Mechanical Design and Error Prediction of a Flexible Manipulator System Applied in Nuclear Fusion Environment

Authors: Shi Shanshuang, Shi Shanshuang

Date: 2017-10-27T00:00:00+00:00

Abstract

Purpose – The purpose of this paper is to develop a serial redundant manipulator system for application in nuclear fusion environments. It will enable remote inspection and maintenance of plasma-facing components within the vacuum vessel of fusion devices without disrupting the ultra-high vacuum condition during physical experiments.

Design/methodology/approach – Firstly, considering the dynamic sealing of actuators to avoid contaminating the vacuum condition inside the fusion reactor, the mechanical design of the robot system is introduced. The redundant manipulator system has a total of 11 degrees of freedom with an identical modular design. Additionally, to improve positional accuracy, an error prediction model has been constructed based on experimental study and the back-propagation neural network (BPNN) algorithm.

Findings – Currently, the implementation of the manipulator system has been successfully completed in both atmospheric and vacuum conditions. Validation of the BPNN model has demonstrated acceptable prediction accuracy (94%~98%) compared with actual measurements.

Originality/value – This is a specialized robot system that is practically applied in a nuclear fusion device in China. Its design, mechanism, and error prediction strategy provide significant reference value for similar robots in vacuum and temperature applications.

Full Text

Preamble

Mechanical Design and Error Prediction of a Manipulator System Applied in Nuclear Fusion Environment

Shanshuang Shi, Huapeng Wu
Laboratory of Intelligent Machines, Lappeenranta University of Technology, Lappeenranta, Finland

Yuntao Song
Institute of Plasma Physics, Chinese Academy of Sciences, Hefei, China, and Laboratory of Intelligent Machines, Lappeenranta University of Technology, Lappeenranta, Finland

Heikki Handroos

Abstract:

Purpose – This paper develops a serial redundant manipulator system for application in nuclear fusion environments, enabling remote inspection and maintenance of plasma-facing components within fusion device vacuum vessels without breaking the ultra-high vacuum condition during physical experiments.

Design/methodology/approach – First, considering the dynamic sealing of actuators to avoid contaminating the vacuum condition inside the fusion reactor, the mechanical design of the robot system is introduced. The redundant manipulator system features 11 degrees of freedom with an identical modular design. Additionally, to improve position accuracy, an error prediction model has been built based on experimental study and the back-propagation neural network (BPNN) algorithm.

Findings – Currently, implementation of the manipulator system has been successfully completed in both atmospheric and vacuum conditions. Validation of the BPNN model demonstrates acceptable prediction accuracy (94%~98%) compared with real measurements.

Originality/value – This is a specialized robot system practically deployed in a nuclear fusion device in China. Its design, mechanism, and error prediction strategy offer valuable reference for similar robots operating in vacuum and temperature-extreme applications.

Keywords: EAMA robot; experimental study; BP neural network; error prediction

1. Introduction

The Experimental Advanced Superconducting Tokamak (EAST) is the world's first fully superconducting tokamak fusion device with a non-circular cross-section, built in China [?]. In recent years, with increasing device performance and experimental parameters, EAST has achieved a series of important research results and scientific discoveries [?, ?]. However, EAST inner components face increasingly harsh operating environments with huge heat flux as plasma current during discharges becomes progressively higher. This leads to easy damage of plasma-facing components (PFCs), jeopardizing effective running time [?, ?].

Therefore, timely maintenance based on the condition of damaged internal components is essential during experimental periods.

The AIA robot is a related application specially developed for the ITER fusion reactor [?] and demonstrated in the Tore-Supra tokamak device [?]. It can inspect in-vessel components under 120°C and 10^{-6} Pa conditions. However, similar to the AIA robot, the EAST Articulated Maintenance Arm (EAMA) system experiences a maximum position error of 200 mm due to flexibility of its 10-meter cantilever structure [?]. This poor position accuracy means the robot can only operate in the middle of the vacuum vessel rather than performing close-range operations or even touching the tokamak wall from a safety perspective.

For the purpose of real-time detection and rapid repair of damaged internal components during plasma discharges, the EAMA system has been developed since 2013. It enables remote inspection and simple repair of PFCs in the EAST vacuum vessel (VV) without breaking the ultra-high vacuum condition (~10^{-5} Pa). Due to its long-reach mechanisms weighing over 100 kg, gravity effects cause significant flexible deformation, which is unacceptable for operation inside the narrow and complex-shaped EAST VV space. Figure 1 [Figure 1: see original paper] shows the cantilever structure of the fully assembled EAMA robot without end-effector and the finite element simulation results for position errors.

