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AN EMG CONTROLLED PROSTHETIC FOREARM IN THREE DEGREES OF FREEDOM USING ULTRASONIC MOTORS

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RACT This paper discusses an EMG controlled .hetic forearm with three degrees of freedom ited by small size ultrasonic motors. Its weight is than 700 g and the size is the same as the adult's irm. It produces no motion noise. In addtion, it is ble to control six kinds of motions i.e. pronation supnation of the forearm, flection and extension e wrist, and grasping and hand-opening.

1. INTRODUCTION

\n EMG controlled forearm with three degrees of lom using small size ultrasonic motors was loped. The arm has six functions, i.e. hand-opening grasping, wrist flexion and extension, and forearm ation and supination. Also, we propose a limb tion discriminaton method where the electrode tions are made relatively free by utilizing the s-information among multi-channel EMG signals.

2. PROSTHETIC FOREARM USING ULTRASONIC MOTOR

Fig.1 shows a prosthetic forearm which was loped on an experimental basis. It is driven by asonic motors installed in the forearm, wrist and t, and has three degrees of freedom, i.e., six ons of wrist flection, wrist extension, forearm ation, forearm supination, hand grasping and hand ing. Table 1 shows the specifications of the red prosthetic forearm.

3. AMPUTEE-PROSTHESIS INTERFACE

Fig. 2 shows a block diagram of the itee-prosthesis interface for controlling the arm. The surface EMG is measured from a part of the les which have actuated the original limb, and the on intended by the amputee, such as flection, nsion, pronation, supination, grasping and l-opening, is estimated. In parallel, the muscle e is estimated from the EMG signals. Then the al to drive and control the prosthesis is produced i both.

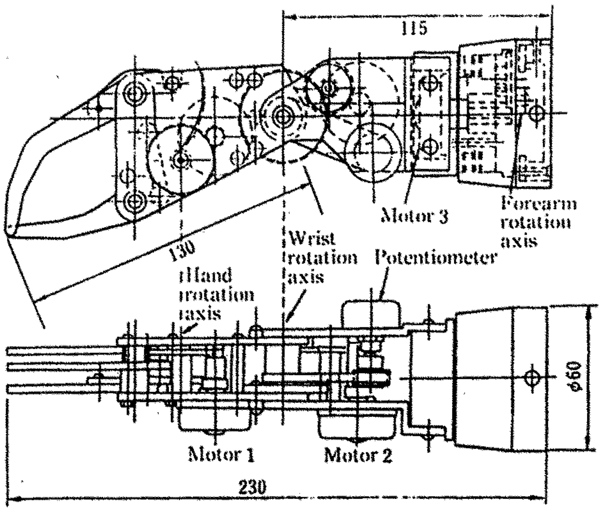

Fig.1 Prosthetic forearm with three degrees of freedom

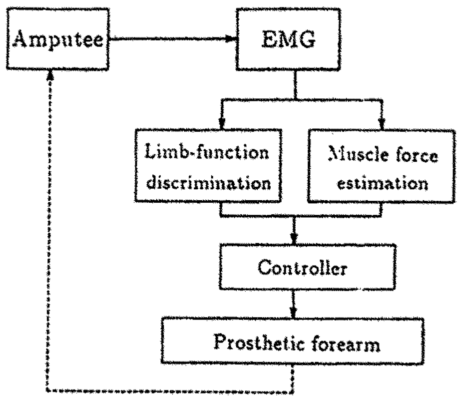

Fig.2 Amputee-prosthesis interface

Table 1 Specifications of the prosthetic forearm with three degrees of freedom

	Motions	Movable range (the time required)	Holding force	Gear ratio
Forearm	Pronation supination	162° (0.6~[illegible] s)	1.71 kg·cm	4.5
Wrist	Flection extention	[illegible]	10.40 kg·cm	17.5
Hand	Grasping opening	125 mm ([illegible])	4.16 kg	29.8

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4. LIMB-FUNCTION DISCRIMINATION BY NEURAL NETWORK

Fig.3 shows a flow chart of the limb-function discrimination procedure proposed here, which is composed of band-pass filters, rectification, smoothing filters and neural network.[1)-5)]

(1) Band-pass filter

The raw EMG signals measured at the surface of the amputee's skin are passed through the band-pass FIR filters. Then each of the four channel EMG signals is divided into three band frequency components.

(2) Rectification and Smoothing

The 4 × 3 EMG signals obtained from the band-pass filters are rectified and passed through individual one-pole Butterworth filters each with a low pass cutoff frequency of 1 Hz.

(3) Neural network

A feedforward type neural network is used to classify the rectified and smoothed EMG signals. The neural network consists of an input layer of 4 × 3 units, a hidden layer of ten units, and a output layer of 6 units. Each unit of the output layer represents one of six kinds of motions.

(4) Network pretraining

Four pairs of surface electrodes were attached on the forearm, 7 cm from the elbow joint. The electrode is dry-type made by Imasen Technical Lab. Three kinds of electrode arrangements are shown in table 1. EMG signal in each channel was A/D converted with the sampling frequency of 1 KHz and were stored in the computer as the data file.

After attaching the prosthetic forearm, the amputee is asked to perform each of six kinds of motions by one time. Then each of the stored EMG data was divided into 10 data sets of 200 msec intervals. The neural network is trained by error back propagation algorithm using these 6 × 10 data.

(5) Function discrimination

It is assumed that the amputee intends to make one of six motions. Since each unit of the output layer has the sigmoidal function, the output value is within 0 and 1. When one of the units of the output layer is more than 0.5 and all the others are less than 0.3, it is concluded that the motion assigned to the unit with the value more than 0.5 is intended by the amputee. Unless these conditions are satisfied, the discrimination is left undetermined.

Table 2 Motion discrimination rates

Experiment	No. 1	No. 2	No. 3	No. 4	No. 5
Subject	Normal A	Normal A	Normal B	Normal B	Amputee
Electrode locations					
Number of iterations	20.1	17.8	9.0	26.0	14.9
Success rates (%)	100.0	100.0	92.7	95.5	93.5
Undetermined rates (%)	3.6	5.7	8.7	12.0	13.4

(Average values for 10 kinds of initial values of the synaptic weights

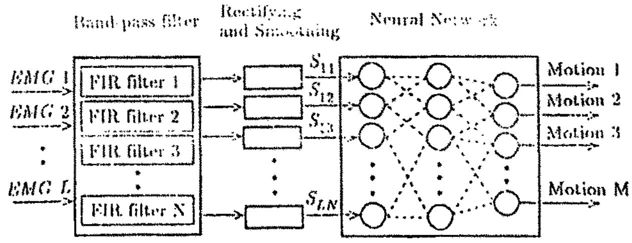

Fig.3 A limb function discrimination method using the neural network

5. DISCRIMINATION RATE AFTER LEARNING

Separately from training data, each of six kinds of motions were performed by 100 times and the EMG signals were used to confirm the function discrimination after learning.

Table 2 represents number of learning iterations, success rates and undetermined rates in different experiment conditions, where the success rate is the ratio of the correct discriminations in discriminated trials and the undetermined rate is the ratio of the undetermined trials in all trials. They are averages over ten kinds of initial values of the network weights. Note that the success rates are more than 90% independently of subjects and electrode locations, and especially the numbers of iterations training the neural networks are less than 30.

6. CONCLUSION

we developed an EMG controlled prosthetic forearm with three degree of freedom using small size ultrasonic motors. It was shown that the prosthetic forearm was well controllable by the amputee. Future research will be directed to develop a small size control box and more lightweight forearm which can be actually fitted.

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