Liu, C.-C. et al. (Eds.) (2014). Proceedings of the 22nd International Conference on Computers in Education. Indonesia: Asia-Pacific Society for Computers in Education

Design of an Environment for Motor-skill Development based on Real-time Feedback

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Abstract: Advancements of information technology and sensing technology enables to support motor-skill development in real-time. The authors propose a supporting model, which improves the form of motion in real-time. Our proposal shows the difference between the present form and the ideal form. In addition, it offers the expected form in future and the result of the performance. It is a reason why the authors consider the process of human motor-skill. The target skill is a sort of closed skill. The retrival in the form database is improved using the k-means algorithm. At last, the authors touch upon an experiment of our proposed model.

Keywords: skill development, motor skill, real-time, motion capture

1. Introduction

Advances in hardware and software technology make it possible to obtain digital data of human motion by video and sensors. In addition, there are several studies that support acquisition of motor skills using the digital data (Hamagami, et al., 2012) (Kosaka, et al., 2011). The field of these studies is called motor-skill development. In this research field, a motion of a human is called "motor-skill". A motor-skill is a physical-activity, which humans can master with a specific education or a training.

The supporting environment of motor-skill requires significant functionalities of "Monitoring", "Analysis" and "Feedback” (Schmidt, 1975). “Monitoring" function provides conversion of a human-motion to data. “Analysis" function is to calculate the difference between the monitored data as a learner and the model data as an instructor. “Feedback" function reports the straightforward information denoted by the difference to the learner using natural language and graphics. In addition, Zimmerman (2008) reported a model of the timing when learners acquire motor-skill in self-learning.

Moreover, motor-skill can be classified according to some criteria. We can classify the supporting-model using the timing of intervention. Intervention by the system is carried out either asynchronously or synchronously. In asynchronous supporting-model, we monitor and record full action of motion from beginning to the end using video and sensors at first. Secondly, we calculate the characteristic difference between the monitored motion and the other one for comparison. Finally, we advise the learner in an appropriate manner due to the result. Such an asynchronous supporting-model has an advantage of low-cost in terms of the system device and the development. Regarding synchronous supporting-model, we also monitor and record motor-action of a target skill using video and sensors at real-time. Secondly, we calculate the difference in parallel to monitoring while the learner performs continuously. At last, we advise the learner during the ongoing performance of the motor-skill. The synchronous supporting-model has a contradistinctive advantage, which the learner can obtain the advice at real-time. Therefore, the learner can correct the behavior using the advice on real-time.

In recent years, the improvement in the throughput of a computer enables high-speed information processing. Therefore, “synchronous supporting" becomes possible. In this research, the authors discuss the system design for "synchronous supporting”.

2. Requirements for Motor-skill Development

Fitts et al. (1967) say that the motor-skill development consists of three process; i.e. cognitive, union, and automatic ones. In a cognitive layer, a learner of motor-skill understands the goal of the target motion and its strategy for the goal. Nextly, in a union layer, the learner practices repeatedly so that s/he can perform the coordinated movement smoothly. In the overtimes practice, the learner needs the feedback in order to proceed effectively. Finally, the learner may get to the automatic layer. In the automatic layer, the learner can perform the skill smoothly and perform without consciousness.

Schmidt (1991) supposes that human performs a skill based on a process. The process consists of “stimulus identification”, “response selection”, and “response program”. In the “stimulus identification”, human recognizes an environment human exists and trajectory of limbs. The trajectory means a trace of own motion. In the “response selection”, human decides internal models within a brain and a physical manner. In the “response program”, human makes a program to perform an action. The action is a body representation of an internal model.

In motor-skill development, a learner in a union layer of Fitts needs to recognize a gap between an ideal motion and a selected internal model. The authors assume that real-time feedback makes easy to recognize the gap. Since the learner performs the skill based on the strategy, the action of a learner in a moment should attain the strategy. In order to attain the strategy, the learner needs to grasp the difference between an ideal motion and a present motion. Moreover, the learner needs to grasp the influence of the present motion on the future. That is, our real-time feedback should include a future’s motion predicted from the present motion.

