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Artificial neural network based geometric error correction model for enhancing positioning accuracy of a robotic sewing manipulator

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Abstract

In order to meet the requirements of extensive and fast fashion changes in the customer demand, there is a need for high flexibility in automation of sewing process. Currently, industrial robots are involved to perform skilful sewing tasks in garment manufacturing; however, it is difficult to achieve the required precision during sewing of typical of geometric shapes in the fabrics due complex mechanical behaviour of fabric materials and geometric errors in the robotic links. In order to control sewing path and its deviation from the desired trajectory, a neural network based approach for predicting the position error correction of a 2R robot manipulator using inverse and forward kinematics models. A simulation study has been performed to investigate the effect of geometric errors of the link lengths on the positioning accuracy of the manipulator in MATLAB environment. Performance of the proposed approach for improved tracking of typical geometric shapes such as circle is demonstrated using simulation results.

Keywords: Geometric errors; Robot manipulator; Positioning errors; Compensation; Neural network; Kinematic model

1. Introduction

In worldwide product pricing, complex shaped products and the increasing need for skilled labor; garment manufacturers are currently using industrial robots for automating the sewing process. In a robot assisted sewing system, with a custom end effector to hold a fabric while the sewing machine feeds the fabric using a typical sewing dog system [1]. The robotic handling of non-rigid materials such as fabrics is a very complicated problem due to the unpredictable behavior of the fabrics. During stitching, the fabric slips and buckles due to its nonlinear mechanical characteristics of the fabric material and it requires the precise position and force control to keep the fabric in the required tension for producing the neat stitch. It becomes more difficult for the curved shapes due to the changing

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directions and curvature during stitching [2]. Also the typical robotic systems exhibit positioning errors in the end effector due to geometric and non-geometric errors [3]. The positioning error of the end effector needs to be corrected for avoiding distortion in the desired seam position and improving the geometric accuracy of robotic stitching process.

Frank Paul used machine vision to detect the edge of a piece of fabric, design a seam path at an offset to that edge and determine the location of the end effector on the fabric. Errors due to link length, non-parallel axes, base misalignment, manufacturing errors cause geometric errors which affect the positioning accuracy of the end effector. Calibration models based forward and inverse kinematic configurations of robots have been proposed for position error correction in the end effector [3]. The kinematics of three DOF was presented for the worse limb of the humanoid robot, finding position and orientation was the solution of kinematics; the joint sequences were presented by Denavit-Hartenberg (DH) transformation matrices [4]. These methods require precise model parameters such as D-H parameters and its estimation using sensors and instrumentation systems. The complexity of the kinematic model increases with higher DOF due to robot geometry, non-linear equations (i.e. trigonometric equations occurring when transforming between Cartesian and joint spaces) and singularity problems. Further, in presence of geometric errors and parameter uncertainties, model based calibration techniques leads to larger errors in compensation accuracy. New approaches using Fourier polynomial, inverse distance weighting, rigging and artificial neural networks (ANN) have been proposed by the researchers to predict the position errors [5]. Among the various methods, Artificial neural network based approaches have been shown lot of interest by many researchers due to its learning capability and adaptability for position error correction in robot end effectors. An inverse kinematic solution for a PUMA 560 robot was calculated by the training neural network with the robot's end effector Cartesian coordinates and its equivalent joint configurations a position error compensation method based on the extreme learning machine model is proposed for enhancing absolute position accuracy for aviation drilling robots [6]. Robot manipulator calibration was proposed using neural network and a camera-based measurement system. A kinematic model and laser tracking system is used for compensating the non-geometric errors in a robotic system. A calibration method using an extended Kalman filter algorithm and an artificial neural network was proposed for enhancing robot accuracy [7]. A neural network based approach is proposed for hand-eye calibration and inverse kinematics of robot arm [8].

