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Improvement of a Neural Network Based Motion Generator with Bimanual Coordination for Upper Limb Prosthesis

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Abstract: We propose to redesign a neural network used as a motion generator with bimanual coordination for upper limb prosthesis in order to improve its learning capability. We assumed that a wearer of the prosthesis is a unilateral amputee. In our previous work, we have proposed a prosthesis control system using a neural network that learns bimanual coordination in advance in order to smoothly implement motion with both hands. However, the previous proposed system has a problem that a neural network cannot generate desire coordina ted motion in special cases. The reason is that a desire posture of the prosthesis is generated from only a cu rrent posture of the healthy arm regardless of a current posture of the prosthesis. We propose to use both a healthy arm's posture and prosthesis' posture as neural network input in order to solve this problem. In this p aper, we showed that a single neural network whose input is current posture of both arms can learn relation of coordinated motions of holding a box with different size and the newly proposed system can generate desi red motions of the prosthesis for such coordinated motions through computer simulation.

Keywords: Upper limb prosthesis, Motion generation, Bimanual coordination, Neural network.

I. INTRODUCTION

We focus on upper limb prostheses for above-elbow amputees. We targeted at a unilateral amputee. Upper limb prostheses are classified into several types in terms of control mechanism. In a myoelectric prosthesis, each joint is controlled by surface myoelectric signals, which are generated from muscles when a human moves it. Utah Arm [1] is a typical myoelectric prosthesis. A wearer can operate a myoelectric prosthesis according to its intention through myoelectric signals. However, operating a myoelectric prosthesis is hard for an above-elbow amputee because it elbow is lost and its remaining muscles are few.

Then we have focused on coordinated motions of both arms to increase an above-elbow amputee's quality of life (QOL). Our basic idea is that an intelligent prosthesis moves according to a healthy arm's motion and facilitates tasks with both arms such as holding a box with both arms. We have proposed a prosthesis control system using a neural network that learns bimanual coordination in advance in our previous work [2]. The trained neural network generates desired posture of the prosthesis from current posture of the healthy arm at each sampling time. A training dataset of the neural network is prepared from healthy volunteer's motion through a motion capture system. We have shown that a neural network can learn a relation of five kinds of coordinated motions such as lifting up a box and turning a steering wheel with both hands. A trained neural network can generate desired prosthesis' motion for healthy arm's motion with different speed from the training dataset due to its generalization capability.

However, the previous proposed system has a problem that a neural network cannot generate desire coordinated motion in special cases. For instance, when a wearer holds a box with both hands, relation of posture of both arms depends on size of the box. It means that desire posture of the prosthesis for the same posture of the healthy arm is determined by size of the box. A single neural network whose input is current posture of the healthy arm cannot learn relation of coordinated motions of holding a box with different size simultaneously. The reason is that the same desire posture of the prosthesis is generated from the same posture of the healthy arm in the single neural network.

We propose to use both a healthy arm's posture and prosthesis' posture as neural network input in order to solve this problem. In the previous proposed system, current posture of the prosthesis is ignored when the desired posture of the prosthesis is generated. On the other hand, in the newly proposed system, desired posture of the prosthesis is generated from current posture of both the prosthesis and the healthy arm. In this paper, we showed that a single neural network whose input is current posture of both arms can learn relation of coordinated motions of holding a box with different size and the newly proposed system can generate desired motions of the prosthesis for such coordinated motions through computer simulation. We also showed experimental results using the previous proposed system, which cannot learn those coordinated motions properly for comparison.

II. MOTION GENERATOR

1. Prosthesis control system

We propose a new prosthesis control system using coordinated motion of both arms as shown in Fig.1. This system is composed of a motion capture system, a motion generator and a prosthesis controller. The motion capture system measures rotation angles of the healthy arms' joints. The motion generation system generates the desired posture of the prosthesis from the current posture of the healthy arm and the prosthesis. These postures are represented in rotation angles of each arm's joints. The controller drives actuators of the prosthesis according to the desired posture.

The motion generator is implemented by using a neural network. The motion generator needs to learn a relation between primitively coordinated motions of both arms before an amputee wears the prosthesis. Motion of a healthy man is used for the training of the motion generator.

