

HUMAN-EMG PROSTHETIC HAND INTERFACE USING NEURAL NETWORK

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Abstract: For the improvement of the amputee's activity of daily living (ADL), several kinds of electromyogram (EMG) controlled prosthetic hands have been developed so far. But there is still significant difference between the movements of these hands and human ones. In this paper, we propose a direct torque control method for the prosthetic hand. In order to estimate the joint torque from EMG signals, an artificial neural network by the feedback error learning schema is used. 2-DOF motions, i.e. hand grasping/opening and arm flexion/extension, are picked up. Then it is verified that the neural network can learn the relation between the EMG signal and joint torque.

Keywords: Prosthetic hand, Neural network, EMG signal

1 INTRODUCTION

Our hands play extremely important and inevitable roles in activity of daily living (ADL). Therefore there are many difficult situations for upper limb amputees. For the expansion and improvement of their ADL, several kinds of EMG controlled prosthetic hands have been developed so far. The EMG controlled prosthetic hand daily used by the amputees has mostly one degree of freedom (DOF) of motion: hand grasping and opening. There is still significant difference between the movements of these hands and human hand. On the other hand at the level of the laboratory, EMG controlled prosthetic hands having 3-DOF have been developed [1] [2], which can distinguish the motion patterns from EMG signals using artificial neural network. But it is difficult to do several motion patterns in the same time.

Human makes the hand motions by the complicated combination of various muscle activities. As a result, the motion combined by multiple joints is made. It is important to make the prosthetic hand move like human hand. In this research, a better approach is examined for controlling the prosthetic hand: the torque control of each joint. The joint torque is estimated from EMG signals using artificial neural network. In order to train the neural network, this research proposes the learning system based on feedback error learning schema [3]. And the prosthetic hand is controlled by the joint torque estimated from EMG signals.

2 TORQUE ESTIMATION METHOD

2.1 Learning method

The estimation of the joint torque from EMG signals is performed using neural network. But it is difficult to know directly the joint torque on the natural condition. The problem is how to get the teacher signals for the neural network. The present paper proposes a learning method as shown in Figure 1.

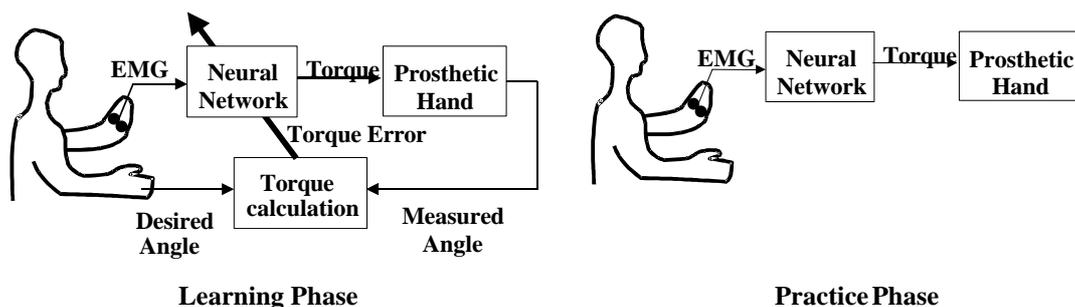


Figure 1. Concept of learning method

The learning method is based on the feedback error learning schema. The neural network is modified by the torque error which is calculated from the desired angle and measured angle.

Since the amputee loses a part of the forearm, however, the desired angle can not obtained directly from his/her amputated forearm. In order to get the angle time variation, we request the amputee to image the same motion for the both hands. Because it is considered that the movement of the normal side hand is almost same as the imaged movement of the lost hand. Then the desired angle is measured from the normal hand, and at the same time, EMG signals are measured from the amputated forearm.

2.2 Torque estimation from EMG signal

The muscle tensions of the extensor and flexor have a great influence on the joint movement. Every muscle is clung to the born. The distance to the joint axis translates the muscle tension into the rotative torque. On the other hand, EMG is the signal of muscle activity. It is known that the EMG signal which is rectified and filtered out through the second-order low-pass filter approximates the muscle tension. Therefore the joint torque is defined as follows.

$$\mathbf{t} = \begin{bmatrix} \mathbf{a}(\mathbf{q}) & 0 \\ 0 & -\mathbf{b}(\mathbf{q}) \end{bmatrix} \begin{bmatrix} u_f \\ u_e \end{bmatrix} \quad (1)$$

$$= {}^t T_u \cdot \mathbf{u}$$

, where u_f and u_e are the tensions approximated by the EMG signals of the extensor and flexor muscles. $\mathbf{a}(\mathbf{q})$ and $\mathbf{b}(\mathbf{q})$ are the distances to the joint axis of the extensor and flexor muscles. These distances nonlinearly depend on the joint angle .

