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신경회로망을 이용한 3관절 로봇 손가락의 역기구학

Inverse Kinematics of Robot Fingers with Three Joints Using Neural Network

김병호

경성대학교 전기전자메카트로닉스공학부 생체모방제어 및 로봇 연구실
E-mail: kimbh@ks.ac.kr

요 약

The inverse kinematics problem in robotics is an essential work for grasping and manipulation tasks by robotic and humanoid hands. In this paper, an intelligent neural learning scheme for solving such inverse kinematics of humanoid fingers is presented. Specifically, a multi-layered neural network is utilized for effective inverse kinematics, where a dynamic neural learning algorithm is employed. Also, a bio-mimetic feature of general human fingers is incorporated to the learning scheme. The usefulness of the proposed approach is verified by simulations.

Key Words : Inverse kinematics, Neural learning scheme, Humanoid hands

1. Introduction

In general, the grasping and manipulation tasks by multi-fingered hands should be realized by ultimately the combined actions of joints. Thus, a methodology to solve effectively the joint angles for the desired fingertip positions is necessary.

In practice, the joint configuration of a finger is very important for an object manipulation by multiple fingers. Actually, it is closely related to the dexterous control of hands. Especially, if a robotic finger is composed of a redundant mechanism, there exists a certain preferable configuration depending on the purpose of a given task, and it is not easy to take such an effective joint configuration due to the redundancy. So, some ideas have been proposed for solving the inverse kinematics of manipulators or fingers [1]-[3]. Yoshikawa and Chiu used a performance index such as a manipulability criterion or a compatibility index, respectively, to determine an effective posture of robot manipulators. These methods have an advantage to resolve the singularity posture of a manipulator as well as to avoid obstacles. However, unbalanced joint configurations can be made by such a performance index-based algorithm. Secco, *et al.* [3] solved the inverse kinematic problem for a prosthetic finger by adopting a physiological constraint between joints. Secco's method gives a simple closed-form solution, but it has a limitation to implement the realistic movement of human fingers. It is because the third joint of a humanoid finger should actuate identically as the second joint. Unfortunately, the motion range of those joints in a human finger is not identical [4][5]. Moreover, since the method doesn't consider the phalangeal length parameters, they may suffer from making a consistent grasp configuration in multi-fingered operations.

Thus, the inverse kinematics solution for effective positioning of a humanoid finger in grasping and manipulation tasks is still needed. In this paper, a method for obtaining the inverse kinematics solution by an intelligent multi-layered neural network is proposed.

2. INVERSE KINEMATICS SCHEME

2.1 Problem Formulation

Consider a humanoid finger manipulating an object as shown in Fig. 1.

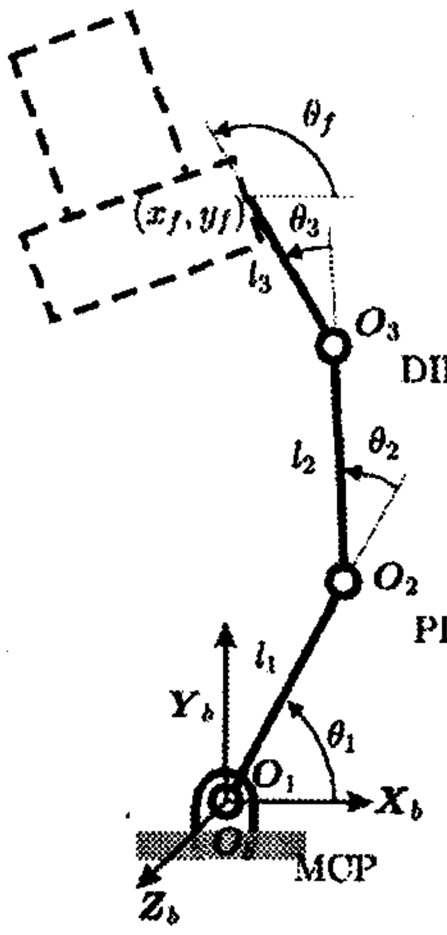

Fig. 1. A humanoid finger with three revolute joints: MCP: MetaCarpoPhalangeal, PIP: Proximal InterPhalangeal, and DIP: Distal InterPhalangeal joints [6].

