Development of Cloud Action for Seamless Robot Using Backpropagation Neural Network

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Abstract

This paper presents the cloud action model for a five DOF Seamless robotic arm using the inverse kinematics solution based on artificial neural network (ANN). Levenberg-Marquardt method is used in training algorithm. The desired position and orientation of the end effector is defined as the input pattern of neural network. In addition, we propose the cloud action which is the movement patterns of the robotic arm. The cloud action platform is created in order to perform the basic behaviors of the Seamless robot such as "Catch", "Approach", "Interest", "Look around", "Alert" and "Avoid" actions. Experimental results show the suitable structure of artificial neural network used for solving the inverse kinematics equation, and the testing points in the robot's workspace were verified with the robotic arm.

Keywords: Inverse kinematics solution, Artificial neural network, Levenberg-Marquardt method.

1. Introduction

Nowadays, the service robot technology is developing and advancing rapidly. Therefore, our researches have concentrated on exploring and studying an artificial intelligent method to create the behavioral and emotional models of the autonomous robot [1] - [3]. The new model for our robot is the dynamic behavior selection model based on emotional states which develops from the Consciousness-Based Architecture (CBA) model combined with Self-Organizing Map (SOM) learning and Markovian model. However, it seems to be the efficient model of the autonomous robot, but we face some problems in posturing the behavior and expressing the emotion of the robot.

Consequently, in this paper, we present the cloud action which is the movement patterns of Seamless robotic arms. The cloud action platform is created in order to perform the behavior of robot smoothly. In addition, we introduce the performance of the training algorithm which is Levenberg-Marquardt learning algorithm [4] that is used for solving the inverse kinematics problem of the Seamless robotic arms.

This paper is organized as follows: Section 2 provides the kinematic modeling of Seamless robotic arm. Section 3 of the paper explains the neural network for determining the inverse kinematics solution. Section 4 describes the process of the cloud action model. Section 5 shows the experimental results of the proposed model, and finally, Section 6 concludes the paper.

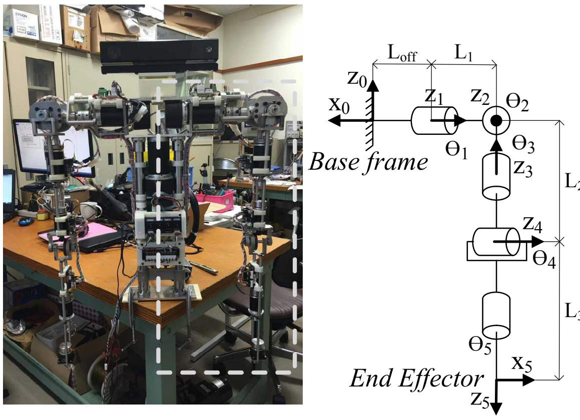

Fig.1 Seamless robotics arm (Left arm)

Table 1. The DH parameters for Seamless robotics arm (Left arm)

Joints	Θ_i	d_i	a_i	α_i
1	Θ_1	$-(L_1+L_{off})$	0	90
2	Θ_2+90	0	0	90
3	Θ_3+90	L_2	0	90
4	Θ_4	0	0	-90
5	Θ_5+90	L_3	0	0

2. Kinematics modeling of Seamless robotic arm

For this research work, Seamless robot in our robotics laboratory is being used shown in Fig.1. Actually, it has two arms, but in this case, we only present the left arm for considering and determining the forward and inverse kinematics solutions. Denavit-Hartenberg (D-H) method [5] is used to derive its kinematics. Fig.1 shows the joints and links of the left side of robotic arm, which has the base frame, shoulder, elbow, and wrist. The DH parameters of the robotic arm are listed in Table 1. According, DH method, the transformation can be formed in the chain product of five homogenous matrices ${}^{i-1}_{i}T$ as expressed by Equation (1).

$$ {}^{0}_{5}T = {}^{0}_{1}T\,{}^{1}_{2}T\,{}^{2}_{3}T\,{}^{3}_{4}T\,{}^{4}_{5}T \quad (1)$$

Where, $\sin\theta_i = s_{\theta_i}$ and $\cos\theta_i = c_{\theta_i}$.

The homogeneous transformation matrix of Seamless robotic left arm can be shown in Equation (2).

$$ {}^{0}_{5}T = \begin{bmatrix} n_x & o_x & a_x & p_x \\ n_y & o_y & a_y & p_y \\ n_z & o_z & a_z & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