Gentile (1972) classifies motor-skill with common criteria. Therefore, we can apply the supporting method according to the classification. For example, a motor-skill is classified as Open-skill or Closed-skill. In the Closed-skill, a performer should perform fixed motion. Therefore, the learner of Closed-skill needs feedback after the end of motion. The feedback should represent a difference between a target motion and the performer’s motion. This feedback enables the performer to obtain routinized and fixed motion. In the Open-skill, a performer should determine the contents of motion along with what the motion changes with time and situations. Therefore the learner should obtain a capability to perceive a situation and obtain a capability to judge contents of motion. We assume that real-time feedback should be considered of the skill’s classification.

In order to show predicted motion, it is necessary to calculate subsequence of future’s motions using present motion data. There are some researches to predict time series data. For example, Autoregressive analysis(AR) and Moving average (MA) are fundamental methods as a prediction with time series data. However, there are few related works about prediction of multi-dimensional data for a human-motion. Moreover, if the authors create the differential equation about the motion using the physical model, it may be possible to predict the next motion by solving the present state analytically. Since it is necessary to create a differential equation for every skill, the authors cannot use general-purpose supporting system. Then, the authors collect a learner's data and calculate the similarity of the stored data and input data. The authors predict future’s motion using data with the highest similarity. Moreover, the authors predict the performance result using similar motion's data. The authors think similar motion has similar performance result. Since AR, or MA and a differential equation predict only motion, these methods cannot predict performance result.

Predicting future’s motion is a motion recognition problem. In other words we classify current data into the past data. There are some researches about motion recognition. For example, many techniques, such as a Fourier transform, discriminant analysis, principal component analysis, and a support vector machine, are proposed. Moreover, Yamada, et al. (2013) recognize a motion by HMM. However, this method recognizes the motion from all sequential data. Therefore, we cannot recognize the motion using sub-sequence of motion data. It means that we cannot predict the future's motion while a performer conducts a motor-skill. Then, the authors calculate similarity about all data of posture and presume the present state. If the present state can be specified, the remainder of the motion is a future motion. A problem is that there is much computational complexity in order to calculate similarity with all data of posture. In this research, the authors create a key to a dataset, and reduce computational complexity.

3. Supporting Scenario

3.1 Preparations

In our proposal, some preparations are necessary before learning. Figure 1 expresses the outline of the preparation that a learner should do until the learning. It also shows the flow of the preparation of the system side. In step (1)(on left side), it is checked whether a skill is "Closed-skill" or not. Otherwise, a learner divides into sub-skill to make "Closed-Skill". In step (2), a learner collects the data of motion and the result of performance about a skill. In process (I)(on right side), our system saves the data of motion and the result of performance into the database. Step (1), (2), and process(I) show preparations. Step (3) and process (Ⅱ) shows practices receiving actual feedback.

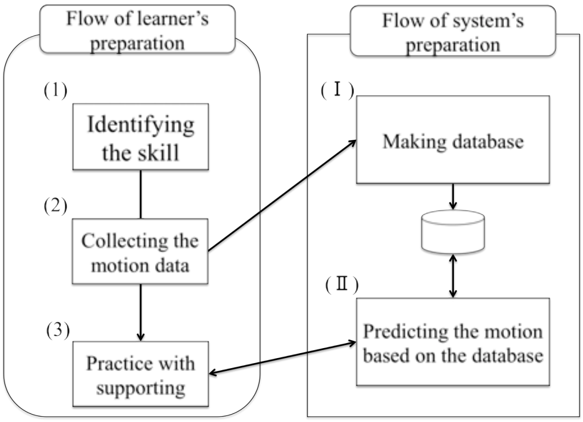

Figure 1. Flow of preparations

3.2 Contents of real-time feedback

Figure 2 shows the outline of supporting. At first, in (a), the system gets a learner's data of posture. In (b), the system finds the similar data of the posture from a database. In (c), the system shows the predicted performance result to the learner as a feedback. By this feedback, the learner can update selected motion. Furthermore, the system shows the sequence of the posture that may happen to the next of the present posture as a feedback. By this feedback, the learner can recognize a gap of own action and past action. In (d), the learner updates own selection. The learner corrects own motion by repeating (a)~ (d).

