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NEURAL NETWORK SOLUTION FOR DIRECT AND INVERSE KINEMATIC ANALYSIS OF 3PRC PARALLEL MANIPULATOR

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Abstract
Artificial Neural Networks (ANNs) have an ability to provide a relationship between inputs and outputs. This paper presents ANN-based kinematic modeling of a three degrees of freedom translational parallel manipulator (TPM) with Prismatic(P), Revolute(R) and Cylindrical (C) joints in each of the three legs is termed as 3-PRC TPM. In order to avoid the computational complexity of solving the kinematics problem in real-time application, two artificial neural networks are trained to estimate the forward and inverse kinematics solutions of the 3PRC manipulator. The obtained results shows that the ANN model can provide an accurate kinematic solution and can these can be useful in the controller design.
Keywords: ANN, PRC, modelling, MLP

I. Introduction

Among the applications of parallel robots, the one that may have the largest economic impact is in machine tools. The first milling machine was presented by the Giddings and Levis Company (now part of Thyssen Krupp) at the IMTS machine tool exhibition in Chicago 1994; it was main attraction under the name Variax. It was designed based on the of the Gough platform. According to the manufacturer, despite the machine contains 6 degrees of freedom, it was 5 times stiffer than a classical machine and has superior advance speed. A new type of manipulator with 3-PRC topology actuated by fixed actuators is proposed to achieve three pure translational DOF. The fixed actuators make it possible that the moving components of the manipulator do not bear any loads of the actuators. This enables large powerful actuators to drive relatively small structures in order to facilitate the design of manipulators with faster, stiffer, and stronger characteristics. Additionally, being an over constrained mechanism, the 3-PRC TPM [1] is constructed using fewer links and joints than it is expected, and possesses a much simpler structure than most of the existed TPMs, that leads to an extensive reduction in cost and complexity. Because of the closed structure of parallel manipulators, the kinematic control of such a mechanism is difficult. The inverse kinematics problem for such manipulators has a mathematical solution but, the forward kinematics problem (FKP) is mathematically intractable. In the forward kinematic solution of a 3dof spatial manipulator uses Sylvester dialytic elimination method to reduce the system of equations established by geometric constraints in to a 16 th degree polynomial in one variable, consequently there are a total of 16 sets of solutions. In this method finding a real time solution by eliminating others is a difficult and time-consuming task. For the real time application and control of parallel manipulators a multi-layer perceptron (MLP) NN structure with feed forward back propagation algorithm is trained and tested for 3PRC parallel manipulator.

II. Literature

Kim et al [2] proposed the inverse kinematics, forward kinematics and workspace determination of a 3-DOF parallel manipulator with a SPR joint structure. An effective approach was developed for the solution of the inverse kinematics task in analytical form, for the given end effector positions. A method for workspace determination, which uses the numerical solution of forward kinematics task, is presented. Brogardh et al [3] proposed a 3-DOF Parallel Kinematic Machine of a large motion range in the Z axis for machine tool application. The direct and inverse kinematics problems were solved in order to implement the real time control of the machine tool. The kinematics results were validated numerically. The singularity analysis was carried out by the reciprocal screw theory. From their work, the authors concluded that the solution of direct kinematics will be affected when the structure is in a singular position, and a reasonable arrangement of geometric dimension is important to avoid singularity. Yangmin Li and Qingsong Xu [4] proposed static analysis of 3-PRC. Artificial neural networks (ANN) have attracted many researchers for solving forward kinematic problems and control of manipulators, due to their considerable potentials to approximate nonlinear functions. Koker et al [5] presents neural network solution for the inverse kinematics of a manipulator. They have designed neural network to solve the inverse kinematics problem and the designed neural network have been simulated for the given cubic trajectory planning according to the given Cartesian coordinates. Sadjadian et al [6] they have used the neural networks with different structures for solving the forward kinematics of parallel manipulators it involves with highly complex nonlinear equations. The accuracy of the results obtained in various structures is analyzed in detail. Li et al [7] presented a method how to use neural networks for computing the forward kinematics of spherical parallel manipulator for laparoscopic surgery application. Instead of solving a set of nonlinear equations for the forward kinematics, neural networks are used to map the input angles of revolute joints to the orientation of the manipulator. The training data are obtained from inverse kinematic relationships and measured from the experimental prototype model of the manipulator. Levenberg-Marquardt algorithm is used to train the neural networks, which leads to the fast convergence of the networks. The trained neural network models of forward kinematics are used in the real time interface between the graphical model and a haptic device for the laparoscope's surgery training applications. Xu et al [8] , Alandhar et al[9] and Kumar et al [10] presented the forward kinematics of 3DOF parallel manipulator using artificial neural network (NN) approach. Based on the trained NN, the kinematic control of the manipulator is carried out by resorting to an ordinary control algorithm. Simulation results illustrate that the NN can approximate the forward kinematics perfectly.