Elastic deformations due to gravity make robot trajectory planning quite complicated, especially for serial long-reach manipulators. Error prediction strategies must always be studied in advance when high accuracy is required. In fact, research on robotic flexibility has become a matter of great concern in recent years due to the pursuit of high accuracy and reliability. Normally, two methods can be considered for building flexible models for error prediction. On one hand, the mathematical model of flexible multibody dynamics can be derived from classical mechanics theories such as Newton-Euler formulation or Lagrange formulation. Then either the finite element method (FEM) or assumed modes method (AMM) can be used to truncate the dynamic formulations for rapid solution with appropriate accuracy [?]. On the other hand, for complex systems with several uncertain coupling factors, the flexible model can be identified using computing algorithms without considering complicated mechanical models and highly nonlinear formulations, such as fuzzy algorithms [?], genetic algorithms [?], or artificial neural network approaches [?].

For the EAMA manipulator case study, mathematical modeling using classical mechanics theories is difficult to achieve high accuracy and efficiency for two reasons. Firstly, the complicated mechanism, transmission chain, and multiple links make accurate flexible modeling quite difficult. Secondly, dynamic formulations with high nonlinearity are unnecessary as the manipulator speed is extremely low (less than 0.5 degree per second), meaning dynamic behaviors are slight enough compared with gravity effects. Therefore, static modeling can be a better choice for error prediction with relatively high accuracy.

This paper first introduces the conceptual design of the manipulator system. Then, an experimental study was deployed to measure errors of the EAMA prototype assembled with different loads through a load-deflection platform. Based on the experimental data, a static error prediction model was built and trained using the back-propagation neural network (BPNN) algorithm. The results show acceptable prediction accuracy with approximately 5% error compared with real measurements. Furthermore, the mathematical formulation for static loads of robot joints in arbitrary positions was derived. The calculated joint loads can be treated as input to the trained BPNN model to predict robot errors in arbitrary positions and postures without future experiments and measurements.

2. Manipulator System Design

The EAMA system consists of a highly redundant manipulator: one mobile base, five serial arms, and an end-effector (CCD cameras, gripper, etc.) for dedicated functional operations. Additionally, a storage cask facility has been developed to maintain equivalent vacuum environment for the manipulator before docking with the EAST vacuum vessel. Figure 2 [Figure 2: see original paper] shows an overall schematic view of the EAMA system, and robot specifications are given in Table 1 [**?**].

For the manipulator arms, an identical modular design with a parallelogram mechanism has been adopted for all five arm segments. Each segment provides both rotation and elevation motions by integrating yaw and pitch joints within one modular arm segment. As shown in Figure 3 [Figure 3: see original paper], the parallelogram structure comprises two clevises (yaw joints), horizontal rods, arm tubes, and diagonal rods (pitch actuator). The five-bar mechanism can produce a huge reduction ratio and withstand strong torques generated from the cantilever arms and gravity effects. Additionally, the yaw joint axis remains always vertical due to the motion characteristics of the parallelogram structure.

The motion actuators are placed inside robot tubes: rotation actuator connected to the tube while elevation actuator located in the diagonal of the parallelogram. To avoid polluting the ultra-high vacuum condition inside the EAST vacuum vessel, motion actuators with dynamic sealing considerations have been developed. All high-speed components (motors, gears, etc.) that require lubrication are sealed in boxes by welding SS bellows, allowing high-temperature grease to be used. Meanwhile, some low-speed components (joint bearings and bushes) use MoS_2-Ti-C coating films for solid lubricating. The detailed actuator design can be summarized as follows:

(1) Yaw actuator: As shown in Figure 4 [Figure 4: see original paper], two planetary roller screws first divide the rotation motion produced by a high-temperature motor and reducer into two parallel linear motions through a gear group. The two screws move at the same speed but in opposite directions due to opposite threads of the screw nut. The screws are then connected with two steel cables that deliver linear motions to the yaw joint rotation through bellows welded together with the seal box. The cables are finally assembled with a pulley system attached to the yaw joint to produce rotation motion. The entire transmission process can be summarized as a "rotation-linear-rotation" chain. Two benefits are provided by this chain: dynamic sealing to protect vacuum condition and huge reduction ratio to generate sufficient driving torque (1:30820 from motor to yaw joint).

(2) Pitch actuator: As shown in Figure 5 [Figure 5: see original paper], the pitch actuator has a similar "rotation-linear-rotation" chain to the yaw actuator. The difference is that only one roller screw is used here to transfer rotation to linear motion. Since the pitch actuator is located in the diagonal position, changes in diagonal length cause the entire parallelogram structure to elevate while other links' lengths remain fixed. The reduction ratio can reach up to 1:51660.

Currently, all manipulator components have been developed, and the complete EAMA robot system was successfully implemented in the EAST vacuum vessel (Figure 6 [Figure 6: see original paper]).