It is found that the use of robots to flexibly handle the fabrics during the sewing process [9]. However, the positioning accuracy of a typical robotic end effector is affected by geometric errors due to link length, non-parallel axes, base misalignment, manufacturing errors, assembly errors etc. [10]. Existing model based correction methods require extensive instrumentations such as laser tracking systems, imaging cameras and complex models [11] [12]. Current research works have focused on developing neural network based approaches for position error correction due its learning capability and adaptive nature. This work presents a neural network based position error correction model for a robotic end effector to improve the geometric accuracy in sewing process.

Nomenclature

l_1	Length of link 1
l_2	Length of link 2
l_1'	Change in original link length of l_1
l_2'	Change in original link length of l_2
P_x	Position of end effector in X direction
P_y	Position of end effector in Y direction
P_{xr}'	real position of end effector in X direction
P_{yr}'	real position of end effector in Y direction
ΔP_x	Position error values of end effector in X direction
ΔP_y	Position error values of end effector in Y direction
θ_1	Angular Position of Link 1with respect to reference axis
θ_2	Angular Position of Link 2with respect to reference axis

2. Kinematic model of robotic sewing manipulator with geometric errors

In the present work, a robot manipulator with two revolute joints (2R) is considered for sewing two dimensional planar geometries in the fabrics. Here the end effector holds the sewing head with the needle and the schematic diagram of the robotic sewing system is shown in Fig.1. Typical geometric errors due to improper assembly, link deformation, wear at the joints, leads to position errors in the end effector and it affects the geometric accuracy of sewing process. Hence a kinematic model of robot is required for describing the relationship between the joint angles and the position, orientation of its end effector.

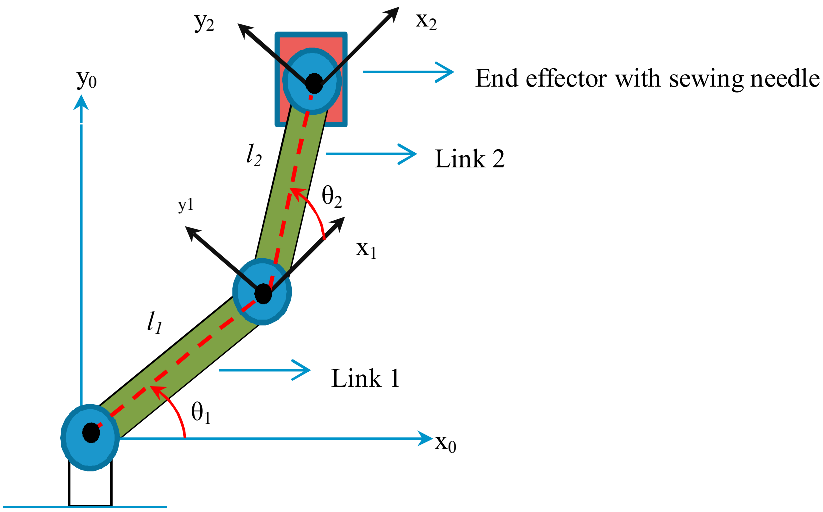

Fig. 1. Configuration of a 2R planar manipulator with D-H link parameters for sewing process.

To perform the kinematic analysis, it is assumed that each joint has a single degree-of-freedom rotation. Coordinate frames (x_0, y_0) (x_1, y_1) (x_2, y_2) are attached to each link as shown in Fig.1 for understanding the position and orientation end effector. Considering the geometric errors in the links, forward and inverse kinematic models are developed in this section using the conventionally followed D-H conventions of robot arms.

2.1 Forward kinematics model

Using the given rotational position of the links (θ_1, θ_2), forward kinematics model is used to identify the coordinates of the end effector in the workspace. Based on the trigonometric principles, the position of the end effector in X and Y axis for the given joint angle (θ_1, θ_2) and link lengths (l_1, l_2) is derived as given by Equations (1) and (2).

$$P_x = (l_1 + l_2 \cos\theta_2)\cos\theta_1 - l_2 \sin\theta_2 \sin\theta_1 \tag{1}$$

$$P_y = l_2 \sin\theta_2 \cos\theta_1 + (l_1 + l_2 \cos\theta_2)\sin\theta_1 \tag{2}$$

In these equations, P_x, P_y refers to the theoretical position of the end effector in X and Y axis, l_1, l_2 represents the ideal link lengths. θ_1, θ_2 are the joint angles of the respective links. The forward kinematic model is useful for identifying the workspace for the 2R robot.