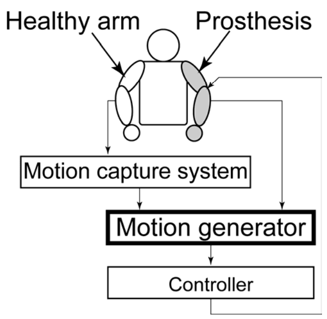

Fig.1. The proposed prosthesis control system

2. Redesign of the motion generator

A difference between the newly proposed system and our previous proposed system [2] is input of the motion generator. Inputs of the newly proposed motion generator are the current posture of the healthy arm and the current posture of the prosthesis as shown in Fig.2. On the other hand, inputs of the newly proposed motion generator are the current posture of the healthy arm and the current posture of the prosthesis as shown in Fig.2. As mentioned in Section I, the previous motion generator cannot generate desire coordinated motion in special cases. An example of the special cases is shown in Fig.4. There are the two movement patterns in which the initial posture of the healthy arm is the same. The previous motion generator cannot learn the two movement patterns simultaneously. The reason is that the two different postures of the prosthesis cannot be generated from the same posture of the healthy arm. Thus the previous proposed motion generator can learn only either Case 1 or Case 2 in Fig.4. It means that the previous motion generator can learn only a coordinated motion of holding a box in either Case 1 or Case 2. To solve this problem, the current posture of the prosthesis is needed in motion generation as shown in Fig.2.

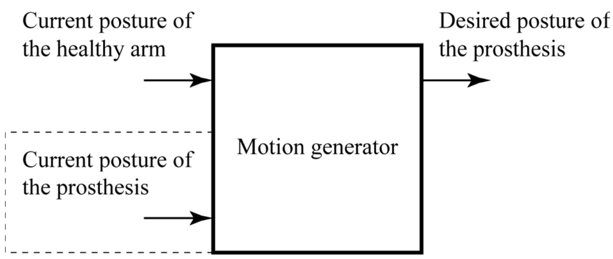

Fig.2. The newly proposed motion generator

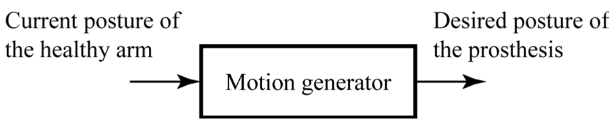

Fig.3. The newly proposed motion generator

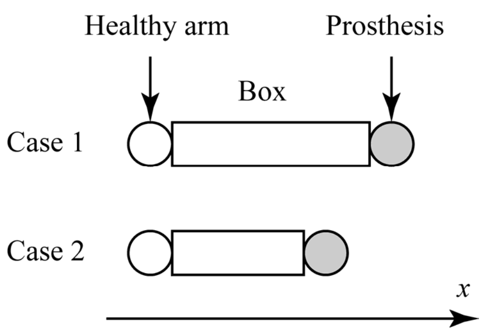

Fig.4. An example of the special relationship of the both arm

III. EXPERIMENT

1. Experimental setup

We compared the two motion generator by using a training dataset including the special cases as shown in Fig.4. The training dataset of the two motion generator was prepared through a kinematics model of both arms rather than a motion capture system because accurate postures of both arms should be given. A posture of the healthy arm is represented by the seven rotation angles; the three rotation angles of the shoulder, the single rotation angle of the elbow and the three rotation angles of the wrist.

In this paper, we targeted at the special cases. We simplified the experiments as much as possible. Rotation angles of the wrist were always set to be zero. Data length of movement patterns was possibly reduced. Training dataset was generated from movements of moving a box. The 9 kinds of movement patterns were made from the 3 different speed and width of both arms under the condition where the movement of the healthy arm is always the same. Fig.5 shows input data of the training dataset. The solid line in Fig.5 is a rotation angle of the healthy arm. The dashed line in Fig.5 is a rotation angle of the prosthesis. In Fig.5, the 9 kinds of movement patterns were a series signal.

We used the 4-layer neural networks as motion generators. In the previous motion generator, a 7-x-y-7 networks was used. In the previous motion generator, a 7-x-y-7 networks was used. The number x and y of neurons in hidden layers was determined through optical design proposed in [3]. It means that best performance of the previous motion generator and the newly proposed motion generator was evaluated.