In Equation (2) indicates the elements of rotational of transformation matrix ($n_x, n_y, n_z, o_x, o_y, o_z, a_x, a_y, a_z$) and the elements of position vector (p_x, p_y, p_z). All elements can be solved as follows:

$$\begin{aligned}
n_x &= -c_{\theta_5+90}(c_{\theta_2+90}s_{\theta_4} - s_{\theta_2+90}c_{\theta_3+90}c_{\theta_4}) \\
&\quad - s_{\theta_2+90}s_{\theta_3+90}s_{\theta_5+90} \\
n_y &= -c_{\theta_5+90}(c_{\theta_4}(c_{\theta_1}s_{\theta_3+90} - s_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) - s_{\theta_1}s_{\theta_2+90}s_{\theta_4}) \\
&\quad - s_{\theta_5+90}(c_{\theta_1}c_{\theta_3+90} + s_{\theta_1}c_{\theta_2+90}s_{\theta_3+90}) \\
n_z &= -c_{\theta_5+90}(c_{\theta_4}(s_{\theta_1}s_{\theta_3+90} + c_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) + c_{\theta_1}s_{\theta_2+90}s_{\theta_4}) \\
&\quad - s_{\theta_5+90}(s_{\theta_1}c_{\theta_3+90} - c_{\theta_1}c_{\theta_2+90}s_{\theta_3+90}) \\
o_x &= s_{\theta_5+90}(c_{\theta_2+90}s_{\theta_4} - s_{\theta_2+90}c_{\theta_3+90}c_{\theta_4}) \\
&\quad - s_{\theta_2+90}s_{\theta_3+90}c_{\theta_5+90} \\
o_y &= s_{\theta_5+90}(c_{\theta_4}(c_{\theta_1}s_{\theta_3+90} - s_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) - s_{\theta_1}s_{\theta_2+90}s_{\theta_4}) \\
&\quad - c_{\theta_5+90}(c_{\theta_1}c_{\theta_3+90} + s_{\theta_1}c_{\theta_2+90}s_{\theta_3+90}) \\
o_z &= s_{\theta_5+90}(c_{\theta_4}(s_{\theta_1}s_{\theta_3+90} + c_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) + c_{\theta_1}s_{\theta_2+90}s_{\theta_4}) \\
&\quad - c_{\theta_5+90}(s_{\theta_1}c_{\theta_3+90} - c_{\theta_1}c_{\theta_2+90}s_{\theta_3+90}) \\
a_x &= -c_{\theta_2+90}c_{\theta_4} - s_{\theta_2+90}c_{\theta_3+90}s_{\theta_4} \\
a_y &= s_{\theta_4}(c_{\theta_1}s_{\theta_3+90} - s_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) + s_{\theta_1}s_{\theta_2+90}c_{\theta_4} \\
a_z &= s_{\theta_4}(s_{\theta_1}s_{\theta_3+90} + c_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) - c_{\theta_1}s_{\theta_2+90}c_{\theta_4} \\
p_x &= -(L_1 + L_{off}) - L_2c_{\theta_2+90} - L_3(c_{\theta_2+90}c_{\theta_4} + s_{\theta_2+90}c_{\theta_3+90}s_{\theta_4}) \\
p_y &= L_2s_{\theta_1}s_{\theta_2+90} \\
&\quad + L_3(s_{\theta_4}(c_{\theta_1}s_{\theta_3+90} - s_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) + s_{\theta_1}s_{\theta_2+90}c_{\theta_4}) \\
p_z &= -L_2c_{\theta_1}s_{\theta_2+90} \\
&\quad + L_3(s_{\theta_4}(s_{\theta_1}s_{\theta_3+90} + c_{\theta_1}c_{\theta_2+90}c_{\theta_3+90}) - c_{\theta_1}s_{\theta_2+90}c_{\theta_4})
\end{aligned}$$

3. Neural network based the inverse kinematics solution

Solving the inverse kinematics problem is one of the most important task in robot kinematics and control. The complexity of this problem is obtained from the robot's geometry and the nonlinear trigonometric equations. Therefore, there are three traditional techniques used for determining inverse kinematics problem that can be

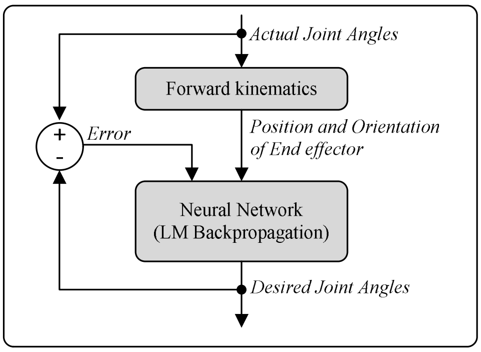

Fig.2 Neural Network based inverse kinematics solution

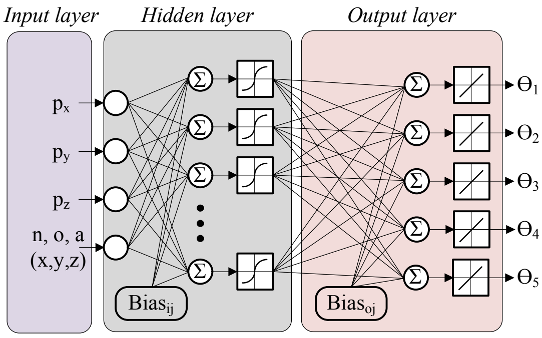

Fig.3 Multi-layered perceptron neural network structure

classified as algebraic, geometric and numerical algorithms. These methods are time consuming, incorrect initial estimation, the inverse kinematics cannot be guaranteed and heavy computational calculation. Consequently, another method can solve the inverse kinematics problems that is Neural Networks. It is possible to formulate the nonlinear mathematical model. Many researchers have verified with this approach in several works [6] - [8].

