31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Control Strategy for a Myoelectric Hand: Measuring Acceptable Time Delay in Human Intention Discrimination

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Abstract— **In order to enhance controllability of a myoelectric hand, we focus on a gap between the time when a human intends to move a myoelectric hand and the time when the hand actually moves (i.e., time delay). Normally, the myoelectric hand users dislike the time delay because it makes them feel uncomfortable. However, the users learn the time delay within some time ranges and, eventually, get feel comfortable to operate the hand. Thus, we assume, if we reveal the acceptable delay time (i.e., the time the users accept the gap with their learning ability), we can provide more time in a human intention discrimination process, and enhance its success rate. Therefore, we developed a mobile myoelectric hand system with an embedded linux computer, and conducted a ball catch experiment: we investigate the acceptable delay time by adding the delay time (i.e., 120[ms], 170[ms], 220[ms], 270[ms], 320[ms]) into the human intention discrimination process. As a result, we confirmed that the max accept delay time was approximately 170 [ms] that achieves 61% success rate.**

I. Introduction

HAND motions are the most basic activity in our daily life. Therefore, it is important to develop a human-like myoelectric hand in order to enhance quality of life (QOL) for amputees.

The myoelectric hand system consists of a mechanical hand with motors, a computer (i.e., a human intention discrimination process and motor motion plan), and a microchip controller (i.e., motor control). As for the control, the control input is electricmyographic (EMG) signals of amputee's remained forearm muscles. The EMG is the electric potential generated when muscles contracted and is measured with a surface electromyogram (EMG) sensor, which placed on the human skin. Then, the output (i.e., hand motions) are generated as follows: (1) EMG signals are measured from the user's body; (2) the human intention discrimination system analyzes the EMG signals, and forms a feature vector; (3) the discrimination system identifies the intended motion of the user by comparing the feature vector with the feature vectors that acquired at the learning phase; (4) the motors in the myoelectric hand are controlled with the pre-planed motion pattern corresponding to the intended motion.

A part of this study is the result of "Brain Machine Interface Development" carried outunder the Strategic Research Program for Brain Sciences by the Ministry of Education, Culture, Sports,Science and Technology of Japan.

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Thus, the process to discriminate human intended motions is one of the most important issues in both commerce and research fields. However, the mechanical hand designs in those two fields take different direction. For example, Myobock system (Otto bock) is the most popular myoelectric hand in the commerce, and has only two DOF. It is because that the few DOF achieves light weight, small size, high drive, and high controllability, and it succeeds to provide high reliability to the users.

Meanwhile, the target in the research field is the mimic of the human hand (i.e., multi-DOF). Thus, they generally develop 5 finger hands and mainly focus on enhancing its controllability: that is, they try to improve the human intention discrimination process from biological signals. For example, Kato and Yokoi developed 5 finger hands mimicked the human tendon mechanism, and implemented an EMG-to-Motion discrimination system: the discrimination system analyzes the frequency and amplitude of the user's EMG, and forms the 27 dimension feature vector; the three-layer neural network, which contains the relationships between feature vectors and hand motions of the users, generate the user's intended motion. As the result, their myoelectric realize 8 motions with 3 EMG sensors [1].

In our research, we also target to enhance the discrimination on a human-hand like myoelectric hand. Especially, we focus on human learn ability to accommodate "delay time" to its system. As for time delay in the human system, it is physiologically proved that the human hand movement has several delay time: (1) A control signal from the brain to hand is delivered thought nerve systems. The speed of the signal is approximately 50 [m/s]; (2) When human movement is perturbed, the movement is stabilized with sensory information (i.e., sensory feedback loops). The sensory feedback loops also has some time delay: the short-loop feedback (e.g., spinal networks) has approx. 30 [ms] to 50 [ms] time delay [2]; the long-loop feedback (e.g., the cortex) has approx. 100 [ms] to 150 [ms] time delay [3].

