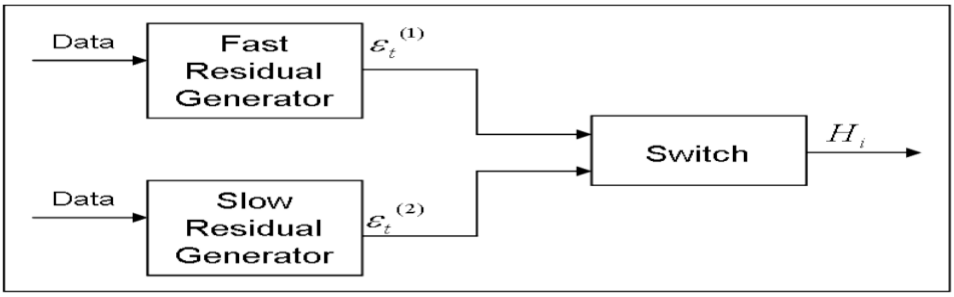

FIGURE 2: DUEL MODEL APPROACH FOR FAULT DETECTION

MODELLING OF EXTENDED JACOBIAN FOR FAULT DETECTION

The Jacobian method, or Jacobian matrices, is commonly utilized in robotics and control systems. In general, the Jacobian method is used to describe the relationship between two representations of a robotic or control system. In this study, an extended Jacobian is used to identify the defect in the robot. The extended Jacobian can help overcome robot redundancy utilizing a non-redundant system. The redundant robots are standard industrial robots with more actuated joints than are needed to complete the task.

Kinematic constraints are assigned based on the robot manipulator's movements. The robot's motion is restricted by linear velocity limitations. That can be stated in the form of equation (1).

$$A(q)q = 0 \quad (1)$$

The output function based on the motion constrain of robot kinematic is given in equation (2).

$$A(q)x = \sum_{i=1}^{m} a_i(\mathrm{q})x_i \quad (2)$$

where;

$y \in A^n$ is vector of generalized coordinates of platform.

$y \cdot\in A^n$ is the task space vector containing the position and orientation.

The admissible control function x(.) from equation (1) is obtained from Lebesgue square integral function on a time interval (0, t). The Hilbert space $x = l^2 m(0, t$ of the permissible control functions with inner product is given in equation (3)

$$\langle x(.), y(.)\rangle = \int_0^t x^t\,(t)y(t)dt \quad (3)$$

The equation will be represented as endogenous configuration space ofrobot. Suppose the fixed initial state is of the robot and every endogenous configuration, then the trajectory will be $a(t) = \vartheta_{a0.t}(\mathrm{x}(.))$ exits for all. $T \in (0, t)$Next the final end point map of the control system will be identified by the kinematics of the robot which is given in equation (4)

$$k_{a0,}t\big(x(.)\big)y(.) = j_{q0,}t\big(x(.)\big)y(.) \quad (4)$$

The kinematics of the robot using Jacobian is given in equation (5)

$$J_{a0,}t\big(x(.)\big)y(.) = A(t)\int_0^t \varphi(t,s)b(s)u(s)ds \quad (5)$$

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The kinematics of the robot given in equation (5) considers a desirable task pace as $\in A^n$. The inverse kinematic problem computing a configuration as $x_d(.)$ and that $y_d = A_{q0,}t(x_d(.))$ The solution of $x_d(.)$ problem can be found out using the Jacobin inverse kinematic method. If the $y_d = A_{q0,}t(x_d(.))$. The error value is computed using the equation (6).

$e^{(\theta)=}A_{q0}t(x_\theta(,)$ - yd (6)

If the $\delta > 0$, the expression becomes,

$$\frac{de(\theta)}{d\theta} = -\delta e(\theta) \quad (7)$$

By using Jacobian technique in the error value in the equation (7) the equation results are as in equation (8).

$$j_{q0,}t(x_\theta(.)).\frac{de(\theta)}{d\theta} = -\delta e(\theta) \quad (8)$$

Ultimately, based on the Wazewski"s equation, the inverse of Jacobian ((.)) is employed. $j^*_{q0,}t(x_\theta(.))$ is employed.

$$\frac{dex(.)}{d\theta} = -\delta j^*_{q0,}t(x_\theta(.))\left(A_{q0,}t(x_\theta(.))\right) - y_d$$

The equation (8) can satisfy the condition $y_d = A_{q0,}t(x_\theta(.))$, where, the result of the inverse kinematic problem arises within the limit range. (.) (9)

The extended Jacobian Inverse (EJI) can obtain by using the following procedure. For the extended Jacobian, the kinematic map is implemented and is given in equation (10).

