A Proposal of EMG-Based Training Support System for Basketball Dribbling

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Abstract. In the paper, we propose a novel HCI methodology for supporting human sports training. The proposed system utilizes electromyogram (EMG) signals as the metrics for evaluating the motor skill acquisition process, because it is well known that EMG signals measured from human experts are notably different from beginners in terms of timing and sharpness. According to this, we hypothesized that visualizing the difference of EMG signals between an expert and a learner, and providing the error information to the learner in real-time accelerates the learning process. The preliminary results show that the proposed method is effective especially in the early stage of training of beginners.

1 Introduction

In the field of sports science, body motions of human experts have been measured for motion analysis. In addition to motion capture systems, recently we can use various lightweight sensors (e.g. acceleration detector) by installing them in each part of body. The measured motion data are analyzed with computers, and it has been tried to clarify the experts' motor skill which is difficult for them to state [1, 2]. Moreover, in the area of motor learning or rehabilitation, these real-time measurements can be used as feedback (i.e. knowledge of results; KR) for acquiring motor skills [3]. Furthermore, nowadays these motion data are utilized for enhancing reality in entertainment applications [4].

When we begin to acquire some new body motion, it is generally accepted that we try to form an image of experts' motion in the brain as a model to imitate. The image we stated here corresponds to the position of body parts, the trajectories of joint angles, timing of motion, etc. It was reported that having the image to imitate accelerates motor learning, especially in the early stage of the learning [5]. However, visually observable information of experts' motor skills is restricted to kinematic one. Due to the lack of dynamic information (e.g. muscle tension), a learner needs to develop an internal model, i.e. a sensorimotor map between somatosensory stimulus and a motor command, via active trial-and-error.

On the other hand, electromyogram (EMG) is a biomedical signal which directly reflects motor commands from the brain to activate muscles. Therefore it has long been investigated in the sports science field. For example, Sakurai repeatedly

M.J. Smith and G. Salvendy (Eds.): Human Interface, Part I, HCII 2009, LNCS 5617, pp. 459–465, 2009.

measured the EMG data during smash motion of badminton, and compared the feature of beginners and experts' myoelectric signals [1]. According to the report, experts' myogenic potential immediately decreases after the impact, while the decrease cannot be observed in the beginners' EMG signal; however it gradually comes close to the experts' as the training goes on.

Based on the above observation, it is assumed that the difference of motor skill between beginners and experts can be quantitatively estimated from the discrepancy of the EMG signals. Thus we hypothesized that visualizing the difference of EMG signals between an expert and a learner, and providing the error information to the learner in real-time accelerates the learning process. Based on the hypothesis, in the paper, we propose a novel HCI methodology for supporting human sports training, in particular basketball dribbling.

2 System

The aim of the present study is to evaluate the effectiveness of the proposed training support system with regard to the basketball dribbling. First of all, we analyzed the EMG data measured from dribbling experts and beginners. In all experiments, we used the dry surface electrodes for EMG recoding (NM-512G, Nihon Kohden) and the multi-telemetry system (WEB-5000, Nihon Kohden). From the result of preliminary experiments, the positions for EMG recoding are determined at the *flexor carpi radialis* (forearm) and the *triceps brachii* (upper arm).

Figure 1 schematically shows a typical pattern of experts' EMG signals in one dribbling cycle (left: upper arm, right: forearm). The three peaks correspond to the following three tricks:

(1) in receiving the bounced ball, pulling up the forearm lightly and decelerate the ball,
(2) in pushing down the ball, pushing down the upper arm and stretching the elbow, and
(3) in sending down the ball, snapping the wrist.

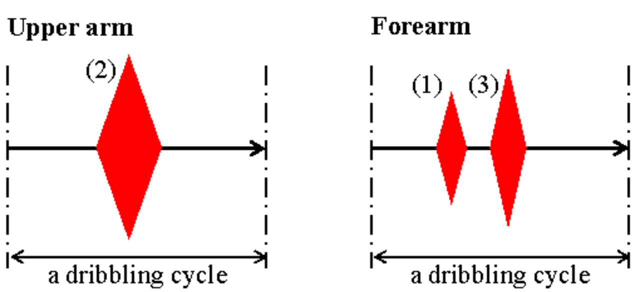

Fig. 1. Schematic shape of the EMG signals of dribbling experts

On the other hand, the EMG captured from beginners frequently lacked these features, especially the peak corresponding to (1). Thus we focused on the region that includes these three features.