The EMG signals are measured as the mixture signals of different muscle's activities. The mixture signal is decided by the distance to the measurement point, the depth from the skin surface, the muscle's condition, and so on. Then, EMG signals can be represented as follows.

$$\mathbf{EMG} = {}^E T_u (\mathbf{u}) \quad (2)$$

, where $\mathbf{EMG} = [EMG_1 \cdots EMG_n]^T$ and $\mathbf{u} = [u_f \ u_e]^T$. From equation (2), the muscle's tension \mathbf{u} is then written as

$$\mathbf{u} = {}^E T_u^{-1} (\mathbf{EMG}) . \quad (3)$$

From equation(1) and (3), the joint torque is written as

$$\boldsymbol{\tau} = {}^t T_u \cdot {}^E T_u^{-1} (\mathbf{EMG}) . \quad (4)$$

Here, an artificial neural network is used to estimate the joint torque from the EMG signals.

2.3 Structure of proposed system

Figure.2 shows the proposed system for the learning of neural network. The system consists of two parts, feedforward controller and feedback controller. The feedforward controller outputs the feedforward torque t_{ff} through the human and the neural network. The feedback controller outputs the feedback torque t_{fb} through the PD controller.

Feedback torque t_{fb} is computed as

$$\hat{\mathbf{t}}_{fb} = \mathbf{K}_p (\hat{\mathbf{e}}_d - \dot{\mathbf{e}}) + \mathbf{K}_D (\dot{\hat{\mathbf{e}}}_d - \dot{\mathbf{e}}) . \quad (5)$$

Here, $\mathbf{K}_p = \text{diag}[K_{p1} \cdots K_{pN}]$ and $\mathbf{K}_D = \text{diag}[K_{D1} \cdots K_{DN}]$ are gain constants. $\hat{\mathbf{e}}_d = [q_{d1} \cdots q_{dN}]^T$

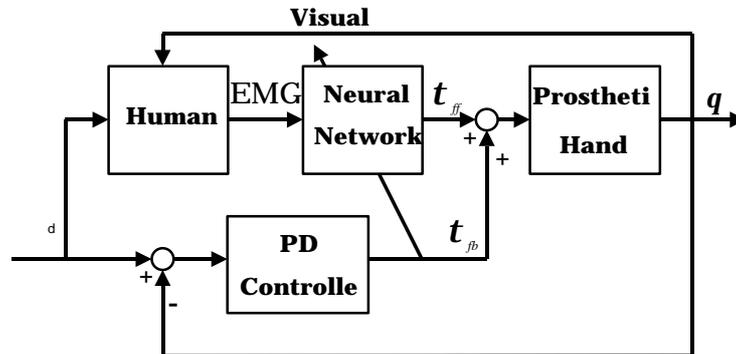


Figure 2. Structure of proposed system

are the desired joint angle. $\hat{e} = [q_1 \dots q_N]^T$ are the measured joint angle. N is the number of DOF.

At first, the amputee generates the EMG signals according to the desired angle $\hat{e}_d(t)$. And they are rectified and filtered out through the second-order low-pass filter and then are inputed to the three layered neural network. Additionally there is a bias cell for the input and hidden layers respectively.

The sum of $\hat{o}_{ff} = [t_{ff}(1) \dots t_{ff}(N)]^T$ and $\hat{o}_{fb} = [t_{fb}(1) \dots t_{fb}(N)]^T$ is the input torque to the prosthetic hand defined as

$$\mathbf{I}\ddot{e} + \mathbf{B}\dot{e} + \mathbf{K}e = \hat{o}_{ff} + \hat{o}_{fb}. \quad (6)$$

$\mathbf{I} = \text{diag}[I_1 \dots I_N]$, $\mathbf{B} = \text{diag}[B_1 \dots B_N]$ and $\mathbf{K} = \text{diag}[K_1 \dots K_N]$ are the moment of inertia, viscosity, and elasticity.

Neural network is renewed by τ_b based on the feedback error learning.

3 EXPERIMENTS

3.1 Experimental methods

Several experiments were conducted to verify the proposed learning method. Instead of measuring the desired angle from the normal forearm, the stick picture on the CRT display was used as the desired angle in these experiments. The subject generates the EMG signals to follow the motion of the stick picture (Figure 3).

2-DOF motions, i.e. the hand grasping/opening and the arm flexion/extension, were picked up ($N=2$): the arm flexion and extension are presented as Joint1 and the hand grasping and opening are presented as Joint2.