2.1 Architecture Description

The computer aided design (CAD) model and schematic diagram of a 3-PRC TPM is shown in Fig. 1. It consists of a mobile platform, a fixed base, and three limbs with identical kinematic structure. Each limb connects the fixed base to the mobile platform by a P joint, a R joint, and a C joint in sequence, where the P joint is driven by a linear actuator assembled on the fixed base. Thus, the mobile platform is attached to the base by three identical PRC linkages. The following mobility analysis shows that in order to keep the mobile platform from changing its orientation, it is sufficient for the three axes of joints within the same limb to satisfy some certain geometric conditions. That is, (i) the R joint axis (r i) and C joint axis (c i) within the itch limb, for i =1, 2, and 3. The design specifications for the modelling and stiffness analysis are given in Table.1.

Table.1 Design Parameters

Parameter	Value(m)	Parameter	Value(deg)
a	0.6	Α	45
b	0.3	β	120
l	0.7	ϒ	240
d_{max}	0.4		
s_{max}	0.2		

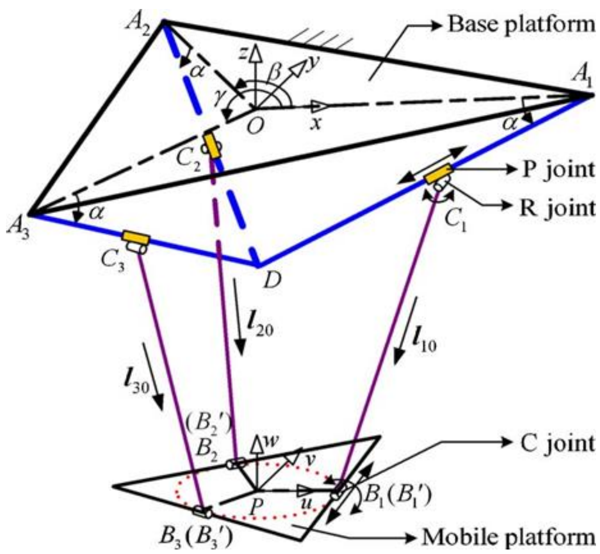

Fig.1 Architecture of 3PRC manipulator

2.2 NN Solution for forward kinematics of 3PRC

In order to train NN structure for solving direct kinematics of 3PRC parallel manipulator, 3000 data points are selected randomly from the workspace of the manipulator. The displacements of the prismatic joints are solved for the selected end-effecter configurations by solving the inverse kinematics and finally the MLP (multi-layer perceptron) is trained with IKP solutions. A MLP network with feed forward back propagation (BP) learning in combination with Levenberg -Marquardt training algorithm is adopted for solving the direct kinematics of the manipulator. The input actuator displacements d1,d2,d3 are fed to the three nodes of the input layer. Similarly three nodes of output variables px, py ,pz . The multi-input and multi output network response can be generalized by the set of input and output pairs. Various MLP network structures are tested by varying the network parameters such as number of hidden layers, number of neurons in the hidden layer for attaining an efficient network configuration.

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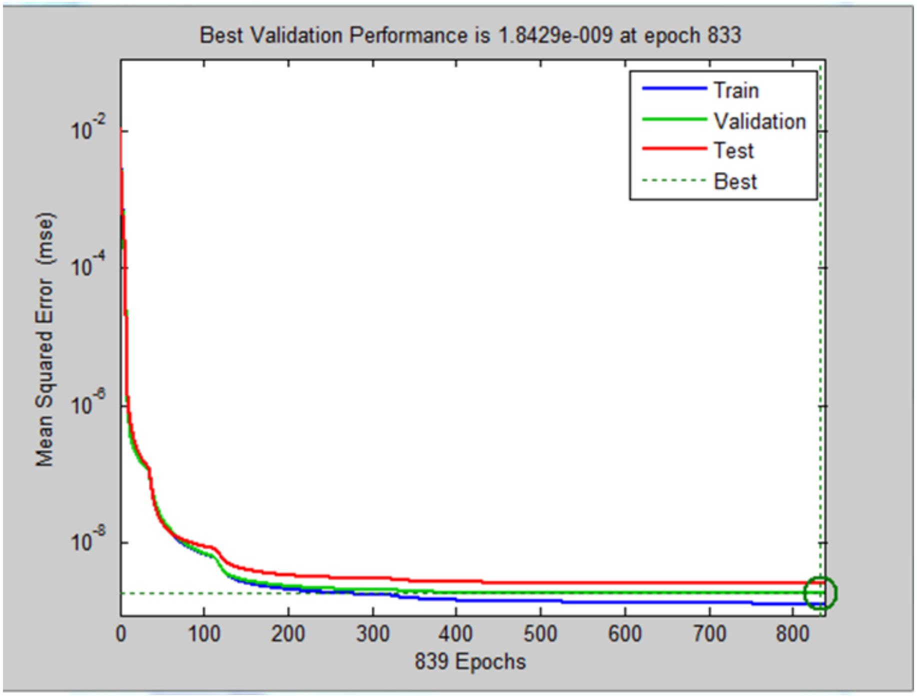