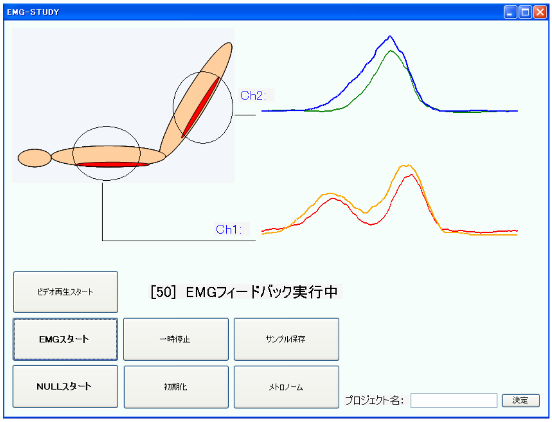

Fig. 2. Visual feedback of the upper arm and forearm EMG patterns. The patterns enable quick comparison of the learner's and the expert's muscle activity features during a cycle of dribbling.

As a measured EMG signal, i.e. raw data, has a lot of frequency components, the wave form itself is too complicated for a learner to understand quickly. To emphasize the three features previously described, we extracted schematic shape of the EMG signal in one dribbling cycle by using a first order differential filter, a full-wave rectification, and a smoothing by moving average with the time window 80 msec. The extracted EMG data is named *EMG patterns*.

In order to effectively provide the difference of expert and beginners' EMG signals during the training, we constructed the visual feedback system shown in Figure 2. As shown in the figure, on the expert's EMG patterns which are collected beforehand (blue and orange lines), the learner's EMG patterns (green and red lines), obtained via the above preprocessing, are superimposed and updated periodically.

During the training with the proposed system, a learner tries to tune his/her own EMG patterns to the expert's EMG patterns. Note that the learner's EMG pattern is updated every 5 sec.

3 Method

To evaluate the effect of the proposed EMG-based training support system, we executed a training experiment. Six healthy subjects (male, aged 21-24) participated in the experiment. None of them has any special training experience of the basketball dribbling task. They were randomly assigned to one of the two groups, i.e. the group of training with the proposed visual feedback system (hereafter, Feedback condition), or without any feedback information (Null condition). The difference of these training conditions was limited only to the presence of the visual feedback of the EMG patterns.

Before starting the training experiment, the experimenter who is a dribbling expert explained the three features observed in the expert dribbling to all subjects, and they were asked to keep these points in mind while the whole training session.

Additionally, the subjects in Feedback condition group were asked to tune their EMG patterns to the expert's ones as much as possible. Moreover, all subjects were made to hear an electronic metronome sound (1.5 Hz) to keep their dribbling period constant.

Each subject did the dribble training for approximately 30 minutes as a whole. It included first half training (15 min.), rest (5 min.), and second half training (15 min.). To evaluate the performance improvement through the training, three *performance tests* (30 sec.) were executed before and after the first half and after the second half, respectively.

4 Results

4.1 Qualitative Comparison of Raw EMG Data

Transition of the raw EMG signals, i.e. their changes from before to after the training, was compared between the two training conditions. In the case of upper arm, we could not confirm any difference between the conditions. Thus the results of forearm muscles are shown in the paper. Figure 3 represents transition of raw EMG signals measured from the forearm of a subject trained under Feedback condition, and Figure 4 shows the results of a subject trained under Null condition.

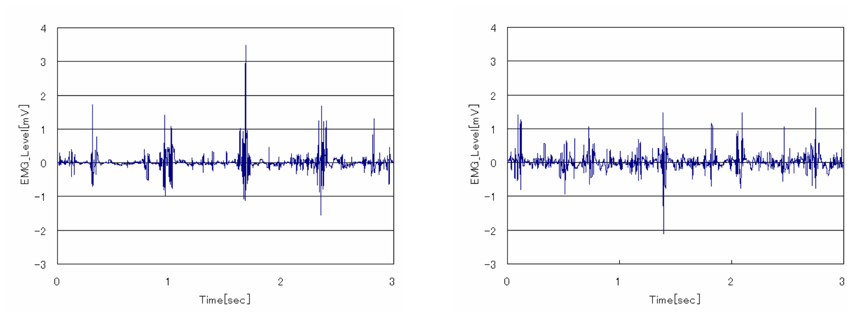

Fig. 3. Transition of raw EMG signals measured from a subject trained under EMG-Feedback condition (left: initial performance test, right: final performance test).