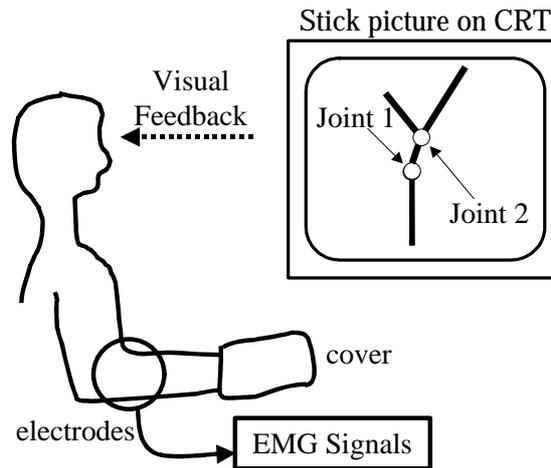


Figure 3. Experiment setup

The EMG signals were measured from four pairs of surface electrodes. The measurement points were 5 [cm] from the elbow joint: radial side (emg1), dorsal side (emg2), ulnar side (emg3), and palmar side (emg4). The EMG signals were digitized by an A/D converter (sampling frequency: 25 [Hz]), and rectified and filtered out through the second-order Butterworth filter (Cut-off frequency : 1 [Hz]).

The numbers of the cells in the input, hidden, and output layers of neural network were $n_1=4$, $n_2=10$ and $n_3=2$. The value of the bias cell in the input and hidden layers was 0.1. The initial weight values between the input and hidden layers were random values between -1 and $+1$. And the initial weight values between the hidden and output layers were 0 at the start.

The desired angles consists of four motions, which were ① flexion (joint1: 0 +45 [deg]), ② extention (joint1: 0 -45 [deg]), ③ hand open (joint2: 0 +45 [deg]) and ④ hand grasp (joint2: 0 -45 [deg]). The duration of each motion was 2 [sec] and the path of each motion was jerk minimum .

The subject tracked the desired motions on CRT display, and the EMG signals were measured at the same time. Several EMG signals corresponding to the desired motions were recorded, and two sets in these collected signals were used as the learning data.

Under these conditions, the experiments of 1-DOF (joint1) and 2-DOF were conducted.