In Fig. 1, the forward kinematic relations of the finger are described by

$$x_f = l_1\cos\theta_1 + l_2\cos\theta_{12} + l_3\cos\theta_{123} \quad (1)$$

$$y_f = l_1\sin\theta_1 + l_2\sin\theta_{12} + l_3\sin\theta_{123} \quad (2)$$

$$\theta_f = \theta_1 + \theta_2 + \theta_3 \quad (3)$$

where x_f and y_f denote the x- and y -directional fingertip positions, respectively, and θ_f represents the orientation of the fingertip, and $\theta_{ijk} = \theta_i + \theta_j + \theta_k$.

From (1)~(3), it is natural that the fingertip position and its orientation are definitely determined when each joint angle of the finger has been given. By the way, its reverse work is usually necessary in an object grasping and manipulation tasks by multi-fingered hands. That is, it is required to obtain each joint angle when the grasping positions of fingers have been assigned. This is called as inverse kinematics which is basically required to control the finger and it is very important to form a proper grasp configuration. On the other hand, it is well-known that the multi-layered neural networks can be applied to obtain an optimal solution by learning strategy [7].

Thus, this paper aims to provide a solution of the inverse kinematics for such humanoid fingers by utilizing an intelligent neural network-based learning technology.

2.2 Multi-layered Neural Learning Scheme

The proposed intelligent neural learning scheme for the inverse kinematics of a humanoid finger with three joints is shown in Fig. 2, where the neural network is constructed as Fig. 3.