Thus, local systems in human body naturally have delay time. However, the human learning ability accommodates the delay time to the system, and does not feel uncomfortable during the dexterous motions. So far, such ability is partially demonstrated with psychophysical experiments. Lee proposed τ-hypothesis from the ecological viewpoint [4]. However, this hypothesis is setup in non-gravity environments. Meanwhile, Koike conducted a virtual reality experiment from internal model hypothesis. He illustrated that human could learn multi-acceleration and could estimate

Time To Contact (TTC) [5]. These results suggest that human can adapt its internal model to the task with the vision input.

As summary of the time delay in human, the time delay naturally exists and the vision feedback greatly contributes to the time delay adaptation. However, as for the myoelectric hands, the researchers conventionally aim at implementing efficient algorithms and try to shorten its computational time in order to discriminate as many human intentions as possible. That is, the discrimination process time is normally determined by the original computation time and tends to set as short as possible (i.e., it is because the researchers believe that, the slower the myoelectric hand starts moving, the more the user feels uncomfortable).

Therefore, our final goal in this research is to apply the human adaptation system for our myoelectric hand system, and to utilize the full acceptable delay time for the discrimination process. Here, we define the delay time as the gap time between the time when the user of a myoelectric hand intends to move the hand and the time when the hand starts moving.

As the first step, we investigate the acceptable delay time on the myoelectric hand, and try to quantitatively show a trade-off between the discrimination performance and the user's comfort in this paper. For the investigation, we choose a ball catch task with the following reasons: the ball catch task requires a quick response so that it is clear to reveal the acceptable delay time / Time To Contact (TTC), which is estimated with the subject's vision feedback before the subject catches a tossed ball with his hands; for the convenience, the evaluation of the hand performance is defined as the success rate of ball catch.

In this paper, we first describe a mobile myoelectric hand system for a health subject. Next, we explain setups of the ball-catch experiment. Then, we show our results such as the delay time and the success rate. Finally, we discuss and conclude the paper.

II. MYOELECTRIC HAND SYSTEM FOR A HEALTHY SUBJECT

The mobile myoelectric hand system consists of a myoelectric hand with a socket for a healthy subject, a mobile embedded linux computer, and a motor controller and RC servo motors. This system is targeted for a health subject and the two reasons are described as follows: (1) it does not matter if subjects of the experiments on time delay are amputee or healthy people. So, we developed a hand socket for a health subject, and try to collect as many data from healthy subjects as possible; (2) on ball catch experiments, the user need to move quick so that we try to eliminate cables to installed equipments (e.g., computer). So, we transplanted the discrimination process in a desktop computer into a mobile embedded linux PC, and achieved to enhance the user's mobility.

In the following sections, we describe the details of three parts, and explain the discrimination process and list the computational time in the system.

A. A Myoelectric Hand with a Socket for Healthy Subject

The hand part is the five finger type robotic hand developed by Hiroshi [1]. The interference wire-tendon mechanism is applied for the hand design so that 5 DOFs are free joints and 13 DOFs are controlled joints (totally 18 DOFs). Moreover, the hand part does not have any actuators inside because of the wire-tendon mechanism (The detail is described in the section "RC Servo Motor unit").

The Socket is specially designed for a healthy subject: that is, there is a grip bar inside the socket. As an advantage of the grip, when the myoelectric hand grasps an object, the user acquires sensor feedback (i.e., pressure) from the grip. That is, the socket provides the illusion of sensor feedback easily (i.e., pseudo-pressure feedback). We believe that it somehow contributes that the user controls the myoelectric hand.