3.2 1-DOF Experiment

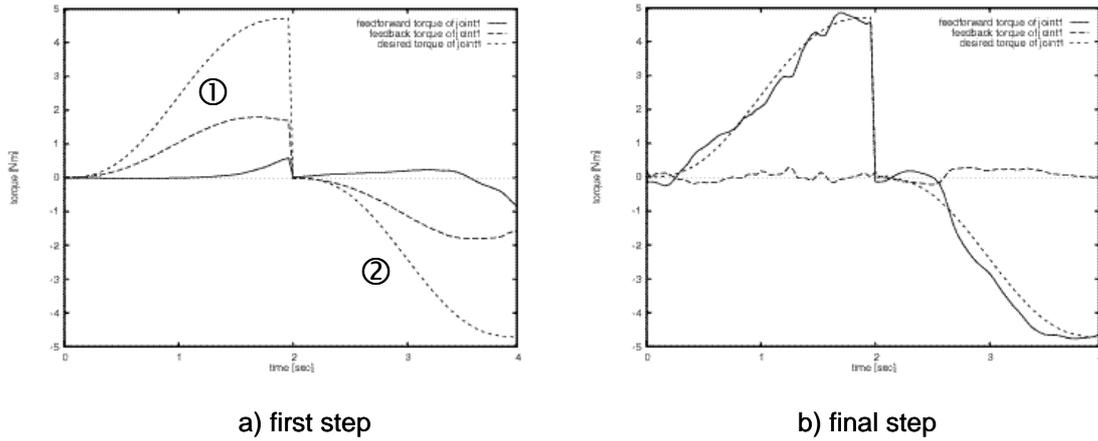


Figure 4. Joint torque of 2-DOF experiment

Table 1. Parameters in the 1-DOF experiment

I [kg.m ²]	0.0046
B [N.m.sec/rad]	0.08
K [N.m/rad]	6
K_{p1}	4.235
K_{d1}	0.15

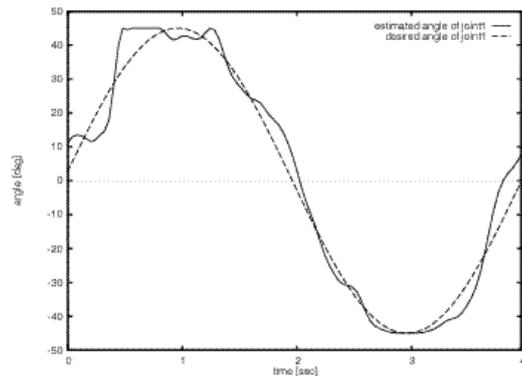


Figure 5. Joint angle of trajectory pursuit experiment

Firstly, in order to confirm whether the neural network can learn the relationship between the EMG signals and joint torque, the experiment of 1-DOF (joint1: flexion and extension) was conducted. In this experiment, the dynamic model of equation (6) was used as the prosthetic hand in Figure 2. The subject was a student: Male, age 26, normal. The values of parameters for this experiment are shown in Table 1. The desired angles consist of two motions for joint1: ① flexion (joint1: 0 +45 [deg]) and ② extension (joint1: 0 -45 [deg]).

Figure 4 shows the estimated torques before and after learning. Figure a) shows the torque before learning, and b) shows the one after learning. In both Figure 4 a) and b), the first half (until 2 [sec]) and the latter half are corresponding to the desired angle ① (flexion) and ② (extension) respectively. At the beginning of learning, the output of neural network, i.e., the feedforward torque illustrated by the solid line in Figure 4 a), is nearly 0. As the learning of neural network advances, the output τ_f of neural network increases and the feedback torque τ_b decreases. When the learning of neural network finishes, it is known that the output of neural network, illustrated by solid line in Figure 4 b), mainly control the prosthetic hand.

Secondly, we tested whether the subject could track a periodic trajectory using the learned neural network, i.e. using only the feedforward controller. The periodic trajectory was a sine curve (period: 4 [sec], amplitude: 45 [deg]). Figure 5 shows the desired periodic trajectory (dashed line) and the estimated trajectory using neural network (solid line). It is known that the neural network after learning can estimate the appropriate torque from the EMG signals.

3.3 2-DOF Experiment

The parameters for 2-DOF experiment are shown in Table 2. The desired angles are four motions stated in section 3.1. The subject was required to follow the desired motions in the order of ① ② ③ ④.

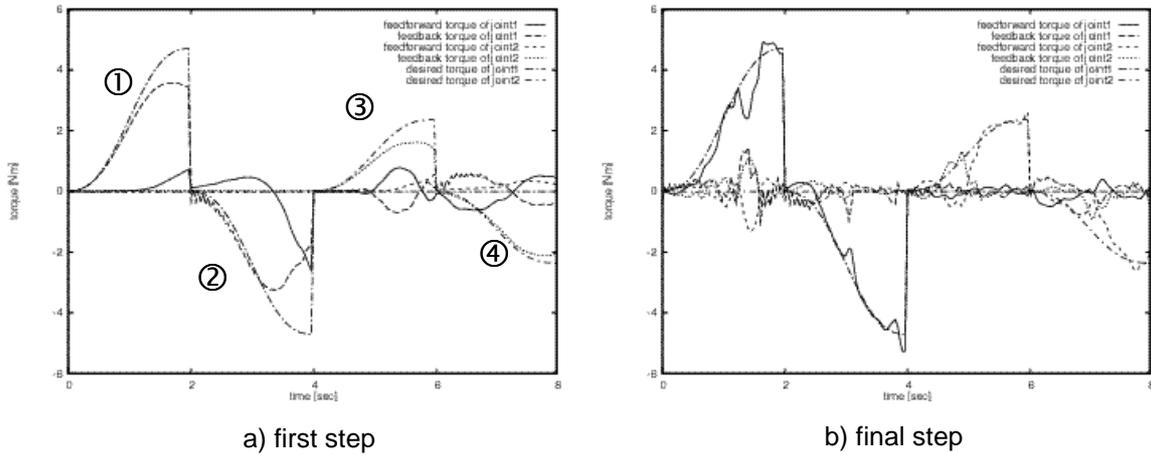


Figure 6. Joint torques of 2-DOF experiment

Table 2. Parameters in 2-DOF experiment

	joint1	joint2
I_N [kg.m ²]	0.031647	0.010236
B_N [N.m.sec/rad]	0.08	0.16
K_N [N.m/rad]	6	3
K_{PN}	40	12
K_{DN}	1.5	0.35

