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Using real-time acceleration data for exercise movement training with a decision tree approach

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ABSTRACT

In this paper, a movement-training system aiming to classify motions for physical education is proposed and analyzed. Traditional physical education requires an instructor teaching exercise movement individually. Teaching every student in a big class demands considerable time and efforts. Utilization of computer-assisted instruction (CAI) becomes pervasive in e-learning trend. However, CAI is often confined in literal form course such as mathematics and language courses. It is necessary to develop a motion-training system for physical education. In this paper, we develop a low-cost motion capture with Wii Remote Control (Wiimote) for training movement exercise, such as tennis and baseball. This system applies Wiimotes to capture acceleration of each part of limbs. Each Wiimote is attached to the limb which then sends back the acceleration information to the computer via Bluetooth wireless link. After gathering the acceleration data of multiple limbs' parts, the computer recognizes the motion and classifies the motion to several correct and incorrect categories. As a result, it is able to provide the appropriate advice to the students. The system applies a modified ID3 inductive learning to generate a decision tree with continuous-valued attributes. We develop an easy-to-use GUI interface for coaches. The results show that the average accuracy of classification is 83%. The system reduces the workload of the coach and improves teaching and learning performance.

1. Introduction

Recent advances in motion detection and computation power create the opportunity of using computer vision and motion detection techniques to video game for entertainment, computer-aided coaching for education. An interesting case study is sports motions' training. During the basic movement training, a coach is obliged to constantly supervise the students' movement. It is difficult for the coach to teach in a big class. In that case, the automated feedback-training system is required.

Previous work related to motion training that requires lab-like environment (Hachimura, Kato, & Tamura, 2004; Kwon & Gross, 2005; Multon, Hoyet, Komura, & Kulpa, 2007), multiple optical or magnetic sensor on the field, retro-reflective markers or magnetic sensors to be placed on an athlete body. These requirements and expensive cost restrain the broader use of motion capture system. The sensors on the body are often wired to the computer and thus constrain the movement of the trainer.

In this project, an easy-to-use motion-training feedback system is developed and analyzed. Exercise such as tennis and baseball needs much time on training basic motion, for example, swing and pitching. This paper proposes an inertial motion capture system for motion training. A system overview is shown in Fig. 1. The system is built of on-the-shelf gadgets. The system is inexpensive and easy to installation. Multiple Wiimotes are attached to limbs to gather a real-time acceleration data. A laptop processes the acceleration data and then classifies the motions to several right or wrong categories. Therefore, the computer displays a suitable feedback message to the trainer according to the motion type.

The motion classification is the crucial component of this system. Wiimotes contain inexpensive accelerometer sensors. However, the acceleration data are not enough to reconstruct the precise motion and posture. The proposed system uses modified ID3 decision tree induction learning for continuous-value acceleration attributes. The training data are generated by a coach. One correct motion type and several incorrect motion types are labeled in our experiment. Each motion type is corresponding to one feedback. The students are able to correct their motion by advices. The proposed system is also a user-friendly physical education system. A graphic user interface (GUI) is implemented in this system. The coach and the athletes are able to get familiar with this system in a few minutes.

The rest of this paper is organized as follows. In Section 2, this paper surveys two related topics which are decision tree and

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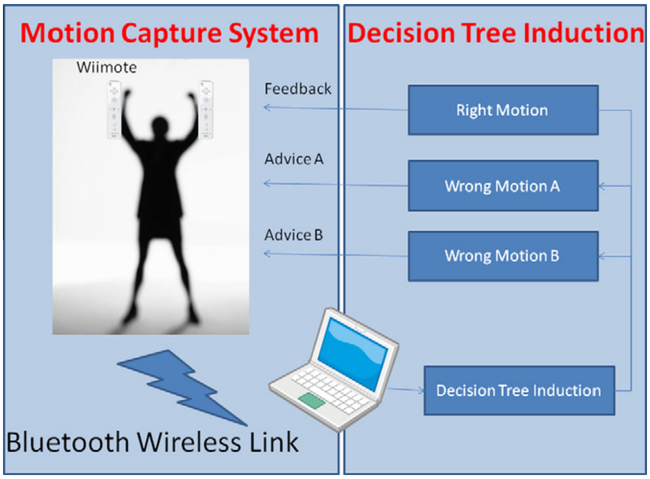

Fig. 1. The training system consists of the posture capture subsystem and motion classification subsystem.

motion capture technique. In Section 3, we propose a motion-training system for physical education, and then discuss the acceleration data gathering and decision tree induction. In Section 4, the experiments are carried out. Tennis forehand swings are our example training dataset. The results show that the average accuracy is above 80%. In Section 5, we conclude the paper and offer some future works and promising research points.

2. Related work

The proposed system combines decision tree and motion capture technique. This section introduces related research of these two techniques.

2.1. Decision tree

Classification is an application of data mining. The design of a classifier can be categorized into tree concept: based on similarity, clustering and probability. Choosing the right model is an important issue in this research.

Decision tree induction creates a comprehended classification model. It simplifies the complicated decision to an explicit decision tree. It provides an explanation to many complex problems. As a result, it is applied to many AI applications such as image recognition, text abstract and expert system.

A decision tree is a tree-like model which is able to determine the class of given instance. Each node is a division point which partitions the space of sample by an attribute test. And then each partitioned subtree is partitioned to subspaces with child node recursively. This is a divide-and-conquer paradigm for classification. Finally, every attribute will be tested and then each sample subspace can be classified into a class which is a leaf node.

Decision tree is an effective model for nominal attribute. However, the decision tree will be too complicated when attribute is a continuous value. It causes the low precision and multiple subtrees. Combining adjacent value into one cluster is a solution for this problem. To conquer this problem, distance function will be applied in López (1991). It could handle continuous-value attribute. Deciding suitable bin will generate the more precised decision tree.