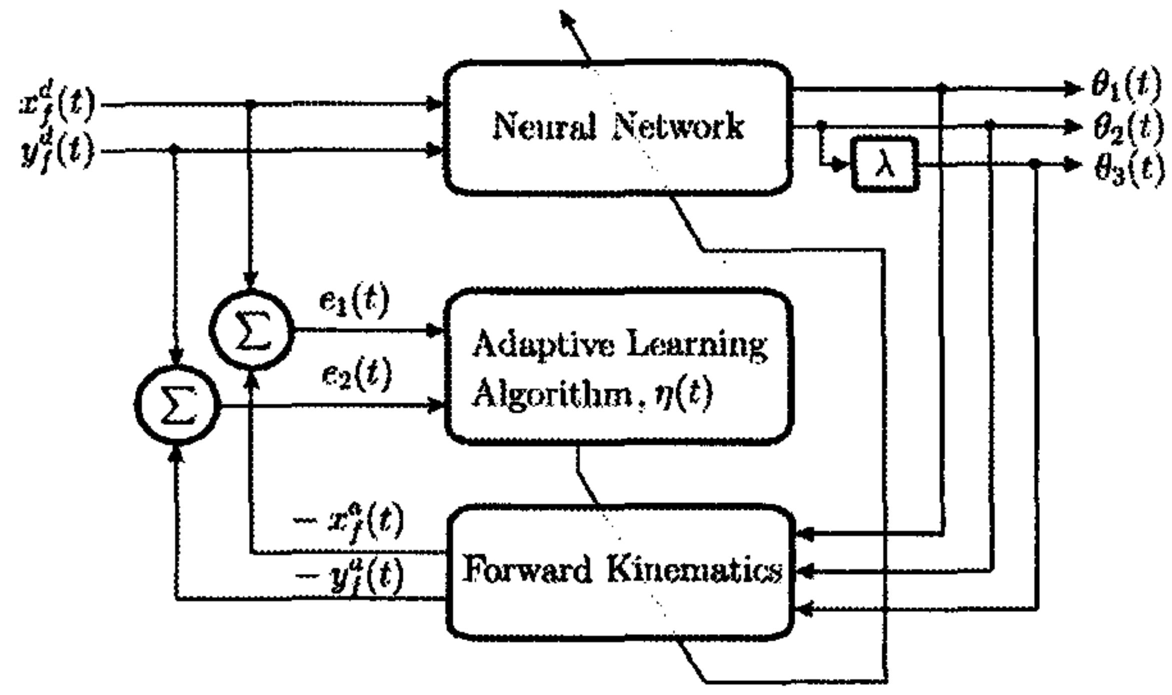

Fig. 2. A neural network scheme for inverse kinematics of a humanoid finger

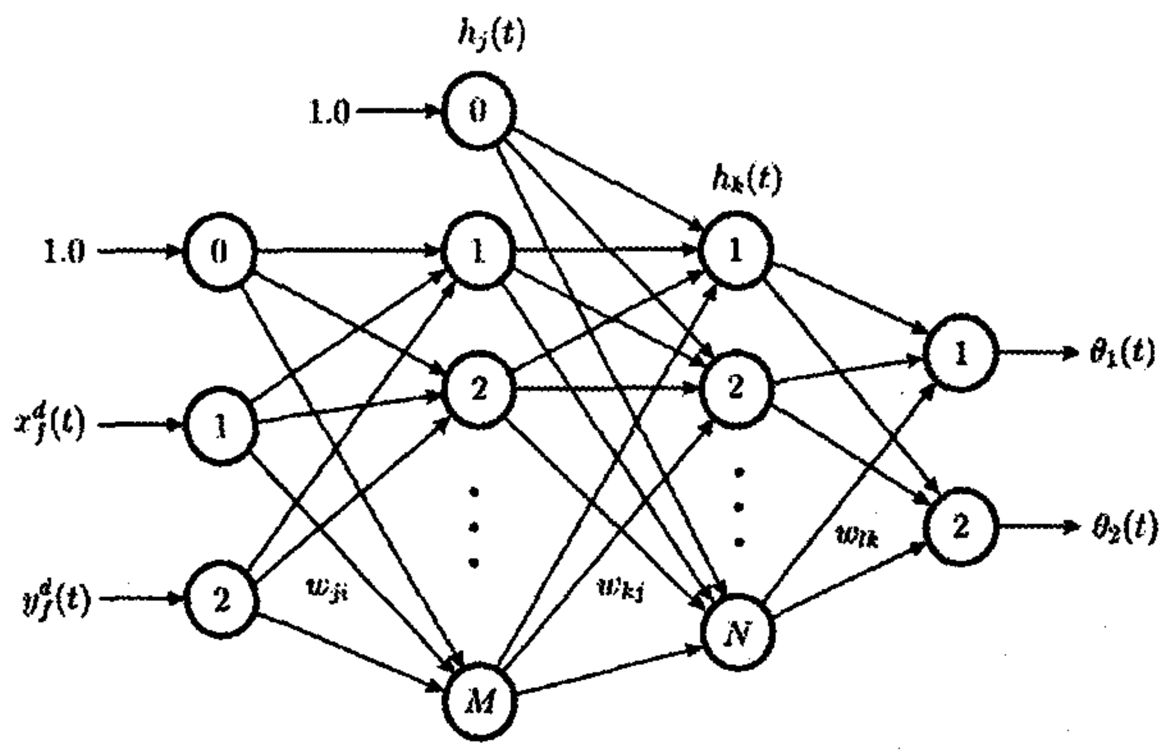

Fig. 3. A multi-layered neural network

In Figs. 2 and 3, the input neurons for the neural network are assigned by the desired fingertip position information, x_f^d and y_f^d. All of the neurons on the hidden layers have a bias connection. The output neurons are represented by the joint angles of the finger, but they are assigned by only θ_1 and θ_2. The parameter λ in Fig. 2 represents a coefficient for the coordinated motion between the third joint and the second joint in human fingers [8][9].

The actual fingertip position is computed by the forward kinematics using the output angles of the neural network. By using each directional position error, the adaptive learning algorithm makes a proper learning rate for the learning of the neural network.