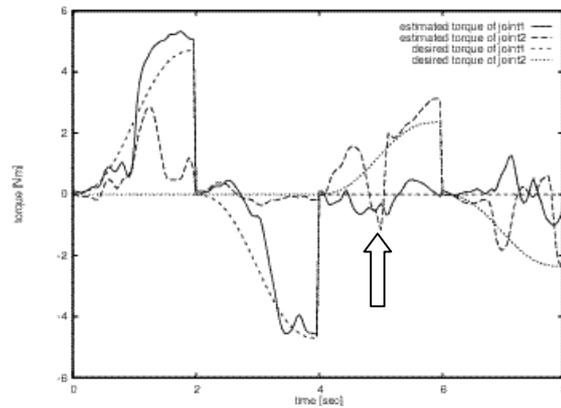
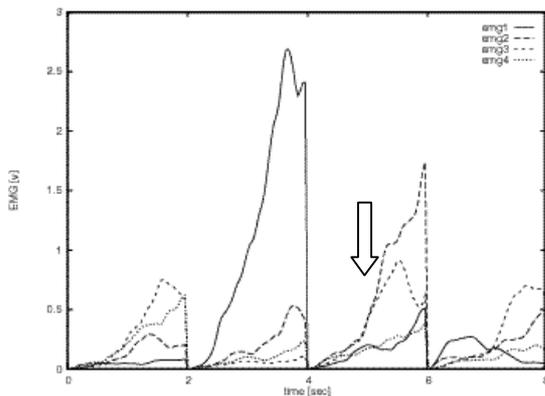
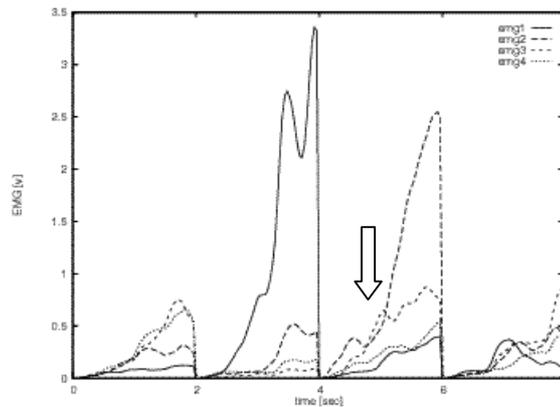


Figure 7. Torque estimation from the EMG signals not used for learning



a) EMG data used for learning



b) EMG data that is not used for learning

Figure 8. Waveform of EMG signals

Figure 6 shows the torque estimations before and after learning. Figure a) shows the torque before learning, and b) shows the one after learning. At the beginning of learning, the output of neural network, i.e., the feedforward torque of each joint illustrated by the solid line (joint1) and the short-dashed line (joint2) in Figure 6 a), is quite different from the desired torque (thick and thin dash-dotted lines). As the learning of neural network advances, the output of neural network increases and the feedback torque decreases. When the learning of neural network finishes, the neural network mainly

controls the hand, as illustrated by solid line (joint1) and short-dashed line (joint2) in Figure 5 b).

4 DISCUSSION

As shown in Figure 4 and 6, it is known that the neural network can learn the relationship between the EMG signals and the joint torque. Especially, in the case of 1-DOF tracking, the feedforward controller can independently follow the desired motion. This is because there are an obvious difference between the EMG signals of the flexor and extensor.

Next, Figure 7 shows the torque estimation from the EMG signals that are not used for learning in the case of 2-DOF experiment. It is seemed that there are some wrong output torques. For example, the estimated torque shows a sharp fall at the point indicated by the arrow. The EMG signals used for learning (Figure 8 a)) and the ones not used for learning (Figure 8 b)) make a difference at this point. This is why the neural network causes the wrong output.

These EMG signals (Figure 8 a) and b)) were recorded together before experiments. But if the neural network can obtain the relationship between the EMG signal and the joint torque, the adaptation of human is expected. The user controls the prosthetic hand while watching its movement. As the user control it repeatedly, he/she knows the relationship between the EMG signals and estimated joint torque, and the EMG signals are expected to become stable by the adaptation. These are the problem to be verified from now on.

5 CONCLUSION

We proposed a new structure of human-prosthetic hand interface. The interface can estimate the joint torque from EMG signals using the neural network. Our method may realize more complicated motions in comparison to the conventional method classifying each motion pattern discretely from EMG signals using the neural network.

The joint torque tracking the desired trajectory depends on the dynamic characteristics of the prosthetic hand. It is difficult to obtain the teacher signals directly from the amputee. Therefore the learning system utilized the feedback error learning schema.

The experiment was conducted using the stick picture on CRT display as the desired angle. And it was verified that the neural network could learn the relation between the EMG signal and the joint torque for 1-DOF (arm flexion and extension) and 2-DOF (arm flexion/extension and hand grasping/opening) pursuit tasks. As a result, the learning using 1-DOF was advanced well. The learning using 2-DOF was advanced when a pair of the learning data have the big coefficient of correlation.

Future research will be directed toward the evaluation of proposed learning method using both of forearm, which uses the prosthetic hand and the apparatus measuring the desired angle from normal forearm.

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