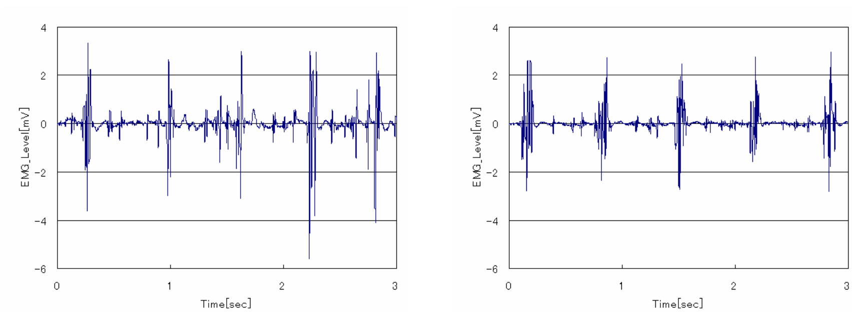

Fig. 4. Transition of raw EMG signals measured from a subject trained under Null condition (left: initial performance test, right: final performance test)

As shown in Figure 3 left and Figure 4 left, there was no distinct difference between the subjects of two conditions in the initial test. On the contrary, in the final test, one of the experts' EMG features—it is connected with the forearm pulling up motion when receiving the bounced ball—was observed in the subjects of Feedback condition (Figure 3 right). On the other hand, no acquisition of the experts' EMG features was observed in the subjects of Null condition (Figure 4 right).

4.2 Quantitative Evaluation of EMG Patterns

We conducted quantitative evaluation of the difference described above. First, standardizing the time interval of EMG patterns of one dribbling cycle as [0, 1], we identified that the muscle activity corresponding to the technique of pulling up forearm appeared in the region of [0.1, 0.45], which we named *technique region* (see Figure 5). Accordingly, we decided to use the amount of forearm muscle activity in this technique region as a measure of the forearm pulling up technique. The amount of muscle activity in a time interval was calculated by applying to EMG signals the following steps: (i) first order differentiation, (ii) full-wave rectification, (iii) standardization of a dribbling cycle into [0, 1], and (iv) integration over the given interval.

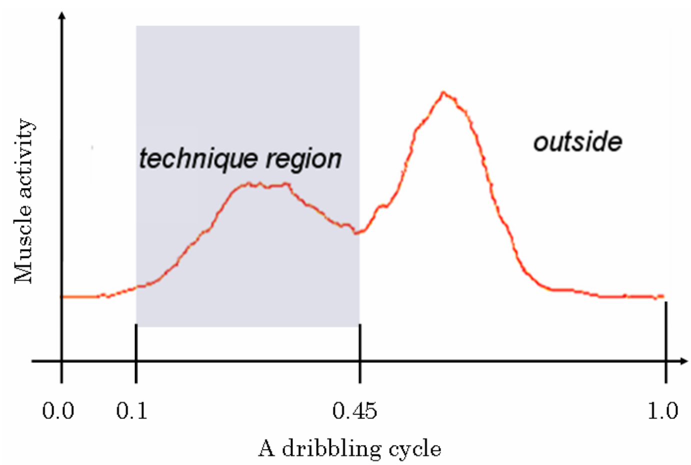

Fig. 5. EMG pattern and technique region

Figure 6 shows mean forearm muscle activity ratios of the technique region in the initial and final test, for each subject ("EMG_X" are the subjects under Feedback condition, and "NULL_X" are those under Null condition). To cancel the difference of muscle activity level between individuals, the amount of muscle activity in the technique region was normalized by the one over whole dribbling cycle. The dribbling cycles (number of samples) that contributed to the evaluation value were about 20 (for stability of evaluation, early parts of the tests were discarded).

T-test (P=0.05) of the mean value between initial and final test showed that for two of the three subjects who exercised under Feedback condition, the muscle activity of forearm at the timing of the technique region increased significantly after the training,

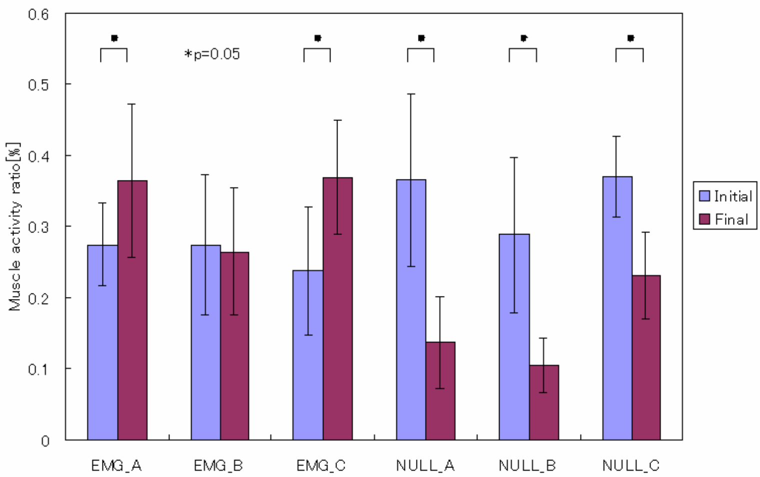

Fig. 6. Comparisons of muscle activities in the arm-pulling region (initial vs. final tests)