3. Experimental Study

Compared with industrial robots, the EAMA system exhibits more significant position errors caused by flexibilities of long-reach links as well as complicated joints and transmission chains. Accurate theoretical models for error prediction are difficult to build because the factors affecting system stiffness are multiple and time-varying. Therefore, a load-deflection platform was developed for experimental study of manipulator flexible properties. Figure 7 [Figure 7: see original paper] illustrates the platform design. Three types of external loads (mass in y-direction, torques along x and z axes) as system inputs were applied to the EAMA modular arm prototype. Correspondingly, three position error components (deflections in x and y directions, angles along z axis) were measured by Laser Tracker. Finally, 272 sets of load-deflection data under different loads were recorded, which serve as samples to train the BPNN prediction model.

4. BPNN Prediction Model

In a BPNN algorithm, several strongly coupled neurons approximate nonlinear functions. The learning process can be summarized in two steps [**?**]. First, training data is input to a multi-layer network to obtain relevant output. Two functions are used: a linear transfer function with different weights and thresholds (Eq. 1) and a sigmoid activation function (Eq. 2). Second, an error is calculated by comparing the output with expected values (normally obtained from experimental measurements). The error is then propagated backwards through the network to modify weights and thresholds of the coupled neurons, with modification rules always aiming to reduce error.

For error prediction of the EAMA manipulator, a final three-layer network was built with the topological structure shown in Figure 8 [Figure 8: see original paper]: (1) 4 neurons in input layer: θ – the pitch angle of robot, T_z – the torque along z axis, T_x – the torque along x axis, F_y – the equivalent gravity; (2) Single hidden layer with 8 neurons; (3) 3 neurons in output layer: the errors of end clevis in different directions (Δx, Δy and $\Delta\theta_z$).

The 272 sets of sample data were divided into two parts: 243 sets were utilized for network training (70% for training, 15% for testing, and 15% for validation), and 29 additional measurement data were utilized to check prediction accuracy of the trained BPNN model.

The mathematical model was established using the Neural Network toolbox in Matlab environment. The network training function is Traingdx, which automatically adjusts learning rate based on the classical BP algorithm [**?**]. Training ended at epoch 6751 when mean squared error converged to 6.7717e-5 (Figure 9 [Figure 9: see original paper]).

To evaluate prediction performance of the trained BPNN model, the extra 29 sets of load data were calculated by the offline BPNN model using trained weights and thresholds listed in Table 2 and Table 3 . Figure 10 [Figure 10: see original paper] shows the fitting between predicted and measured values, indicating prediction error ranging from 2% to 6% (Figure 11 [Figure 11: see original paper]). Considering the significant flexibility and complicated structure of the EAMA manipulator, this prediction accuracy is acceptable. The trained BPNN model can be integrated into the control system to compensate deflection errors and improve final position accuracy.

5. Formulation of Static Loads

Since the EAMA manipulator motion speed is quite slow (less than 0.6 deg/second), dynamic characteristics are not significant when considering payloads on each joint. To simplify calculation, static loads due to gravity were derived using the model built in Figure 12 [Figure 12: see original paper]. With these load results, deflections of all segments can be predicted using the trained BPNN model from the previous section.

Considering static loads on the end point O_i of Link i, the gravity load can be easily written as Eq. 3:

$$F_{yi} = \sum_{j=i}^{n} m_j g$$

For the torques, the effect on Link i caused by Link j was first considered as Eq. 4, where the torque is divided into two parts representing torque along x and y axes in the local coordinate system of Link i-CS(i):

$$T_{ij} = \vec{r}_{ij} \times (m_j \vec{g})$$

Here, $\vec{r}_{ij}$ is the position vector of point P_j (mass center of Link j) with respect to point O_i in CS(i), while $\vec{r}_{ij}$ can be derived into Eq. 5, where ${}^{i}T_j$ is the transfer matrix from CS(i) to CS(j) obtained using the D-H method [?], and $\vec{r}_{Pj}$ is the position vector of mass center P_j in CS(j), determined by the geometry and mass properties of Link j:

$$\vec{r}_{ij} = {}^{i}T_j \vec{r}_{Pj}$$

Combining Eq. 4 and Eq. 5, the total torque applied on the end point O_i of Link i can be derived as:

$$T_i = \sum_{j=i}^{n} T_{ij}$$

With these formulations, static loads on each joint can be calculated when the manipulator position is known. These loads can be treated as input to the trained BPNN model for error evaluation without requiring future experiments and measurements.