2.2 Effect of geometric errors in link length

Due to improper assembly, link deformation, wear at the joints, the link lengths of the robotic arm differs from the nominal values and it leads to position errors in the end effector. The effect of change in link length is addressed by real link length l'_1, l'_2 and its effect on position of the end effector in X and Y axis is calculated using the following equations:

$$P_{xr'} = (l'_1 + l'_2 \cos\theta_2)\cos_1 - l'_2 \sin\theta_2 \sin\theta_1 \quad (3)$$

$$P_{yr'} = l'_2 \sin\theta_2 \cos\theta_1 + (l'_1 + l'_2 \cos\theta_2)\sin\theta_1 \quad (4)$$

Here P'_{xr}, P'_{yr} refers to the real position of the end effector in X and Y axis considering the geometric errors in the link lengths. Using the equations (1), (2), (3) and (4), the position errors in the end effector in X and Y directions due to the change in link length can be calculated as given by equations (5) and (6).

$$\Delta P_x = P_{xr'} - P_x \quad (5)$$

$$\Delta P_y = P_{yr'} - P_y \quad (6)$$

These equations are useful for determining the position errors of the end effector in the workspace for the given change in link length of the robot.

2.3 Trajectory planning and Inverse Kinematics

For sewing the specified planar geometries like circle, square and also other complex geometries in the fabrics, the end effector needs to be moved at the in the desired position in the workspace. An inverse kinematics model is derived to find the required joint angles to be given to the links for achieving the desired position of the end effector. Using the trigonometric principles, the joint angles of the links for the given position of the end effector is derived and it is given by equations (7) and (8).

$$\theta_2 = \pm a\tan\frac{\sin\theta_2}{\cos\theta_2} \quad (7)$$

$$\theta_1 = a\tan\frac{(l_1 + l_2\cos\theta_2)P_y \mp l_2\sin\theta_2 P_x}{(l_1 + l_2\cos\theta_2)P_x \pm l_2\sin\theta_2 P_y} \quad (8)$$

For sewing user specified planar geometries, these equations are useful for motion control of joints to move the end effector at the specified locations. The derived inverse and forward kinematic models are useful determining the position error values at the given the coordinates of workspace. However, position error of the end effector in X and Y directions will lead to distorted sewing at the specified location and it needs to be corrected for improving the geometric accuracy of sewing process.

3 Proposed ANN based feed forward approach for position error correction in robotic sewing process

In the proposed approach, a feed forward control frame work is followed for the correcting the position errors associated with the target coordinates to be sewed by the robot manipulator in the work space. A neural network is trained to predict the position error in the workspace for the given input coordinates of the planar geometry to be sewed in the fabrics. Frame work of the proposed approach for position error correction in the robot manipulator is shown in Fig.2. An artificial neural network model is developed in the MATLAB environment for mapping the input coordinates of workspace (P_x, P_y) and the corresponding position error values *(ΔPx, ΔPy)* as the output data.