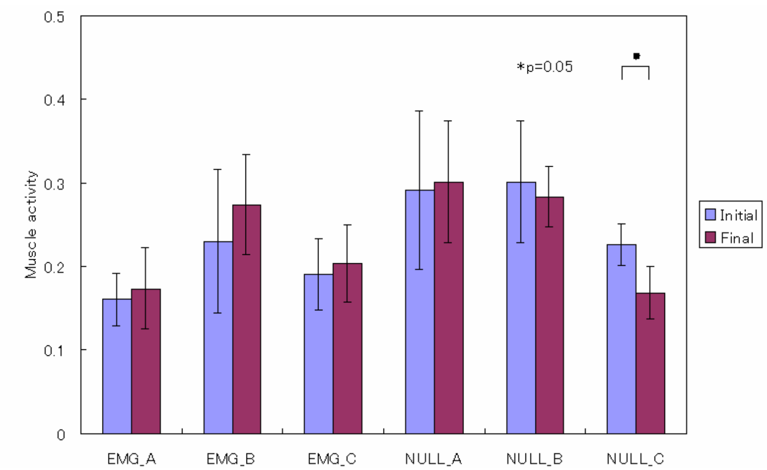

Fig. 7. Comparison of muscle activities outside the arm-pulling region (initial vs. final tests)

indicating the acquisition of the forearm pulling up technique. On the other hand, forearm muscle activity at the same timing significantly decreased for all the three subjects with Null condition, confirming their failure to acquire the technique. These results suggest that the proposed system is effective in supporting the acquisition of the forearm pulling up technique. A possible interpretation of these results is that the real-time feedback of EMG pattern made the learners conscious of their own muscle activity, and that promoted their learning process. In contrast, the learners under Null condition had no external information to judge whether they are achieving proper movement (desirable technique).

We also studied the change of muscle activity *outside* the technique region. As shown in Figure 7, for the subjects in both conditions, the amount of muscle activity outside the technique region indicated no significant change before and after training. This result confirms that Feedback condition worked to raise the muscle activity only at necessary point and timing, excluding the possibility that it just augmented general muscle stress and induced overstrain by making the learners too sensitive to their muscle activity.

In sum, our study supported the hypothesis that the EMG feedback in real time is effective in motor learning, especially with respect to timing and power (i.e. coordination).

5 Conclusions

In this study, we proposed a new motor skill acquisition support system. The proposed system utilizes electromyogram (EMG) signals as the metrics for evaluating the motor skill acquisition process, because EMG signals measured from human experts are notably different from beginners in terms of timing and sharpness. According to this, we hypothesized that visualizing the difference of EMG signals between an expert and a learner, and providing the error information to the learner in real-time accelerates the learning process. The preliminary results show that the proposed method is effective especially in the early stage training of beginners.

However, retainment of the motor skill acquired through the proposed system is not confirmed yet, because in our experiment, final performance test was executed immediately after the training. Furthermore, we should also confirm the causation that the similarity of EMG pattern results in improvement of the basketball dribbling skill of the subject.

Acknowledgments. This research was partially supported by the Ministry of Education, Culture, Sports, Science, and Technology, Grant-in-Aid for Scientific Research on Priority Areas (No.20033007), and “Symbiotic Information Technology Research Project” of Tokyo University of Agriculture and Technology.

References

1. Sakurai, S., Ohtsuki, T.: Muscle activity and accuracy of performance of the smash stroke in badminton with reference to skill and practice. Journal of Sports Sciences 18, 901–914 (2000)
2. Furukawa, K., Yoshinaga, S., Sawai, K., Shimizu, S., Kinjo, K.: On modeling bow arm movement in cello playing by whip motion. In: Proc. of 3rd European Medical and Biological Engineering Conference (2005)
3. Bilodeau, E.A., Bilodeau, I.M., Schumsky, D.A.: Some effects of introducing and withdrawing knowledge of results early and late in practice. Journal of Experimental Psychology 58, 142–144 (1959)
4. Nintendo Wii (2009), `http://www.nintendo.com/wii`
5. Mattar, A., Paul, G.: Motor Learning by Observing. Neuron 46, 153–160 (2005)