Thus, the neural network is recursively learned by a modified error back propagation method [10]. Especially, the learning rate made by the algorithm is dynamic because it is adjusted according to the state of learning. If the assigned maximum position error in the fingertip space is satisfied by the repeated learning, the learning is terminated and the output of the neural network is finally accepted as the solution of the inverse kinematics.

In Fig. 3, the function of the input layer is only to pass the input to the first hidden layer. The output of the first hidden layer $h_j(t)$ is determined by

$$h_j(t) = \begin{cases} 1.0, & j = 0 \\ \dfrac{1}{1 + e^{-s_j\left(\sum_{i=0}^{2} w_{ji}(t) z_i(t)\right)}}, & j = 1,2,\ldots,M \end{cases} \quad (4)$$

where $z_i(t)$ and $w_{ji}(t)$ denote respectively the ith input component and the weighting factor between the ith input layer and the jth first hidden layer. The parameter s_j implies the slope of the jth sigmoid function on the first hidden layer and M indicates the number of neurons on the first hidden layer.

The function on the second hidden layer is the same as the first hidden layer. The final output of the network $\theta_l(t)$ is determined by

$$\theta_l(t) = \begin{cases} \sum_{k=1}^{N} w_{lk}(t) h_k(t), & l = 1 \\ \left(\sum_{k=1}^{N} w_{lk}(t) h_k(t)\right)^2, & l = 2 \end{cases} \quad (5)$$

where $w_{lk}(t)$ denotes the weighting factor between the second hidden layer and the output layer.

2.3 Dynamic Learning Algorithm

For the learning of the neural network in Fig. 3, define an error function as follows:

$$J(t) = \frac{1}{2} \sum_{m=1}^{2} (e_m(t))^2 \quad (6)$$

where

$$e_m(t) = \begin{cases} x_f^d - x_f^a, & m = 1 \\ y_f^d - y_f^a, & m = 2. \end{cases}$$

By considering the error effect according to the change of each weight, all of the weights on each layer can be updated by the following rule:

$$w_{lk}(t+1) = w_{lk}(t) + \eta(t)\delta_{ol}(t)h_k(t) \quad (7)$$

$$w_{kj}(t+1) = w_{kj}(t) + \eta(t)\delta_{h2k}(t)h_j(t) \quad (8)$$

$$w_{ji}(t+1) = w_{ji}(t) + \eta(t)\delta_{h1j}(t)z_i(t) \quad (9)$$

where $\delta_{ol}(t)$, $\delta_{h2k}(t)$, and $\delta_{h1j}(t)$ denote the error terms propagated back from the fingertip position to the output and hidden layers. The learning rate $\eta(t)$ is dynamically determined by the state of the neural network's learning [11].

3. SIMULATION RESULTS

For the simulation study, the link parameters of the finger is set as a human scale given by l_1=0.050m, l_2=0.030m, and l_3 =0.025m. The λ in Fig. 2 is assigned by 0.62 which is referred in [9]. Also, some test points on the following curve are assigned for the finger in the simulation:

$$y_f = -13.53x_f^2 + 0.86x_f + 0.06 \quad (10)$$

The function in (10) means that human fingers moves along a second-order function approximately in a free grasping motion[17].

The employed neural network has four layers. The neurons on the input layer, the first hidden layer, the second hidden layer, and the output layer are determined by 2, 5, 3, and 2, respectively. The parameters for the learning algorithm [11], β, σ, P, and Q, are assigned by 0.0015, 0.5, 3, and 5, respectively. In this simulation, the acceptable position error range is assigned as $\pm$0.5mm.

Through the proposed neural learning process, the fingertip trajectories to the x- and y-directions have been plotted in Fig. 4. Here, the given fingertip trajectories are to be assigned successively after the previous learning, and the actual fingertip trajectories have been taken by the forward kinematics using the joint angles which are resultantly obtained by the neural learning. From Fig. 4, we can see that the actual fingertip positions are gradually approached to the desired positions satisfactorily. Practically, the inverse kinematics is completed at the moment of each circle in Fig. 4 and the corresponding joint angles of the neural network can be taken as the solution of the given inverse kinematics. Those inverse kinematics solutions for the given fingertip positions have been shown in Fig. 5.