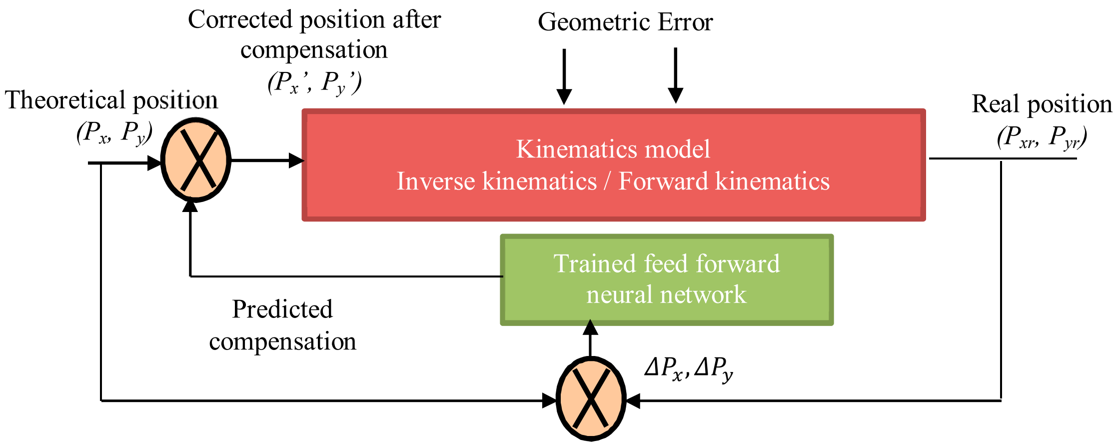

Fig. 2. Proposed methodology for position error correction using ANN in the robot manipulator.

3.1 Compensation of position error

In this approach, the corrected position of workspace coordinates (P'_x, P'_y) are calculated according to the predicted position error values ($\Delta Px, \Delta Py$) by the trained ANN as given below. These values are given as the target coordinates to the robot manipulator for sewing the geometry in the fabrics.

$$P'_x = \Delta P_x + P_{xr'} \tag{9}$$

$$P'_y = \Delta P_y + P_{yr'} \tag{10}$$

3.2 Training of neural network for prediction of position error

In order to train the neural network for prediction of position error, a simulated data set for the input position coordinates (P_x, P_y) and the corresponding position error values ($\Delta P_x, \Delta P_y$) is generated using the forward and inverse kinematic models considering the geometric errors in the link length as described in section.2. Fig. 4 shows the input-output architecture of the proposed neural network with 10 hidden neurons, 2 inputs as workspace coordinates (P_x, P_y) and 2 outputs ($\Delta P_x, \Delta P_y$) as the corresponding position errors in the workspace coordinates.

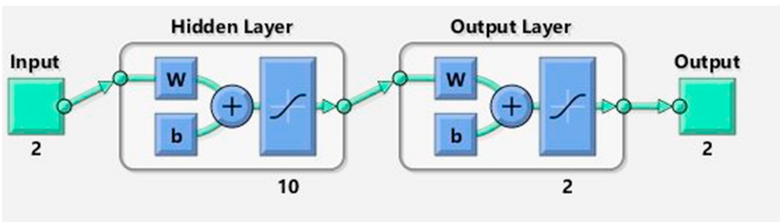

Fig. 3. Artificial neural network architecture.

The training of the ANN uses back propagation algorithm which changes the weight of a connection between neurons the network includes the input and target values in the training data set and tries to reduce the difference between the target and output values. The error is minimized during many training cycles named epoch. While training this network, the weights and bias values are updated with each batch (epoch) until the lowest mean squared error value is reached.

4. Simulation results and discussion

In order to study the performance of the proposed approach, a simulation study has been performed in the MATLAB environment using the developed kinematic models and neural network. In order to analyse the position error in the end effector due to geometric error, a simulated data set is generated using the derived kinematic models based on the ideal D-H parameters of link lengths $l_1 = l_2 = 0.5$m and $l'_1 = 0.4999$m $l'_2 = 0.4998$m. This data set is used for training the neural network for predicting position error values in the workspace. Further, the proposed approach is applied position error correction of circle and the results are presented in this section.

4.1 Theoretical workspace for the robotic sewing manipulator

Forward kinematic model is used for identifying the theoretical workspace for the 2R robot and it is shown in Fig.4. It can be seen that workspace coordinates shows the curvilinear paths due to revolute nature of the joints of 2R robot. We can also determine task space for sewing application of typical planar geometry using the workspace.

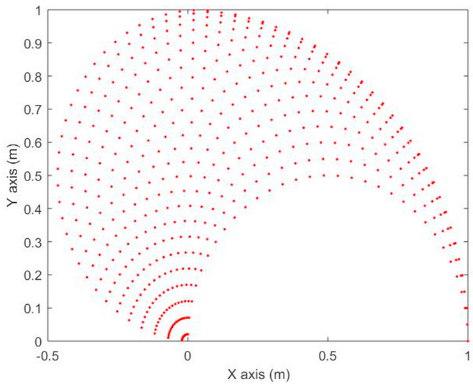

Fig. 4. Simulated workspace of 2R robot for the link length of $l_1 = l_2 = 0.5$m.