Fig.2 Performance of MLP

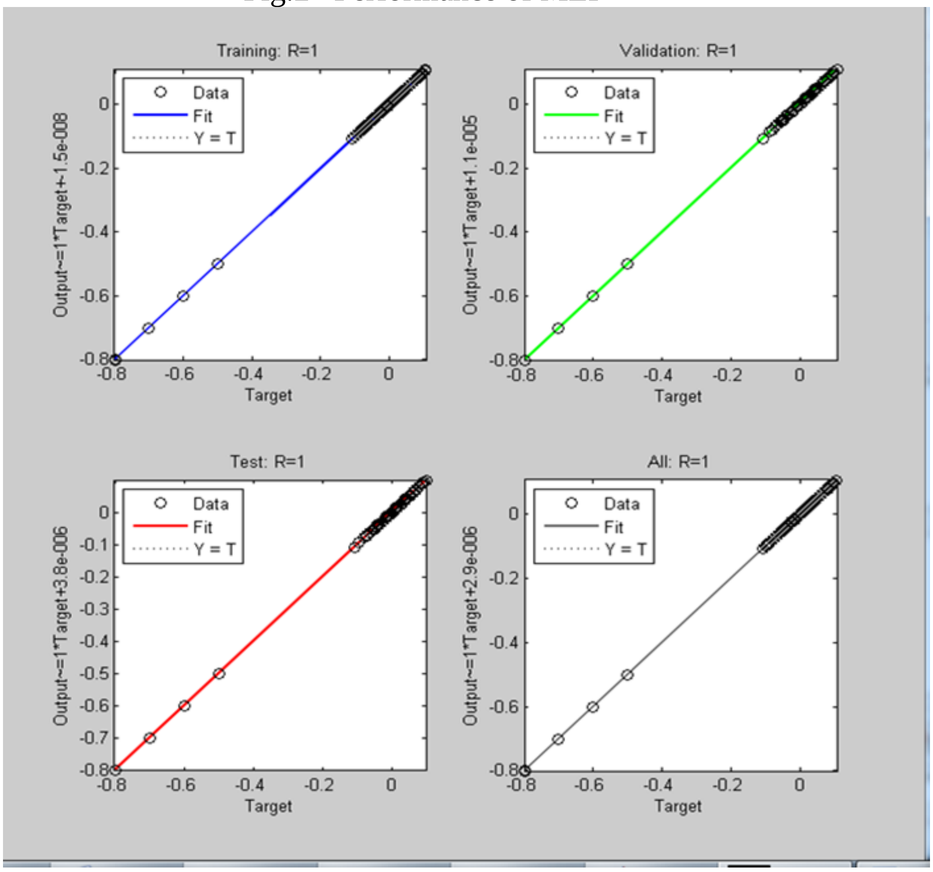

Fig.3 Regression plot of MLP

The tangent sigmoid, linear transfer functions are considered in the hidden and the output layers respectively. The performance measures mean square error (MSE), sum squared error (SSE) and auto correlation coefficient (R) are considered to estimate the performance of NN structures. It is observed that the networks having lesser number of hidden layers with fewer neurons are to be considered for efficient network configuration. The NN configuration having two hidden layers with neurons 12, 10

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in first and second layers respectively is observed as the efficient NN structure, it yields performance measures of MSE=1.3e-09, SSE=4.12 and auto correlation coefficient R=1. The performance plot for the above NN configuration is shown in Fig.8.12, from which it is observed that the training, testing and validation curves have good consistency. The MLP structure have attained the best validation performance of 1.8429e-009 at epoch 833. The regression plot for training, validation and testing is also shown in Fig.2 and Fig.3, it yields the overall regression coefficient (R) of 1.