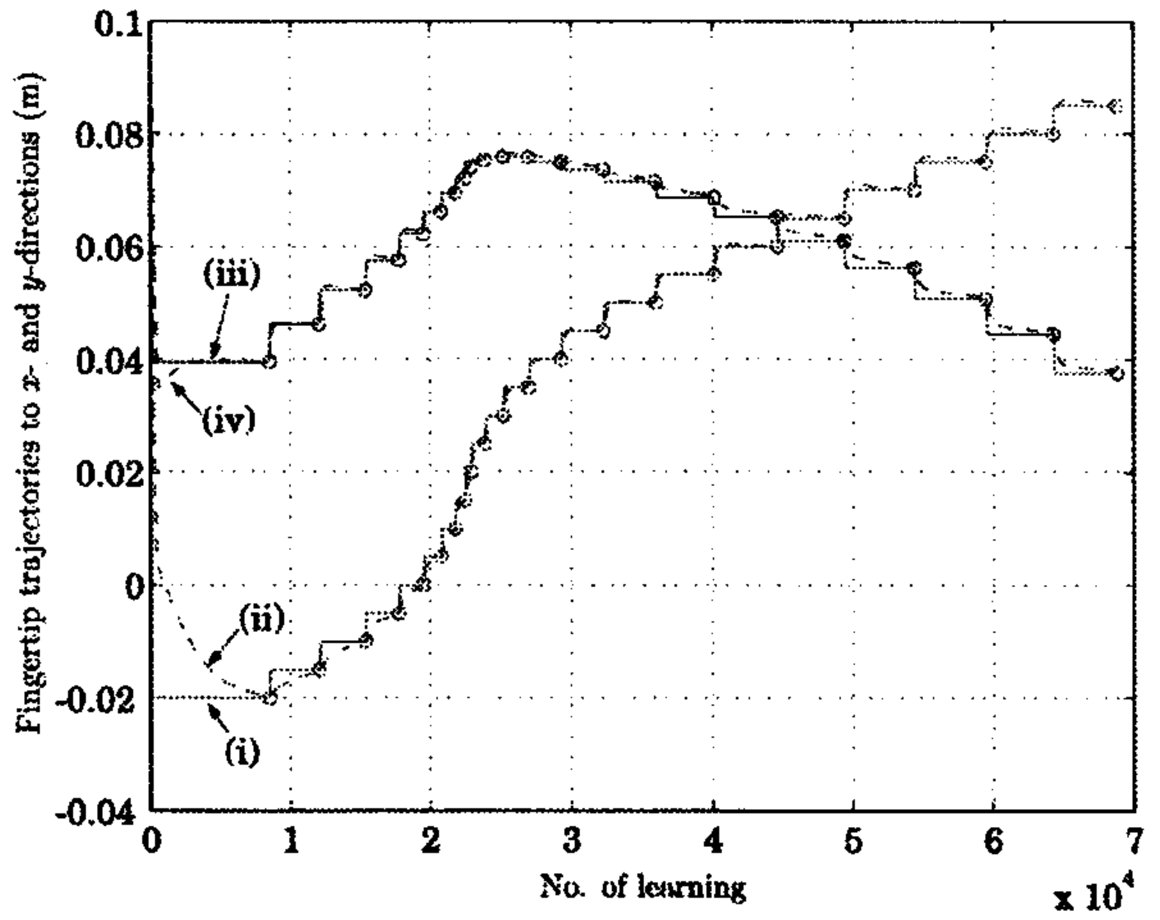

Fig. 4. Fingertip trajectories: (i) x_f^d, (ii) x_f^a, (iii) y_f^d, and (iv) y_f^a, where the inverse kinematics is completed at the moment of each circle.