4.2 Effect of change in D-H parameter on positioning error of end effector

The real position coordinates of end effector are simulated using the forward kinematic model with real D-H parameters shown Table 2. Simulation results for the position error values of end effector in X and Y direction due to change in link lengths are shown in Fig. 5. (a) and (b). It can be seen that the maximum position error in X and Y axis is found to be 300 microns and 300 microns respectively. The sample values of position error in the work space are shown in Table 1.

Table 1. Effects of geometric error in link length and the position error in the workspace

S.No	P_x(m)	P_y(m)	P_x'(m)	P_y'(m)	ΔP_x(μm)	ΔP_y(μm)
1	1.000000	0.000000	0.99970	0.000000	300.0000	0.000000
2	0.997502	0.049917	0.997203	0.049897	299.0008	19.96668
3	0.990033	0.099335	0.989737	0.099295	296.0133	39.73387
4	0.977668	0.14776	0.977377	0.147701	291.0673	59.10404
5	0.96053	0.194709	0.960246	0.194631	284.2122	77.88367
6	0.938791	0.239713	0.938516	0.239617	275.5165	95.88511
7	0.912668	0.282321	0.912403	0.282208	265.0671	112.9285
8	0.882421	0.322109	0.882168	0.32198	252.9684	128.8435
9	0.848353	0.358678	0.848114	0.358535	239.3413	143.4712
10	0.810805	0.391663	0.810581	0.391507	224.322	156.6654

It can be seen that there is an increasing trend in position error when the coordinates are increasing in X and Y axis. These errors will affect the geometric accuracy of sewing and it needs to be corrected by the proposed neural network.

(a) (b)

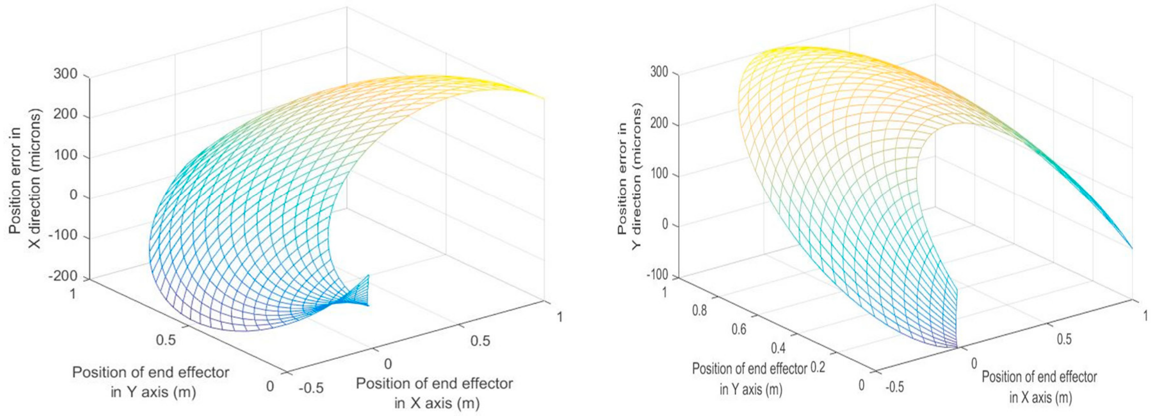

Fig. 5. (a) Position error of the end effector in X direction; (b) Position error of the end effector in Y direction.

4.3 Training results of neural network for prediction of position error

Simulated workspace coordinates and the position error values of robotic sewing manipulator with link length of $l'_1 = 0.4999m$; $l'_2 = 0.4998m$ is used for training the neural network in MATLAB Neural network tool box. The training results are shown in Fig. 6. (a) and (b). It can be seen that the training, testing and validation and correlation between the target values and output of the neural network is 0.99 which indicates the performance of the neural network for the accurate prediction of position error. The mean squared error value is found to be 1.9352 x 10-7.