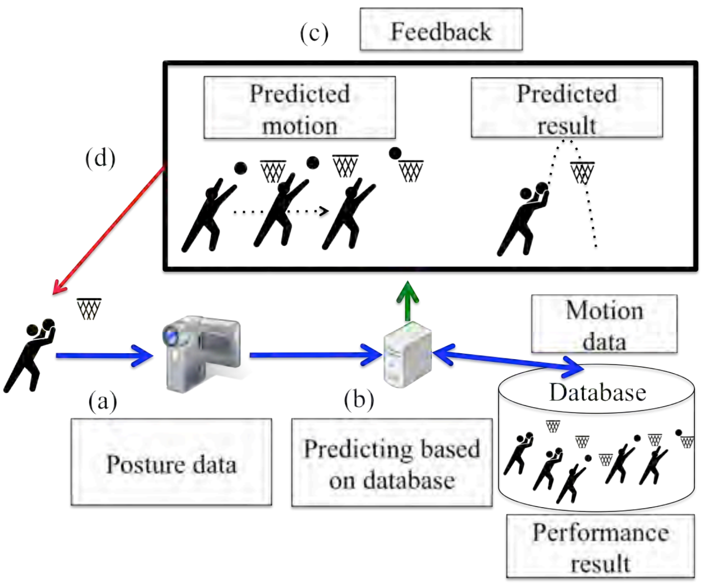

Figure 2. Flow of supporting system.

4. Development of Supporting System

Our system obtains data of the posture using a motion capture. The motion capture is the optical type in our system, while there are optical type, mechanical type, magnetic type, and so on. By using motion capture, posture's data of time-series can be obtained by the three-dimensional data of limbs. Since it is related to performance, the authors don't obtain the information about a tool using motion capture. When a performance is related to the locus of a motion, the authors may obtain the information of a tool using motion capture. Our supporting system predicts motion using accumulated data. Furthermore, a data structure that enables high-speed recognition is required. In our system, an input is multi-dimensional data describing the posture. Moreover, the similar data is required as an output. A simple algorithm that fills these inputs and outputs is to calculate similarity with all posture's data in a database. The similarity between postures is sum of Euclid distance about three-dimensional coordinate in each limbs. Therefore computational complexity is 3 x (number of limbs) x (number of postures) x (number of forms in database). However, depending on the number of the stored data, it is not a realistic method. Then, by segmenting the data using the k-means algorithm, the authors make other data structure, which can search faster than the simple algorithm. Segmenting a motion with the posture, or its acceleration, the authors create the average posture. When our system has posture data as an input, our system calculate similarity with this average posture.

The authors use the k-means algorithm for segmentation. A k-means algorithm is a kind of non-hierarchical clustering. A given dataset is classified into k clusters using the average of a cluster(hereinafter centroid). The k-means clustering consists of following procedure.

1. A cluster's label is assigned at random to each data.
2. The centroids are created using an arithmetic average.
3. Calculating a distance between a data and each centroid of the new cluster. A cluster that has minimum distance is assigned to the data.
4. Procedure 2~3 are repeated. In "procedure 3", when no cluster updates, a loop becomes an end. Furthermore, the loop is an end when the criteria of updating are cleared.

The reason of using k-means algorithm is that a motion of motor-skill doesn't have clear hierarchy.