By implementing the kinematic map in equation (10), the extended kinematics can be obtained and is given in equation (11).

$$i_{q0,}t = \left(A_{q0,}tH_{q0,t}\right): a \to a \quad (11)$$

The derivative form of the extended kinematics is given in equation (12)

$$Dl_{q0,}(x(.)) = (j_{q0,}t(x(.)), DH_{q0,}t(y(.)) = \bar{J}_{q0,}t(x(.)) \quad (12)$$

The equation (12) is called the extended Jacobian of the PUMA 560 robot. In the endogenous configuration space, the extended Jacobian inverse can be defined as in equation (13).

$$j^{et}_{q0}t(x(.))\omega = \bar{J}_{q0,}t(x(.))(\omega, 0(.)) \quad (13)$$

The extended Jacobian has two properties, such as identity and annihilation property. The identity and annihilation properties are given in equations (14) and (15) respectively.

$$j_{q0}t(x(.))j^{et*}_{q0} = \bar{J}_{q0,}t(x(.)) = t^r \quad (14)$$

$$dH_{q0,}t(x(.))j^{et*}_{q0}t(x(.)) = 0 \quad (15)$$

PROBLEM FORMULATION

In this study, an extended Jacobian is used, which is similar to the conventional Jacobian. Here the major objective is to determine the error value using the extended Jacobian algorithm. The systematic diagram of PUMA 560 robot is given in figure 3. The equations for the PUMA 560 robot model are given in equations \ (16) to (18). ,

$$x_1 = d\cos\vartheta, \quad (16)$$

$$y_1 = d\sin\vartheta, \quad (17)$$

$$\vartheta = \frac{v(\omega_l - \omega_r}{2a}, \quad (18)$$

where; x_1 is the coordinate of the point t; y_1 is the coordinate of the point, the heading angle is, ϑ the right arm rotation angular velocity is indicated as, ω_r the left arm rotation angular velocity is denoted as, $\omega_l$and the speed is written as $d = \frac{v(\omega_l - \omega_r}{2a}$,.

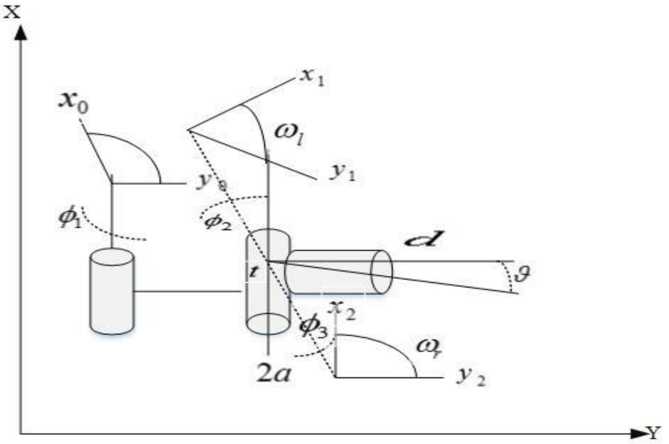

FIGURE 3: ROBOT SYSTEMATIC DIAGRAM

FAULT DETECTION

The endogenous configuration space of the robot system at interval x = (0,T), and its task space is equal to A^n. Let j_{q0}t (x(.)) denote the Jacobian in this method. Then the control function is assigned to the robot system using orthogonal series.

$$x_i(t) = \sum_{t=0}^{\infty} \omega_{it}\varphi_t(t) \tag{19}$$

where; i=1, 2.

The functions φ_t(t),t ≥0 form an orthogonal on the basis of the endogenous configuration x. For every pair of $x_1 = d\cos\vartheta, y_1 = d\sin\vartheta$ of bounded controls there exists a trajectory of the system, which defines the kinematics. In order to accomplish the endogenous space, choose coordinating coefficients $(x_2, y_2) \in A^n$ and include in the quotient space $^x/_{A^n}$ pairs of functions such as

$$\bar{x}_1(t) = \sum_{k=1}^{\infty} x_2 k_{\varphi k}(t), \bar{y}_1(t) = \sum_{k=1}^{\infty} y_2 k_{\varphi k}(t) \tag{20}$$