(a) (b)

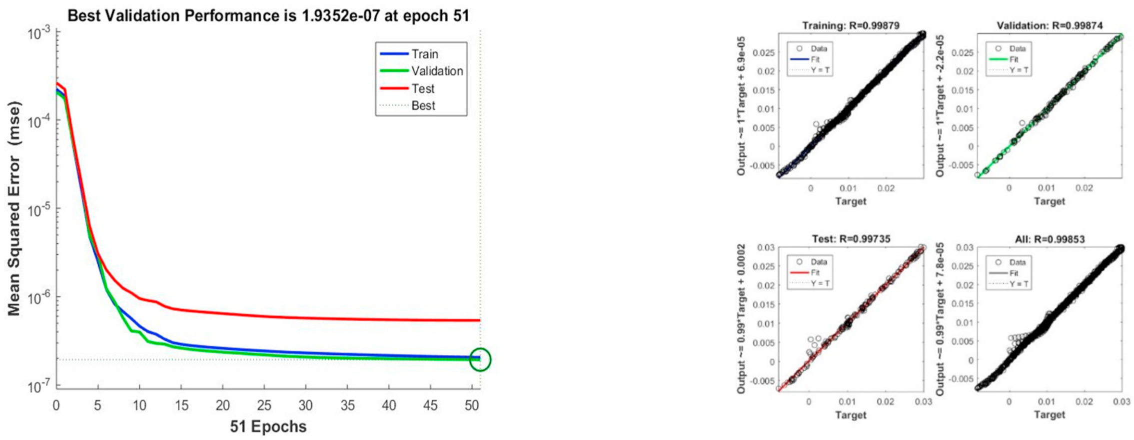

Fig. 6. (a) Training results of proposed best validation; (b) Neural network model for prediction of position error.

4.4 Application of proposed position error correction approach for sewing circle geometry

The coordinates of the circle is generated using the parametric equation with the radius of the circle as 0.2m. The trained neural network is applied for predicting the position error values of sewing circle. The simulation results of the proposed approach for correcting position error in circle are shown in Fig.7.

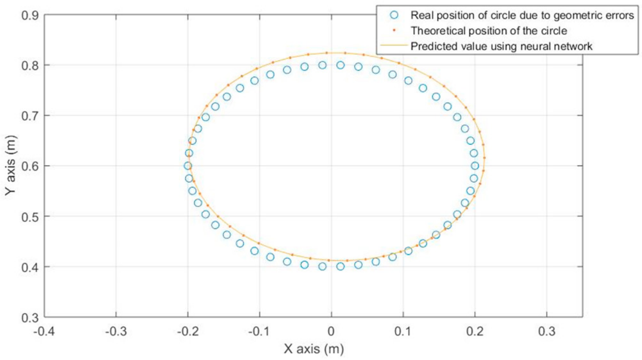

Fig.7. Simulation results of proposed approach for position error correction of circle.

It can be seen that the before correction the robot manipulator shows the distorted circle from the theoretical position. However, the proposed approach exactly follows the circle after correcting the position error due to the change in length in the link. Proposed approach can be easily implemented with minimum instrumentations in the robotic systems for improving the positioning accuracy of end effector.

Conclusions

This paper presented a neural network based approach for correcting position errors of the end effector in a robotic sewing process. A two revolute link length configuration is considered in the present work for sewing planar geometries. Kinematic models for analysing the effect of change in link length using D-H parameters are derived and presented. Position error of the end effector due to the change in link length is simulated using the derived kinematic models and it is further used for training the neural network to predict the position errors in the coordinates of the workspace. Simulation results indicate that the change in link length of 0.0001 m, 0.0002 m, respectively results in the maximum position error of the end effector in X and Y axis of 300 microns and 300 microns respectively. A neural network based feed forward control strategy has been followed for correcting the position errors in the end effector. It is found that the proposed approach corrects the position error due to the change in link length of 2R robot. This approach can be implemented for improving the positioning accuracy of end effector in robotic sewing process.

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