Visual Feedback System for Intuitive Comprehension of Self-movement and Sensor Data for Effective Motor Learning

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1 OBJECTIVES

Information feedback systems for motor learning have been widely studied. Means of providing feedback can be divided into two approaches: auditory and visual. Audio information can provide feedback without preventing training motions a trainee makes when moving (Effenberg et al., 2011). However, due to the intrinsic feature of sound, i.e., that is one-dimensional temporal data, the information it can express is quite limited.

Visual feedback has also been widely studied (Guadagnoli et al., 2002; Wieringen et al., 1989). Feedback of this type can provide a great deal of information through the use of visual information. For example, Chua et al. have developed a training system in a VR environment (Chua et al., 2003). The system uses a motion capturing technique to capture a trainee's movements and shows the corresponding trainer's movements. Choi et al., have proposed a system that estimates motion proficiency on the basis of motion capture data (Choi et al., 2008). However, though visual information may enhance motor learning efficacy, there are two problems that make it difficult for most existing visual feedback systems to be used in practice.

One problem is in setting. The aforementioned systems employ motion capture techniques to obtain human movement. The overhead for setting mocap systems and training site restrictions deteriorate the systems' efficacy. The other problem is in the timing of visual feedbacks. The simplest visual feedback system is training in front of a mirror. In this case, the trainee has to get visual feedback while he or she is moving, which disrupts practice. Another simple visual feedback system is capturing and watching a video. In this case, the temporal gap between capturing and watching gets longer, and this degrades feedback efficacy.

In recent years, small sensors have been developed that enable information of various types such as surface electromyography (EMG), cardiac rate, and respiration rate to be captured with only a small amount of interventions required on the part of trainees. These can be used as additional information for motor learning feedback. Here, we should note that a considerable amount of information does not always result in effective motor learning; in fact, too much information may well disturb motor learning efficacy.

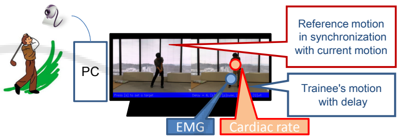

Figure 1: Typical use case of the proposed system.

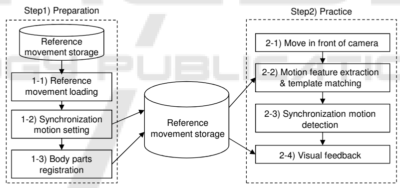

Figure 2: Flowchart of proposed system.

We aim at providing visual feedback of a trainee's movements for effective motor learning. This paper describes a new visual feedback method we propose with this aim in mind. It has three main features: (1) automatic temporal synchronization of trainer and trainee motions, (2) intuitive presentation of sensor data, e.g. surface electromyography (EMG) and cardiac rate, based on the position of the equipped sensor, and (3) an absence of restrictions on clothing and on illumination conditions.

2 METHODS

Figures 1 and 2 show a typical use case of the proposed system and the system flowchart, respectively. The system consists of two parts: a preparation part and a practice part. At the preparation part, a user registers a reference movement. Then, at the prac-

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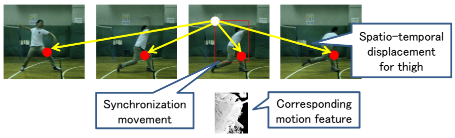

Figure 3: Synchronization movement registration.

tice part, the system provides visual feedback of the user's movement in synchronization with the reference movement, and provides sensor output on the corresponding body part. The following subsections describe the two parts in more detail. After the descriptions we introduce the motion feature employed in the system, i.e., MHI or motion history image.

2.1 Preparation Part

The preparation part consists of three steps; (1) loading of reference movement, (2) registration of synchronization movement, and (3) registration of positions of body part on which a sensor is equipped.

Step1-1. This step loads the reference movement. The reference movement can be one captured by the system with a camera; alternatively, it can be one already available on a video file.

Step1-2. The synchronization movement, as well as its timing and area, is registered at this step. Figure 3 shows an example of synchronization movement registration. Movements inherently include spatial and temporal information. The synchronization target of the trainee's and reference movements varies according to the purpose of practice. Therefore, the system registers synchronization movements interactively. Hereafter, the synchronization timing of a reference movement is depicted by T_{sync}. The extracted feature of the synchronization movement is stored in a reference movement storage area. The motion feature used in the system is described in Sect. 2.3.

Step1-3. This step registers the positions of the body part on which a sensor is equipped. As mentioned previously, too much information may actually hinder effective motor learning. Therefore, the system displays the sensor's output on a body part to which the sensor is attached to enhance the ease of information comprehension. The positions of body parts are used not for analysis but for displaying, so high accuracy is not required. To the extent of described in this paper, spatio-temporal displacement from the reference movement is manually obtained as the position of a body part. Table 1 and the yellow lines in Fig.3 show an the example of spatio-temporal displacement. In the example shown, the thigh is located at $x_n^{(t)}, y_n^{(t)}$ from the synchronization point n frames prior to the synchronization timing .