4. Cloud action of Seamless robotic arm

After solving the inverse kinematics problem base on Neural Network, We try to generate the trajectory path between the target position and the end effector position. But trajectory path of Seamless robotic arm differs from the existing trajectory paths, because Seamless robot that is used to perform the suitable behavior and express the intelligent emotion. Therefore, Cloud action model is introduced in this paper. The procedure of the Cloud action can explain by the following steps:

Table 2. Results of each Neural Network structure

In hidden layer (Hidden node)	Epoch	MSE	Regression
30	205	51.6	0.99291
32	145	51.3	0.99293
34	193	51.2	0.99295
36	238	51.3	0.99293
38	276	51.2	0.99295
40	**167**	**50.9**	**0.99296**
42	230	52.0	0.99286
44	254	52.1	0.99284

Step 1: Determine the straight line (distance) between the target object and end effector position.
Step 2: Find the center point of each behavior on the straight line. Then, the sphere of each action is created, depending on the rate action.
Step 3: Verify the response action for selecting the group action.
Step 4: Random the point in the selecting workspace based on the random distribution technique.

5. Experimental results

In this study, Seamless robotic arm was used to verify the movement of the robot based on Cloud action model. In Fig.2 shows the process of inverse kinematics solution. Levenberg-Marquardt method (trainlm) from MATLAB toolbox was used to train and update the weight and bias values, because it is the fastest back propagation neural network algorithm (Supervised learning). The designed neural network model is illustrated in Fig.3. The Multi-layered perceptron neural network model consists of 12 node inputs (the position vector and nine elements of rotation matrix), 5 node outputs and only one hidden layer. For training and testing data of neural network that was determined by the equation of each element in Equation (2). A work space data set 33880 data. While 80% of the data set was set as the training data, 10% to validation and 10% data for testing data. Table 2 shows the experiment results of the suitable structure of Neural Network based inverse kinematics solution for Seamless robotic arm. After modeling the neural network to calculate the inverse kinematics solution, the movement paths of robotics arms were verified by the Cloud action method as shown in Fig.4.

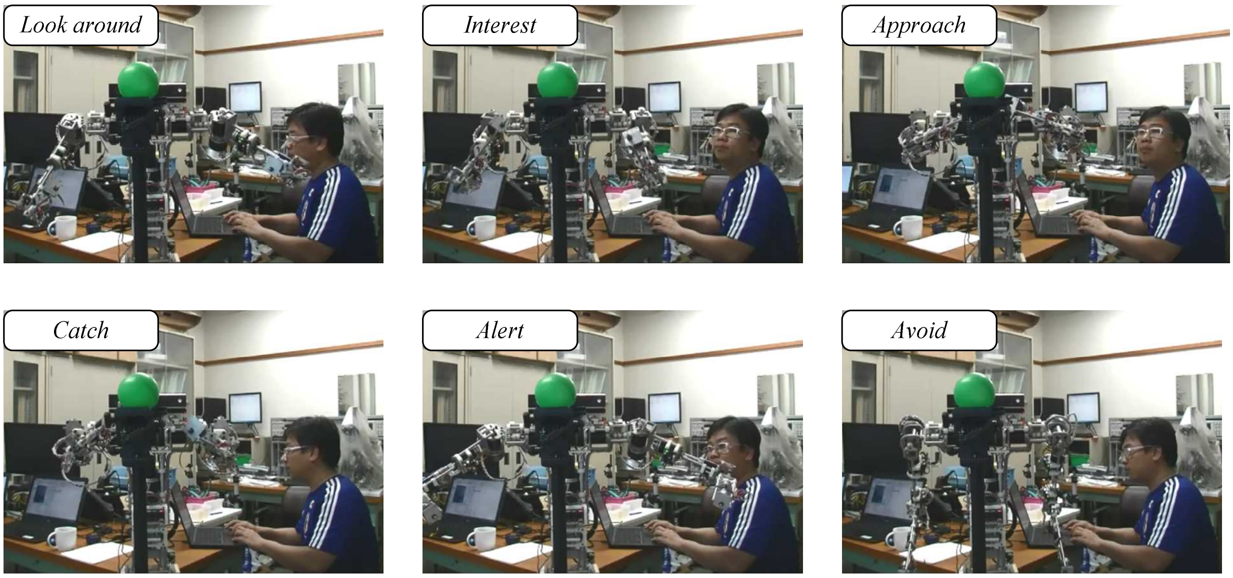

Fig.4 Results of the six actions with cloud action model

6. Conclusions

In this paper, we propose the new control system for designing and developing a 5 DOF revolute robot arm, using a backpropagation neural network and the cloud action model. Results have shown that the Seamless robot arm can move randomly in the workspace of the six basic actions. For future work, we would like to improve this model into the conventional action selection system (Consciousness-Based Architecture (CBA) model combined with Self-Organizing Map (SOM) learning and Markovian model), in order to create the intelligent service robot perfectly.

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