For augmenting kinematics map, choose the following way

$$H_{q0,}t(x(.))(t): \left(\frac{\bar{x}_1(t)}{\sqrt{x_2^2+\epsilon}}, \frac{\bar{y}_1(t)}{\sqrt{y_2^2+\epsilon}}\right) \tag{21}$$

The derivative of the equation (21) is given in equation(22)

$$\left(dh_{q0,}t(x(.))y(.)\right)(t) = \begin{pmatrix} \frac{(x_2^2+\epsilon)\bar{y}_1(t) - x_2\omega_2\bar{x}_1(t)}{(x_2^2+\epsilon)^{\frac{1}{2}}} \\ \frac{(x_2^2+\epsilon)\bar{y}_1(t) - y_2\omega_2\bar{x}_2(t)}{(y_2^2+\epsilon)^{\frac{1}{2}}} \end{pmatrix} \tag{22}$$

where;

$$y(t) = \begin{bmatrix} \varphi_0(t) & 0 & 0 & 0 \\ 0 & \varphi_0(t) & \varphi_0(t) & \varphi_0(t) \end{bmatrix} \omega + \bar{y}(t) \tag{23}$$

$\bar{y}(.)\epsilon\, ^x/_{a^4}$ *and* $\omega = (\omega_{1,}\omega_{2,}\omega_3)$.

The function

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In order to calculate the extended Jacobian, invoke the properties of, extended Jacobian. From the above equation, to develop the extended Jacobian, it is given in equation (24).

$$j_{q0}^{et} = \begin{bmatrix} \varphi_0(t) & 0 & 0 & 0 \\ 0 & \varphi_0(t) & \varphi_0(t) & \varphi_0(t) \end{bmatrix} \omega(ŋ) + \left(\bar{J}_{q0}^{et}(x(.))\right)ŋ)(t) \qquad (24)$$

In equation (25), substitute the equation (3.49) for annihilation property,

$$\left(j_{q0}^{et*}(x(.))ŋ\right)(t) = \begin{pmatrix} \frac{x_2\bar{x}_1(t)}{x_2^2+\epsilon}\omega_1(ŋ) \\ \frac{y_2\bar{y}_2(t)}{y_2^2+\epsilon}\omega_2(ŋ) \end{pmatrix} \qquad (25)$$

The result of equation (25) is given in equation (26).

$$\left(\bar{J}_{q0}^{et*}(x(.))ŋ\right)(t) = f_{q0,}t\left(x(.)\right)(t)\omega\ (ŋ) \qquad (27)$$

While using the annihilation property by getting the result as equation (26) but the property must be a condition as in equation (15). By deriving the equation using extended Jacobian algorithm, can conclude that the equation (26) is not satisfactory. The error rate function is given in equation (27).

$$\left(\bar{J}_{q0}^{et*}(x(.))ŋ\right)(t) = \int_0^t \varphi(T,t)a(t)f_{q0,}t\left(x(.)\right)tdt \qquad (27)$$

$$\varphi(T,t) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \varphi_1(T,t) & 1 & 0 \\ 0 & \varphi_2(T,t) & \varphi_3(T,t) & 0 \end{bmatrix} \qquad (28)$$

where

$$a(t) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ x_1(t) & 0 \\ y_1(t) & 0 \end{bmatrix} \qquad (29)$$

$$f_{q0,}t\left(x(.)\right)t = \begin{bmatrix} \varphi_0(t)+\frac{x_2\bar{x}_1(t)}{x_2^2+\epsilon} & 0 & 0 & 0 \\ 0 & \varphi_0(t)+\frac{y_2\bar{y}_2(t)}{x_2^2+\epsilon} & 0 & 0 \end{bmatrix} \qquad (30)$$

where,

$$\varphi_1(T,t) = \int_t^T x_1(t)dt$$

$$\varphi_2(T,t) = \int_t^T \varphi_1(T,t)$$

$$\varphi_3(T,t) = \int_t^T \varphi_1(T,t)dt0 \qquad (31)$$

In the subsequent chapters for propose of optimization technique to reduce the error obtained in equation (27) were used.

CONCLUSION

The primary goal of this chapter is to establish an appropriate technique for defect detection in an industrial robot manipulator. The PUMA 560 robot is being considered for examination of the proposed technique. The PUMA 560 robot's fault or error value is determined using an enhanced Jacobian approach. The mathematical model of the PUMA 560 six-DOF robot is created. The forward and inverse kinematics of the PUMA 560 robot are then derived using the DH approach. Finally, the extended Jacobian approach is used to determine the error function. The resulting error function serves as the optimization's goal function.

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