2.3 Simulation of NN for FKP Solution

Best representative structure of MLP is tested for a given trajectory within the typical workspace. The simulated network outputs and targets for a given trajectory are shown in Fig 3, Fig.4, Fig.5 for each position variable px, py, pz respectively. The approximate errors for px, py, pz coordinates using the multi-layer perceptron (MLP) neural network are found to be 2mm, 3mm, 2mm respectively. The desired and targets are very close to each other showing minimal errors for each output variables of the 3PRC parallel manipulator. For the given input variables here the prismatic joint variables d_1, d_2, d_3 can be predicted the end-effector position variables p_x, p_y, p_z . The errors between the desired and predicted values is almost less than 1% for p_x, p_z coordinates, whereas the errors between the desired and predicted values for p_y coordinate is 1% . Not only limited to specific trajectory points, for all the reachable workspace points the same error is observed. A MLP network with feed forward back propagation (BP) yields a good solution approximation to all inverse and direct kinematic solutions.

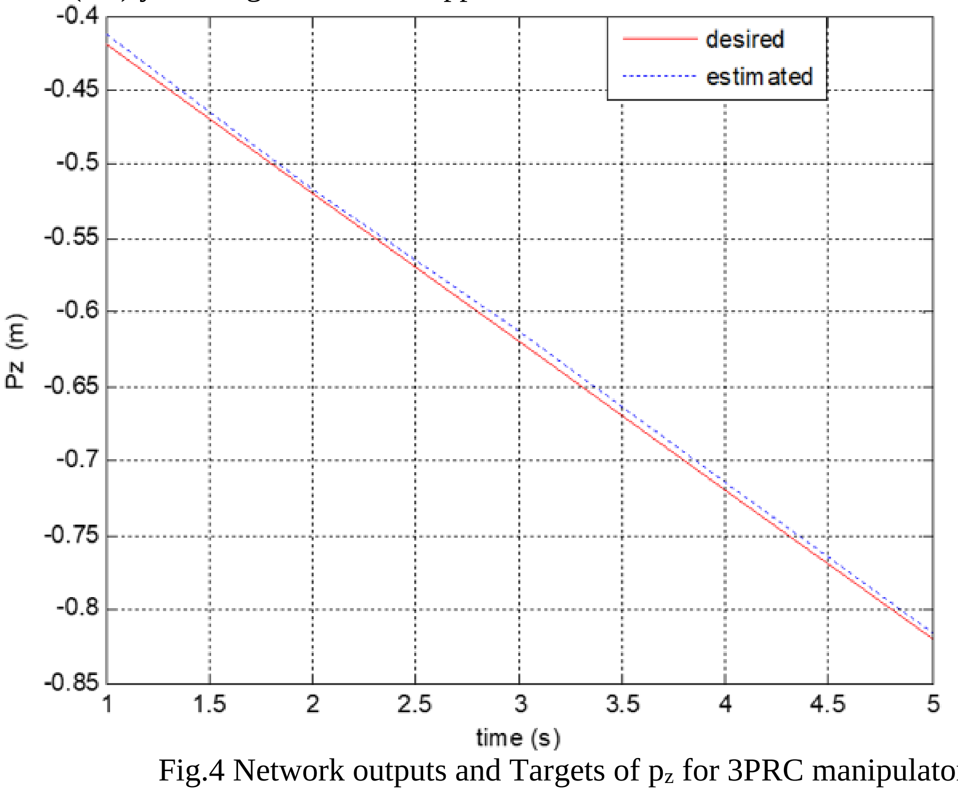

Fig.4 Network outputs and Targets of p_z for 3PRC manipulator

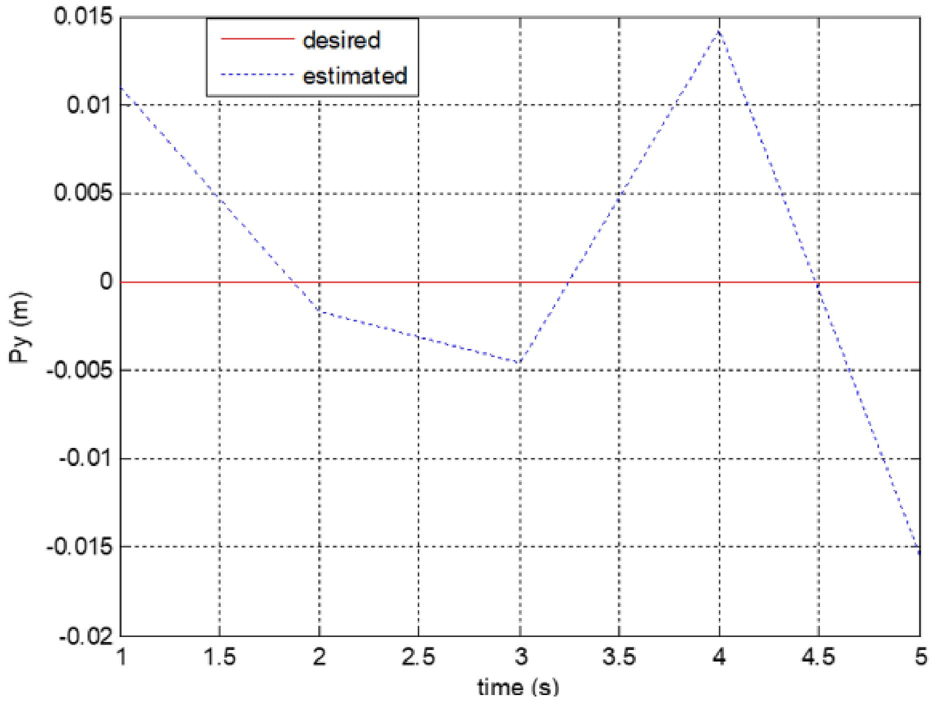

Fig.5 Network outputs and Targets of py for 3PRC manipulator

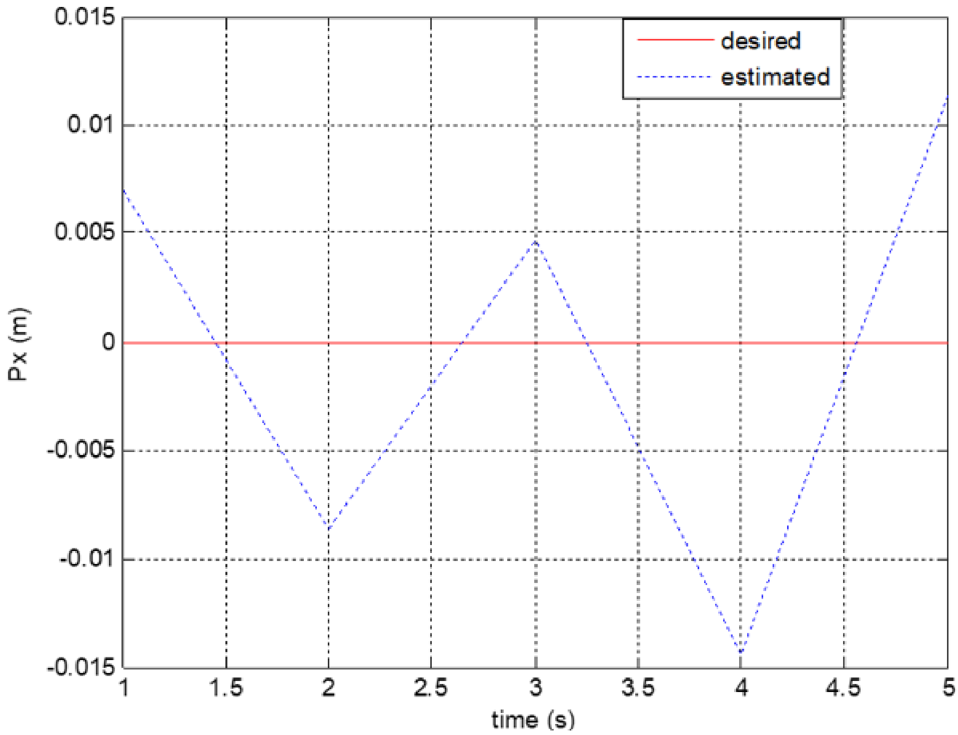

Fig.6 Network outputs and Targets of px for 3PRC manipulator

III. Conclusion

A novel 3-PRC manipulator with fixed actuators is modelled as per the design parameters and workspace of manipulator is generated in CAD environment. The MLP structure for 3PRC parallel manipulator is provided on successful training and testing using the MATLAB Neural network Toolbox. The NN based forward kinematic solution prediction model can be useful tool for the manufacturing engineers to estimate the motion of the manipulator precisely. The network simulated results for the given specific path yields an error of 1% only.

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