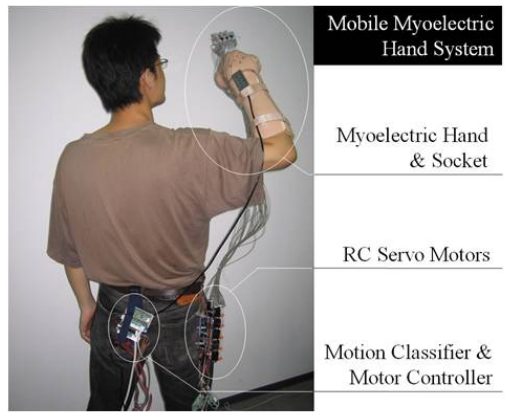

Fig 1 Appearance of the mobile myoelectric hand system

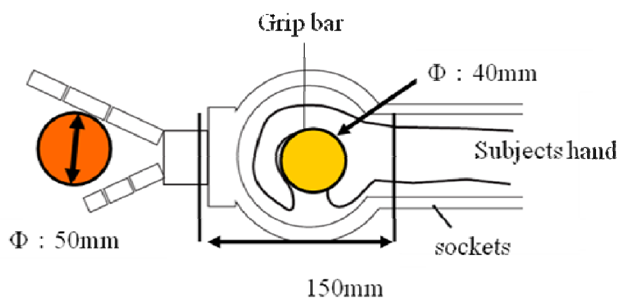

Fig 2 Myoelectric hand socket for healthy hand

B. RC Servo Motor unit

There are 13 RC servo motors (11 Motors: GWS Micro 2BBMG, 2 Motors: Kondo Kagaku KRS2350ICS) in RC servo motor unit. As an advantage, we applied a wire-tendon mechanism for the hand so that the fingers actuated through wires and the RC servo unit can be placed anywhere on the user. Therefore, the unit is placed in the waist.

C. A Mobile Embedded Linux Computer

The mobile embedded linux computer consists of four parts: an embedded linux computer "Gumstix" and a microchip "Robostix", EMG sensors, and a control pannel. The total size of the system is 85[mm]*58[mm]*24[mm]. It lasts 11 hours with 4 batteries (NIMH 3A).

The embedded computer works as follows: (1) EMG sensors acquire surface EMG signals at the sampling rate 1.6 [kHz] and feeds into Robostix at the resolution 8 [bit]. (2) Robostix sends the EMG values to Gumstix via a I2C communication; (3) Gumstix process human intention discrimination, and identifies a human intended motion, and the corresponding motor patterns are transferred to the motor controller via a serial communication. Actually, there are two phases (i.e., teaching phase and practice phase) to use the system, and the description above is about the practice phase. The details of both phases are in the next section. The control panel is used only in the teaching phase.

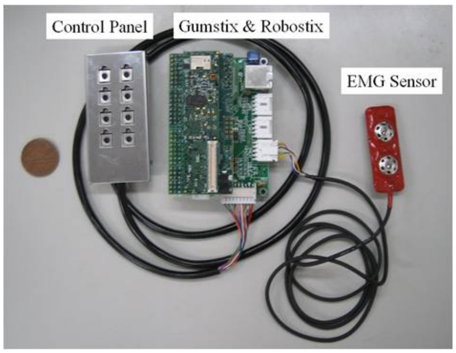

Fig 3 mobile Motion classification hardware

1) Discrimination Process

The discrimination process has two phases as shown in Fig.3: teaching phase and practice phase. The teaching phase is in charge of the process that the computer learns the relationship between the EMG signals and the human motions: (1) the user pushes Button 1 on the control panel, and the myoelectric hand moves as a pre-planed motor pattern (i.e., each button corresponds to each pre-planed motor motion on the myoelectric hand) and, during it, the user makes a hand motion and feeds EMG signals into the embedded computer; (2) the embedded computer has two algorithms (i.e., the First Fourier Transfer (FFT) algorithm and a 3-layer neural network with the back propagation algorithm). The FFT continuously analyzes the EMG data (i.e., every 128 sampling time), and generates 27 dimension feature vectors. Then, the 3-layer neural network (i.e., 24 input neurons, 32 hidden neurons, and 8 output neurons) learns the relationship between the feature vectors and the corresponded pre-planed motion (i.e., each button on the control panel) with the back propagation algorithm. The processes (1) to (3) present 1 myoelectric hand motion/1 button.

