# 로봇 캘리브레이션을 위한 뉴럴네트워크 기반 위치오차 예측

# Neural Network Based Prediction of Positioning Error for Robot Calibration

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## 1. Introduction

Robot calibration is well-known as a remedy to improve robot position accuracy by software than hardware [1]. Robot calibration can be classified into parametric [1,2] and non-parametric methods [3,4]. Because of simplicity and effectiveness, the non-parametric methods are applied widely.

There are many works related to robot calibration (or compensation) using non-parametric methods [3,4]. However, it is concluded that it is not really effective because in their studies the position of end-effector is used as input for interpolation in non-parametric method while robot end-effector position error (as output) practically depend on the robot joint configuration (as input).

This paper presents an artificial neural network based prediction of robot end-point error, which naturally depends on robot joint configuration, for purpose of calibration. We consider that the endpoint position error is a function of robot joint angles. Then determination of position error is considered as an black box problem by employing a neural network. The input of the black box is robot joint angle and the out put is position error. The simulation is carried out for a 3 DOF robot manipulator to demonstrate the effectiveness of proposed method. Also, comparison is performed for both NN-based and non-parametric method, the simulation result shows that the former archives more accurate prediction over the latter (accuracy is improved significantly over 85% of the average value).

## 2. Robot Kinematic Model

A 3 DOF serial robot manipulator, of which schematic is shown in Fig.1, was used in the simulation. A kinematic model of 3 DOF robot is formulated to obtain forward kinematic solution. The DH (Danevit Hartenberg) parameters [1], and frames assignments are also shown in the Fig.1. The nominal values of DH parameters are listed in Table 1. It is assumed that, the assumed real robot has geometric errors { $\delta\alpha_0 = 0.8$, $\delta\alpha_1 = 0.5$, $\delta\alpha_2 = 0.4$, $\delta a_0 = 1$, $\delta a_2 = 1$, $\delta a_3 = 0.5$, $\delta d_1 = 2$, $\delta d_4 = 0.4$, $\delta\theta_1 = 0.8$, $\delta\theta_2 = 0.5$, $\delta\theta_3 = 0.4$, angle [deg], length [mm] } and also suffers the joint compliance at joints 2, 3 by gravitational forces.

Table 1. Nominal parameter of simulated robot; angle [deg], length [mm]

| Joint | $\alpha_{i-1}$ | $a_{i-1}$ | $\beta_{i-1}$ | $b_{i-1}$ | $d_i$ | $\theta_i$ |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 350 | $\theta_1$ |
| 2 | 90 | 0 | 0 | 0 | 0 | $\theta_2$ |
| 3 | 0 | 260 | 0 | 0 | 0 | $\theta_3$ |
| 4 | 0 | 240 | 0 | 0 | 0 | 0 |

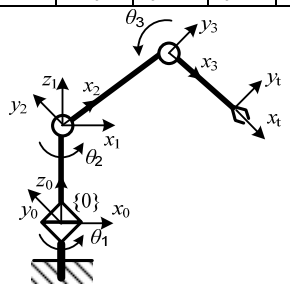


Fig.1 Schematic of 3 Degree of freedom Robot

To describe the robot end-effector pose in term of robot base coordinate frames, the forward kinematic solution for robot is calculated by performing the homogenous transformation from base frame {0} to tool frame {t} by matrix multiplication as follows:

$$ {}^{0}_{t}\boldsymbol{T} = {}^{0}_{1}\boldsymbol{T}\,{}^{1}_{2}\boldsymbol{T}\,{}^{2}_{3}\boldsymbol{T}\,{}^{3}_{t}\boldsymbol{T} , \quad (1) $$

where

$$ {}^{i-1}_{i}\boldsymbol{T} = Rot(x,\alpha_{i-1}) * Trans(x,a_{i-1}) * Trans(z,d_i) * Rot(z,\theta_i), \quad , \; i = 1 \div 4 $$

and $\alpha_{i-1}, a_{i-1}, d_i, \theta_i$ are joint offset, link twist, link length, link offset of link i, respectively. so, endpoint position is a function of robot parameters $\boldsymbol{p}$ and set of joint angles $\boldsymbol{\theta}$, which is derived by according entries of row 1 to 3 of column 4 of matrix equations (1).

$$\boldsymbol{P} = \boldsymbol{f}(\boldsymbol{p}, \boldsymbol{\theta}), \quad (2)$$

Given joint encoder readings, the predicted position of endpoint $\boldsymbol{P}_c$ is calculated by (2) and the according measured robot endpoint position $\boldsymbol{P}_m$ by using laser tracker measuring devices, the endpoint position error vector is computed as:

$$\Delta\boldsymbol{P} = \boldsymbol{P}_m - \boldsymbol{P}_c, \quad (3)$$

where $\boldsymbol{P}_m$ , $\boldsymbol{P}_c$ are measured and computed endpoint $[3 \times 1]$ position vector, respectively.