The authors describe an algorithm applying a k-means algorithm to segment the motion. Firstly, if a target skill is continuous skill, the learner saves a motion of one cycle to the database. The next procedure is following.

i. A data is divided into k pieces at equal intervals in order of a time series, and a cluster's label 0~(k-1) is assigned to each data. The reason why the first cluster is not random is for the data to change according to time series.
ii. The centroid is calculated for every data. The centroid is an arithmetic average of the coordinates of each limb.
iii. Our system calculates the similarity between the centroid and each data. Our system assigns the cluster's label using the minimum Euclid distance.
iv. "Procedure ii~iii" is repeated until updating is lost.

Thus, the centroid is created with a cluster. The learner or the instructor using this system determines the number of clusters. For example, they measure the acceleration of the limbs and determine the number of clusters on the basis of the number of peaks. In addition, if the number of typical postures is decided, they use it. Moreover, the reason for using the Euclid distance, the authors think that it is easy for the learner to understand an absolute distance between parts.

The authors show a flow that the system searches for a similar data. The searching procedure is as follows.

A) The posture's data is input into the system.
B) The system calculates the Euclid distance with each centroid that exists in the database.
C) The system determines the cluster with the shortest distance.

The computational complexity is 3 x (limbs) x (number of centroids) x (number of forms in database) by using the k-means method. Compared with a simple method, it has succeeded in reducing the computational complexity. Since the centroid has the index set, the our system feed back the posture data with the next index as predicted data.