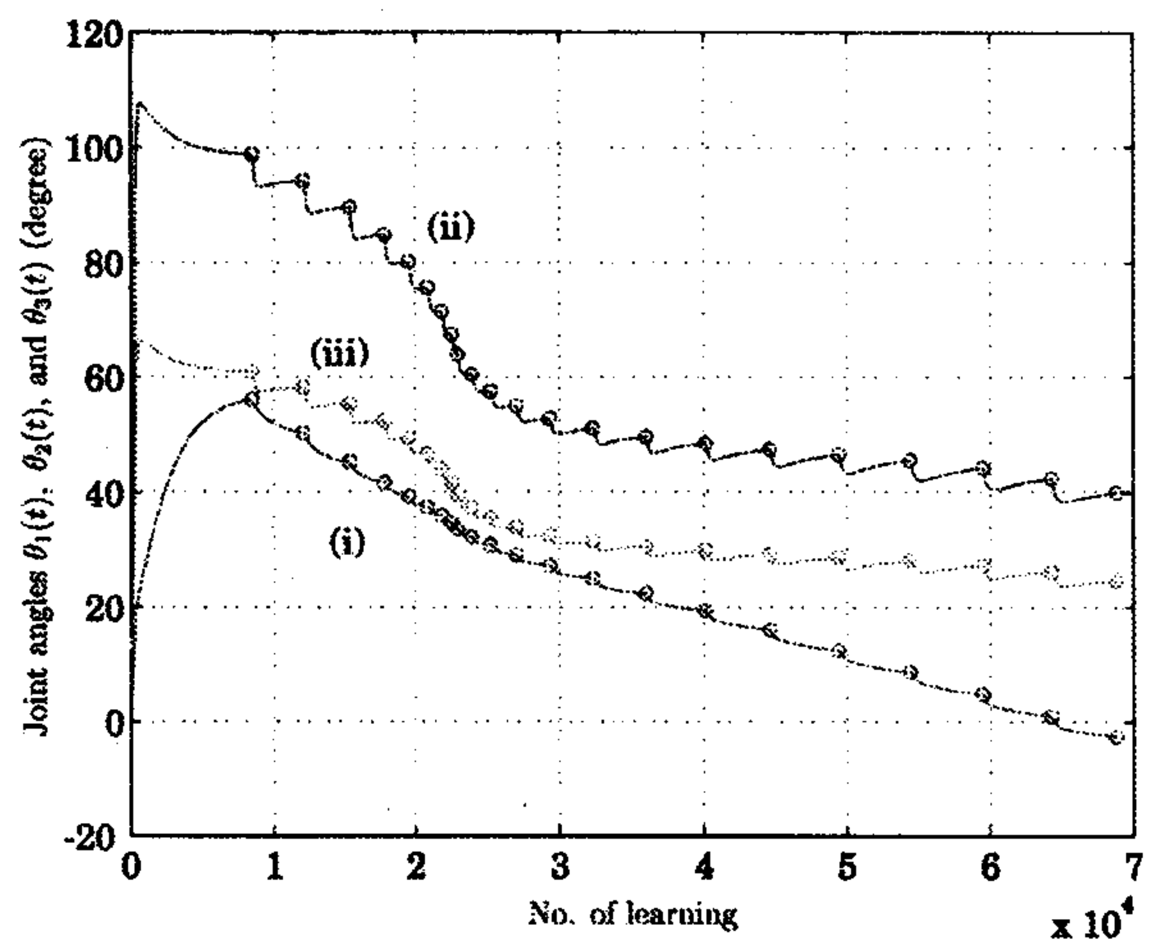

Fig. 5. Joint angles obtained by the neural learning-based inverse kinematics: (i) $\theta_1(t)$, (ii) $\theta_2(t)$, and (iii) $\theta_3(t)$, where the joint angles at the moment of each circle are the solution of the inverse kinematics.

4. CONCLUDING REMARKS

Through simulations, it is confirmed that the inverse kinematics of a humanoid finger can be effectively determined by the proposed learning technology and the resultant finger's configuration is like a human finger in the viewpoint of joint coordination. As a result, the accuracy of the computed fingertip positions is satisfactory and more precise finger configuration is also obtainable by the learning scheme. The proposed method is useful for solving the inverse kinematics which is impossible in a closed-form.

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