In practice phase, the control input is the EMG sensors. That is, the EMG signals are fed into the computer, and the computer generates one feature vector at each control time (This process is the same as the process in the teaching phase). Then, the feature vector is directly fed into the 3-layer neural network, and 8 values are acquired from the 8 output neurons corresponding to the 8 pre-planed motor patterns. Finally, a neuron, which is the highest value among the 8 neurons and more than 0.5 values, is chosen and the corresponding motor pattern is transferred to the motor control.

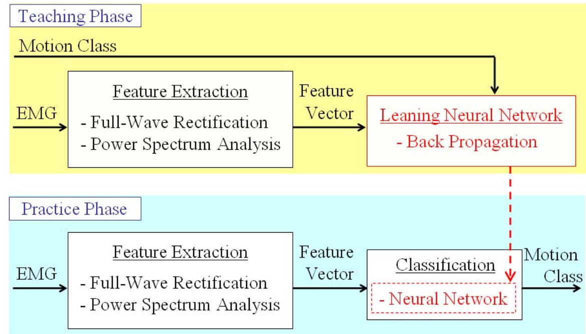

Fig 4 Classification algorithm

1) Computational time for the discrimination process

We measured the process in the practice phase 1000 times, and listed the computation time at each process in Table 1.

Table 1 Computational Time at Each Process

	Mean value[ms]	Standard deviation [ms]
128points FFT	0.432	0.0004
Data transmition I2c fast mode	22.8	5.38
Neural Network	0.768	0.0001
Total	50.24	0.142

III. EXPERIMENT: CATCH BALL

Fig.5 shows experimental environments. The Subject catch a tossed ball with the myoelectric hand. 40 balls are tossed every 10 seconds. The initial ball speed is about 5.2[m/s] and its angle is about $\pi/3$[rad]. So the subject catches the ball at 1[m] height above the ground.

For investigating the acceptable delay time, we set specific additional time such as 0[ms], 50[ms], 100[ms], 150[ms], and 200[ms] into the discrimination process (Referring to the Table 1, we estimate the based delay time 122±12 [ms] and, therefore, the actual time delay for the user would be 120 [ms], 170 [ms], 220 [ms], 270 [ms], and 320 [ms]), and record ball catch success rates at each delay time.

We utilize EMG sensors, bending sensors, and pressure sensors. The EMG sensors are placed on the palmaris longus muscle and the biceps brachii muscle. The bending sensors are used to record the joint angle of the myoelectic hand. The pressure sensors are placed on the palm, and target to measure the timing of ball catches.

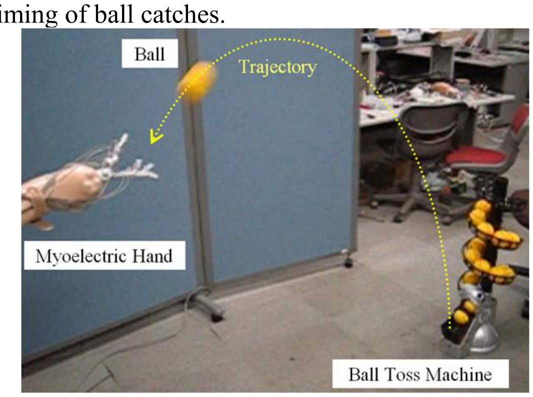

Fig 5 Experiment environments

Table 2 shows the success rate of ball catch experiments. Fig.6 (a)-(e) show the EMG data at the palmaris longus muscle and the biceps brachii muscle, and the pressure sensors on the hand and the bending sensors of the seconds finger. It is clear that the pressure sensors indicate the ball catch timing, and the bending sensor shows the trajectory of the finger angle.