6. Conclusions

An articulated manipulator system for fusion environments has been developed in China for real-time detection and rapid repair of damaged internal components in the EAST tokamak device. This paper first introduced the mechanical design of the EAMA system, including the modular parallelogram mechanism and the "rotation-linear-rotation" actuator design for dynamic sealing. Additionally, to predict and compensate flexible errors due to gravity effects, a load-deflection platform for the EAMA prototype was built. Based on 272 sets of deformation data, a BPNN model was established using the Neural Network toolbox in Matlab environment. After training, the fitting between BPNN-predicted and experimentally measured values indicates a prediction error range from 2% to 6%. Finally, static loads of each manipulator link were formulated, which can be integrated with the BPNN model for error evaluation in the control system. The conceptual design and error prediction strategy introduced in this paper provide beneficial reference for similar robotic applications in vacuum and temperature-extreme conditions.

Acknowledgements

This work was supported by the National "973" Program of China (Chinese ITER Special Support Project, No. 2014GB101000), funding from the China Scholarship Council, and a collaboration framework between ASIPP China and LUT Finland.

References

Wan, Y., Li, J., and Weng, P. (2006), "First engineering commissioning of EAST tokamak", *Plasma Science and Technology*, Vol. 8 No. 3.

Li, J., Guo, H. Y., Wan, B. N., Gong, X. Z., Liang, Y. F., Xu, G. S., … & Zeng, L. (2013), "A long-pulse high-confinement plasma regime in the Experimental Advanced Superconducting Tokamak", *Nature Physics*, Vol. 8 No. 3, pp. 817-.

Wang, H. Q., Xu, G. S., Wan, B. N., Ding, S. Y., Guo, H. Y., Shao, L. M., … & Naulin, V. (2014), "New edge coherent mode providing continuous transport in long-pulse h-mode plasmas", *Physical Review Letters*, Vol. 112 No. 18, pp.

Yang, Z., Fang, J., Gong, X., Gan, K., Luo, J., Zhao, H., and Chen, M. (2016), "The study of heat flux for disruption on experimental advanced superconducting tokamak", *Physics of Plasmas (1994-present)*, Vol. 5 No. 23, pp. 052502.

Li, W. X., Song, Y. T., Ye, M. Y., Peng, X. B., Wu, S. T., Qian, X. Y. and Zhu, C. C. (2016), "Thermo-mechanical and damage analyses of EAST carbon divertor under type-I ELMy H-mode operation", *Fusion Engineering and Design*, Vol. 105, pp. 15-21.

Gargiulo, L., Bayetti, P., Bruno, V., Hatchressian, J.C., Hernandez, C., Houry, M., Keller, D., Martins, J.P., Measson, Y., Perrot, Y. and Samaille, F. (2009), "Operation of an ITER relevant inspection robot on Tore Supra tokamak", *Fusion Engineering and Design*, Vol. 84 No. 2, pp.

Shimomura, Y., Aymar, R., Chuyanov, V., Huguet, M., and Parker, R. (1999), "ITER overview". *Nuclear Fusion*, Vol. 39 No. 9Y, pp. 1295.

Perrot, Y., Gargiulo, L., Houry, M., Kammerer, N., Keller, D., Measson, Y., Piolain, G. and Verney, A. (2012), "Long-reach articulated and mini-invasive robots interventions in hazardous environments: Recent robotics research, qualification testing, and tool inspection developments", *Journal of Field Robotics*, Vol. 29 No. 1, pp. 175-185.

Dwivedy, S. K. and Eberhard, P. (2006), "Dynamic analysis of flexible manipulators, a literature review", *Mechanism and Machine Theory*, Vol. 41 No. 7, pp. 749-777.

Schiavo, A. L. and Luciano, A. M. (2001), "Powerful and flexible fuzzy algorithm for nonlinear dynamic system identification", *IEEE Transactions on Fuzzy Systems*, Vol. 9 No. 6, pp. 828-835.

Chang, W. D. (2007), "Nonlinear system identification and control using a real-coded genetic algorithm", *Applied Mathematical Modelling*, Vol. 31 No. 3, pp. 541-550.

Liu, G. P. (2012), "Nonlinear identification and control: a neural network approach", Springer Science & Business Media.

Shi, S., Song, Y., Cheng, Y., Villedieu, E., Bruno, V., Feng, H. … and Wang, K. (2016), "Conceptual design and main progress of EAST Articulated Maintenance Arm (EAMA) system", *Fusion Engineering and Design*, Vol. 104, pp. 40-45.

Negnevitsky, M. (2005), "Artificial intelligence: a guide to intelligent systems", Pearson Education.

Shi, Y., Zhao, X. T., Zhang, Y. M., and Ren, N. Q. (2009), "Back propagation neural network (BPNN) prediction model and control strategies of methanogen phase reactor treating traditional Chinese medicine wastewater (TCMW)", *Journal of Biotechnology*, Vol. 144 No. 1, pp. 70-.

Denavit, J., & Hartenberg, R. S. (1955). "A kinematic notation for lower-pair mechanisms based on matrices", *Journal of Applied Mechanics*, vol. 22, pp. 215–221.

Note: Figure translations are in progress. See original paper for figures.