We showed the experimental results in Fig.6 and 7. Fig.6 shows that the newly proposed motion generator can successfully generate the desired posture of the prosthesis for all the 9 kinds of movement patterns. On the other hands, Fig.5 shows that the previous motion generator cannot generate the desired posture of the prosthesis. The reason is that the movements of the healthy arm are the same and those of the prosthesis are different. That is, a neural network cannot generate different outputs from the same inputs. These experimental results showed that the newly proposed motion generate worked successfully in the special case under the condition where patterns of the same movements of the healthy arm and the different movements of the prosthesis was included in the training dataset.

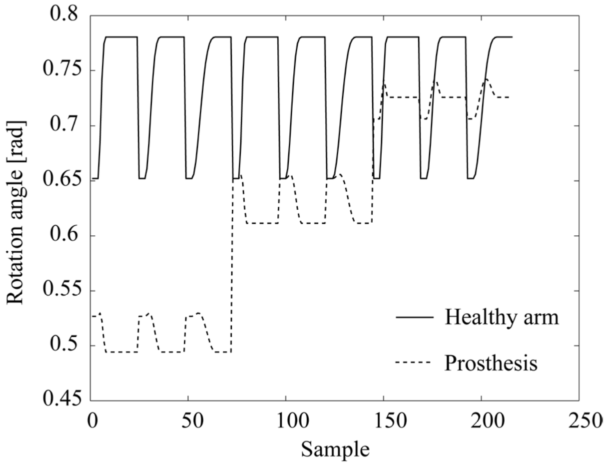

Fig.5. Input data given to motion generators

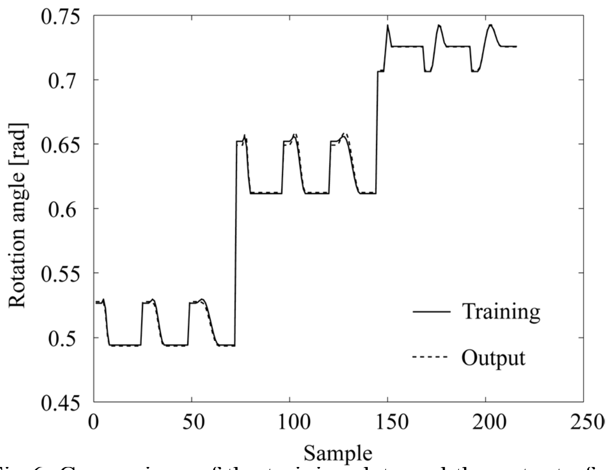

Fig.6. Comparison of the training data and the output of the newly proposed motion generator

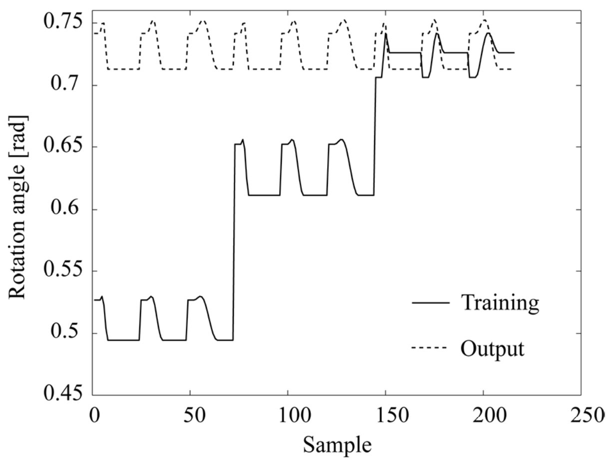

Fig.7. Comparison of the training data and the output of the previous motion generator

IV. DISCUSSION

From the results of Fig.6, the newly proposed motion generator can generate desired posture of the prosthesis even in the special cases. The reason is that current posture of the prosthesis is given to the motion generator.

Desire posture of the prosthesis is a future posture by one sampling time. The current posture and the desire posture of the prosthesis are very near. Thus it is expected that the newly proposed motion generator can generate the desired motion more accurately than the previous one because the current posture of the prosthesis is available.

VI. CONCLUSION

This paper proposed the motion generator using both a healthy arm's posture and prosthesis' posture as its input. We demonstrated that the newly proposed motion generator can generate desired posture of the prosthesis under the special case.

In the future work, performance of the newly proposed motion generate will be evaluated by using practical movement patterns.

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