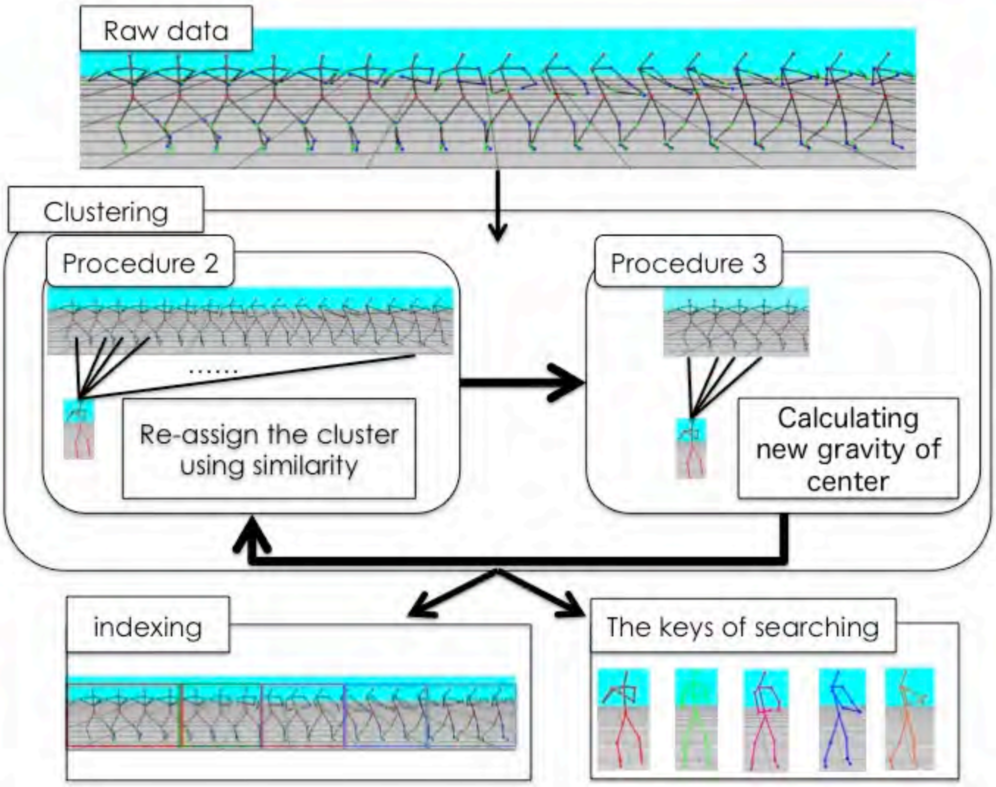

Figure 3. Flow of clustering the motion data

Figure 3 illustrates the flow of creating the keys with proposal algorithm. "Raw data" shows three-dimensional data of a motion and it is the form of the batting of baseball. Since this motion has "establishing", "backswing", "beginning to shake", "impact", and "follow-through", these five states are set to the keys. "Clustering" in Figure 3 describes "procedure2" and "procedure3". "Procedure2" in Figure 3 describes calculating the similarity for all data and updating the cluster. In "procedure3", the new centroid is created based on the updating a data. "The keys of searching" expresses the centroids in searching. "indexing" shows assignment of cluster's label to each posture's data.

5. Evaluation Method

The authors conduct an experiment for verifying the prototype system. The authors propose the system that performs real-time feedback for closed skill. By using this system, recognition of the gap with "response selection" and "response program" becomes easy. This system makes efficiently for a learner to acquire a closed skill. The authors think that the learner using the system can acquire the motion much earlier compared with no supporting learner. Then, the authors create a control group and an experimental group. Next, a learner practices respectively. The authors measure an effect without supporting of the system after one practice. Figure 4 express a flow of an experiment. In "Pre-test", the learner performs the target motion without supporting of the system. The authors record the form to verify the effect of the support. In "First learning", the learner looks at animation of an ideal motion to know what is an ideal motion. In "First learning", the learner doesn't perform the skill actually. In ”Learning with support”, the learner practices with an actual movement. In an experimental group, the learner practices based on the proposed supporting system. In the control group, the learner practices without the supporting system. In "Post-test", the learner performs the target motion without the supporting system. The authors record these forms and calculate a difference between the forms in "Post-test", and the motion in "Pre-test".

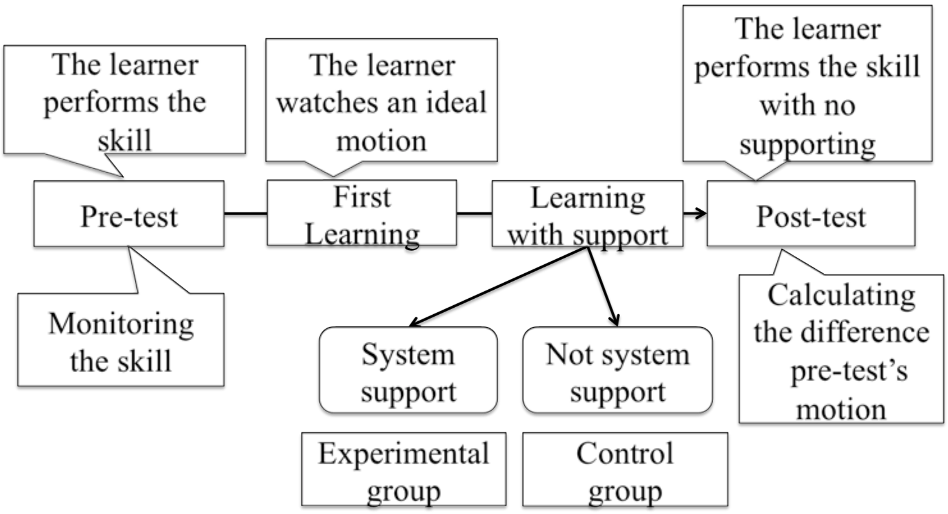

Figure 4. Flow of experiment

6. Concluding Remarks

The authors propose the environment for motor-skill development based on the real-time feedback using sensing technology, such as motion capture. From the information on the present form, the system predicts the next form and performance. Furthermore, the system feed back a predicted result to a learner. The authors think the learner who is in a union layer acquires the skill earlier. About prediction, the system calculates the similarity with the past learner's data. Furthermore, the system outputs the performance result with the largest similarity of forms. As a technique on the computer, our system segments the motion data using k-means algorithm. The computational complexity is reduced by the clustering. In order to verify this support model, the authors should apply the concrete skill.

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