Table 2 Success rate at each time delay conditions

Additional delay time[ms]	1st ~10th catch	11th ~20th catch	21th ~30th catch	31th ~40th catch	Average rate
0	50%	50%	50%	50%	50%
50	80%	60%	70%	80%	72.5%
100	30%	30%	20%	50%	32.5%
150	30%	30%	60%	40%	40%
200	10%	0%	0%	10%	5%

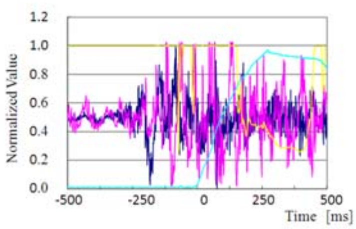

Fig 6 (a) In condition of delay 0 [ms]

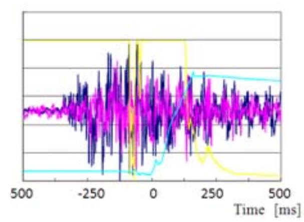

Fig 6 (b) In condition of delay 50 [ms]

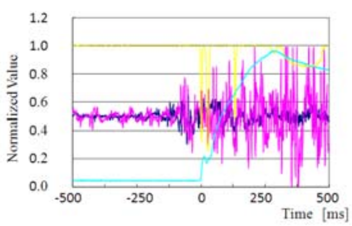

Fig 6 (c) In condition of delay 100 [ms]

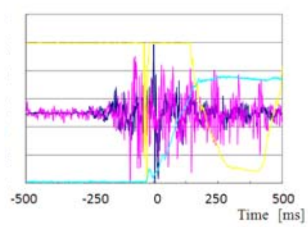

Fig 6 (d) In condition of delay 150 [ms]

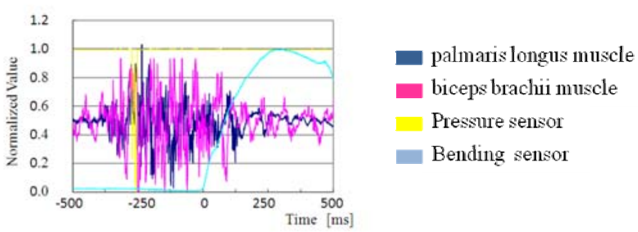

Fig 6 (e) In condition of delay 200 [ms]

Fig 6 Emg signal of palmaris longus muscle and biceps brachii muscle, pressure sensor on the palm, and bending sensor along with second finger. (a) to (e) in each delay conditions.

Table 2 shows the results at the delay time 0 [ms] and 50 [ms]. The subject caught the balls at over 50% success rate. Especially at 50 [ms], the success rate is superior to the rate at 0 [ms]. We assume that it is influenced by its experiment procedure: that is, the time delay 50[ms] is conducted after the time delay 0[ms], and the subjects are well-trained.

In Fig. 6(a) and (b), we confirmed that the transition of the pressure sensors indicates the timing of the ball catch. Especially, the timing is close to the timing that the fingers moves (i.e., the bending sensors recorded the finger motions). This result suggests that subject adapted to the delay time 0[ms] and 50[ms].

The average success rates dropped to 32.5 [%] at 100 [ms] and 40 [%] at 50 [ms] although the subject should be well trained compared to the delay time 0 [ms] and 50 [ms] (i.e., early experimental conditions).

It is known that human is able to adapt approximately 200 [ms] to 300 [ms] delay time with the vision feedback. At 100[ms], we assume that the subjects feel their tactile sensor feedback with the healthy hand at the ball catch. In short, before the myoelectric hand moves, the tactile sensor feedback possible substituted for the vision feedback.

At the delay time 200[ms], it was hard for the subjects to catch the balls. We assume that the subjects are required to estimate the position where to catch without visual information of 322[ms] before the catch timing.

IV. Conclusion

In this research, we aims at enhancing the EMG-to-Motion discrimination process for a myoelectric hand, and focus on acceptable delay time, which human can adapts: that is, conventionally the time delay in the system is avoided because the user feels uncomfortable. However in our strategy, we try to reveal the maximum acceptable delay time which the user does not feel uncomfortable, and try to spend the max time for the EMG-to-Motion discrimination. Then in this paper, we developed a mobile myoelectric hand system, and conducted ball-catch experiments for investigating the acceptable delay time. As results, the relation between the success rates of ball catches and the delay time (i.e., 120 [ms], 170 [ms], 220 [ms], 270 [ms], 320 [ms]) demonstrated that the delay time 170[ms] is the maximum acceptable delay time.

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