Table 1: Example of spatio-temporal displacement.

temporal displacement from sync timing	spatial displacement thigh	arm
n	$x_n^{(t)}, y_n^{(t)}$	$x_n^{(a)}, y_n^{(a)}$
:	:	:
0	20,0	30.0
1	$x_1^{(t)}, y_1^{(t)}$	$x_2^{(a)}, y_2^{(a)}$
:	:	:

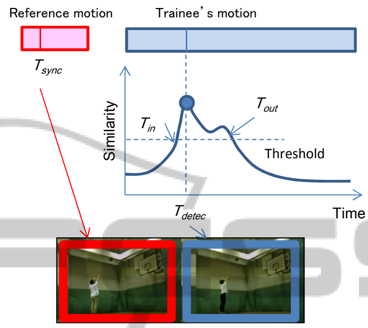

Figure 4: Practice part.

2.2 Practice Part

The practice part, which consists of four steps, provides visual feedback of a trainee's movements for effective motor learning. The reminder of this subsection describes the practice part in more detail with reference to Fig.4.

Step2-1. First, a trainee practices the target movement in front of the camera.

Step2-2. Then, in this step, the motion feature is extracted at each frame. The similarity between the extracted feature and the reference movement's feature is calculated by template matching.

Step2-3. After that, the peak similarity timing is extracted as the synchronization timing T_{detec}.

Step2-4. Finally, the reference video at T_{sync} and the trainee's video at T_{detec} are synchronized on a display, and additional sensor information is displayed at a place designated by Tab. 1.

2.3 MHI or Motion History Image

As a means of calculation and representation of motions, the MHI method has been widely used because of its ease of implementation (Bobick and Davis, 2001), and is employed in the proposed system. Figure 5 shows an MHI and snapshots of the corresponding image sequence, where the snapshots are shown from left to right in time order. In the MHI, the value of each pixel shows how recently a motion was detected on the pixel. Bright (white) pixels denote pixels at which motions are detected. As the time proceeds from the most recent motion, the pixels turn dark.

3 RESULTS

Currently, we have not yet verified the motor learning efficacy obtained with the proposed method. This section only shows the appropriate motion synchronization and body part estimation it provides.

First, we verified the system provides realtime and automatic motion synchronization. Fig.6 shows an example of the results obtained in the verification procedure. As shown in Fig.6, the trainee's movement in front of camera is correctly synchronized with the reference movement on the display within one second by using a tablet PC.

We also verified the accuracy with which the system estimates body parts for displaying sensor data. The result sequences are shown in Fig.7. The red, yellow and green dots denote arm thigh, and toe, respectively; the left row denotes reference and the right one denotes synchronized practice sequences. As shown in Fig.7, the proposed system works well for different types of clothing worn by trainees. A few errors were found to have occurred in the body parts estimation, but the accuracy is good enough for showing sensor data. So far, we sensors' output didn't be used, but they can be assigned to size and/or color of dot for intuitive feedback.

4 SUMMARY

In this paper we proposed a new visual feedback method with the aim of providing visual feedback of trainee's movements for effective motor learning. The method incorporates three main features: (1) automatic temporal synchronization of trainer and trainee motions, (2) intuitive presentation of sensor data, e.g. surface electromyography (EMG) and cardiac rate, based on spatial position of a sensor attached to the user, and (3) an absence of restrictions on clothing worn by the user and on illumination conditions. Future work will include verifying the actual motor learning obtained with the proposed method.

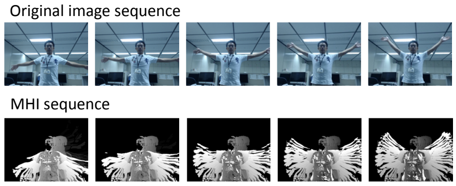

Figure 5: Motion feature MHI.

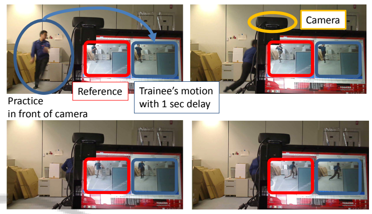

Figure 6: Realtime processing on tablet PC is verified.

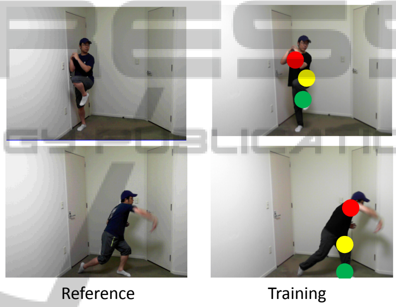

Figure 7: Body parts estimation; red dots denote arm, yellow dots denotes thigh, and green dots denotes toe.

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