The set of pairs $\{\boldsymbol{\theta}(k), \Delta\boldsymbol{P}(k)\}$ ( $k = 1 \div n_m$ ; $n_m$ : number of measurement configurations) is used as training set for the NN

The model-based method is studied widely in previous works [1,2], in these works the least square algorithm is used as optimization tool to identify physical robot parameters. The kinematic calibration is applied to the simulated robot by adopting previous research [1,2] for purpose of comparing with the performance of the proposed NN method.

## 2. Neural Network and Network Training

In this paper, a used NN consists of an input layer (3 nodes for joint encoders), a hidden layer and an output layer (3 nodes for endpoint position error), as presented in Fig.2a. In the simulation, number of hidden layer neurons is optimized with 20 nodes. The transfer functions of neurons on the hidden layer and output layer are log sigmoid and linear, respectively.

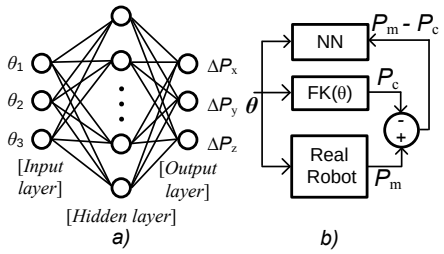


Fig 2. a) Neural network model and b) Network training

The feed-forward back propagation method is used to training the network with the pairs, joint encoder readings and robot endpoint error $\{\boldsymbol{\theta}(k), \Delta\boldsymbol{P}(k)\}$, Fig.2b.

## 3. Simulation and Result

Simulation is performed to verify the effectiveness of the method. Positions of a total 252 configurations which cover the whole robot workspace were measured and their according joint encoder readings were recorded. The proposed method was evaluated by calculating distance between the measured position and predicted position obtained by (2). The residual distance errors after training NN, calculated by (4), is shown in the second column of Table 2 with two figures mean and maximum on according rows. The performance of the proposed algorithm was compared to that of least square method. The compensated robot by using conventional algorithm, the residual distance errors values are shown in third column of Table 2. The position accuracy in the former case improved significantly over the latter case 85% of the average value.

$$\varepsilon = \sqrt{\left(P_{mx} - P_{cx}\right)^2 + \left(P_{my} - P_{cy}\right)^2 + \left(P_{mz} - P_{cz}\right)^2} \quad (4)$$

Table 2. the residual distance error between measured and predicted position [mm]

| Distance error | NN based prediction | Least square |
|---|---|---|
| Mean | 0.010977 | 0.073252 |
| Maximum | 0.029956 | 0.242740 |

## 4. Conclusion

This paper proposed an artificial neural network based prediction of robot end-point error which naturally depends on robot configuration for purpose of calibration. The relationship between the actual end-effector and the joint encoder are realized by using the neural network. The simulation result confirms that the proposed technique allow us to predict physical robot end-effector when given joint encoder readings. The comparison of proposed NN method and Least Square method shows the robot accuracy improvement of the first one over the second one.

## Reference

1. Omodei A., Legnani G., "Calibration of a Measuring Robots: Experimental Results on a 5 DOF Structure, " Journal of Robotic Systems, **18**, 237-250, 2001.
2. Driels M. R., Swayze W. E., "Automated Partial Pose Measurement System for Manipulator Calibration Experiments," IEEE Trans. on Robotics, **10**, no. 4, 430-440, 1994.
3. Takanashi N., "6 DOF Manipulator Absolute Positioning Accuracy Improvement Using a Neural-network," IEEE Int. Workshop on IRS, 635-640, 1990.
4. Wang D., Bai Y, "Improving Position Accuracy of Robot Manipulators Using Neural Networks," IEEE Control Systems, 17-19, 2005.