2.2. Motion capture

To do the motion training, several motion-tracking methods with different motion capture system are developed. This part introduces a variety of motion capture on motion-training application.

Optical motion capture systems track optical marker to locate the human body (Hachimura et al., 2004). Exact 3D marker locations are computed from the images recorded by the surrounding cameras using triangulation methods. These systems are favored in the computer-animation community and the film industry because of their exceptional accuracy and extremely fast update rates. The major disadvantages of this approach are extreme cost and lack of portability. Specific area and equipment are needed. To reduce the cost and improve the portability, some systems use a small number of markers in conjunction with standard video cameras. Besides optical maker method, another emerging technology is markless motion capture (Kwon & Gross, 2005; Liu, Lin, Zhang, & Tao, 2007). It uses computer vision-obtained motion parameters directly from video footage without using special markers. These approaches are less accurate than optical systems, however, they are more affordable and more portable. Still, they are not entirely self-contained since they rely on one or more external cameras. Furthermore, they suffer from line-of-sight problems, especially in the case of monocular video.

Magnetic systems detect position and orientation by the relative magnetic flux created by coils or earth. Metallic objects interfere with magnetic and electrical fields (Foody et al., 2006). So, these systems may detect metallic marker. The advantages of these systems are good accuracy and medium update rates. They also eliminate line-of-sight problems. The disadvantages are expensive cost, high power consumption, nonlinear measurement accuracy, and are sensitive to the presence of metallic objects in the environment.

Mechanical systems require performers to wear exoskeletons. These systems measure joint angles directly rather than estimating the positions of points on the body and can record motions almost anywhere. Exoskeletons are uncomfortable to wear for extended time periods and impede motion, although these problems are alleviated in some of the modern systems, such as Measurand's ShapeWrapTM.

Both radio frequency (RF) and acoustic systems are remote sensing techniques. They use the time-of-flight of an audio or RF signal to compute the marker locations. Most current systems are not portable and handle only a small number of markers.

Inertial motion capture systems measure rotation of the joint angles using gyroscopes or accelerometers placed on each body limb (Foody et al., 2006; Slyper & Hodgins, 2008; Vlasic et al., 2007). Like the mechanical systems, they are portable, but cannot measure positions and distances directly for applications that must sample the geometry of objects in the environment. More importantly, the measurements drift by significant amounts over extended time periods. In addition, the motion of the root cannot be reliably recovered from inertial sensors alone, although in some cases this problem can be alleviated by detecting foot plants.

Nowadays, motion and rotation capture technology propagate into the education and recreation. Wii console is a very popular game console. It creates the possibility by using low-cost approach to capture the motion of user. Wiimote is the master component of the Wii console. It usually captures the human motion. Like the Motion capture technology improves the motion-training systems, motion capture system is able to support gymnast's training (Liu et al., 2007; Multon et al., 2007). A user can directly interact with the virtual gymnast. The user's arm motions are blended to the original aerial motions in order to verify their consequences on the virtual gymnast's performance.

3. System architecture

The proposed motion-training system consists of two subsystems, a motion capture subsystem and a decision tree induction subsystem. A motion capture subsystem is able to acquire acceleration data of each body part by Wiimote. These data are encoded and jointly transmitted to a laptop. The main program is installed in laptop which samples the signals from all the Wiimote and transfers them onto the storage drive for off-line data processing and ID3 inductive learning. This section describes our hardware and its operation. The motion capture subsystem captures the motion and induction tree subsystem using ID3 inductive learning to generate a decision tree model for motion classification. It classifies user motion according to limbs' acceleration of X, Y and Z axes. This process is real-time when training. The trainer can review the advice when training.

Fig. 2 depicts the flow chart of this system. It shows the data processing procedure. In motion capture subsystem, the acceleration of each limb is acquired by Wiimote. Then the acceleration data are transmitted to a laptop via WiimoteLib (Schlömer, Poppinga, Henze, & Boll, 2008). The laptop stores these data to its database. In decision tree induction subsystem, the data are retrieved from data warehouse, and then use the ID3 inductive learning algorithm to build a decision tree. The building process will be mentioned later in this paper.

3.1. Motion capture subsystem

The purpose of motion capture subsystem is to capture the acceleration data of the user. This subsystem still needs to satisfy additional requirement which decreases the cost and facilitates the setup. Thus, this system adopts on-the-shelf gadgets such as Wiimote and conventional laptop. The software architecture is illustrated in Fig. 3.

The Wiimote is a wireless device which uses the Bluetooth standard which allows two-way communication to other Bluetooth devices including PCs (Coding4Fun). Up to four controllers can be used with same Wii console at the same time. The Wiimote has nine buttons which provide control availability. The extraordinary feature of Wiimote is the motion-sensing capability. The controller has one three axes ADXL330 accelerometer which can be used to determine acceleration of x, y and z displacement vectors. The measurement range of the accelerometer is typically ±5G. The controller has a speaker and provides limited rumble feedback.

The accelerometers of Wiimotes are able to capture the acceleration data while limbs are exerting. The Wiimote are fastened on each limb during users' training. The acceleration data will be translated to x, y, z displacement vectors and then the data will be transferred to laptop. The motion capture program handles these processes. In Fig. 3, the WiimoteLib objects are responsible for initiating and managing Bluetooth communication link to Wiimote. The Wiimote collection object creates and manages WiimoteLib. The WiimoteInfo object is a graphical user interface which displays the detailed information of each Wiimote. The Multiple Wiimote Form is an object which allows the user to control the training process.

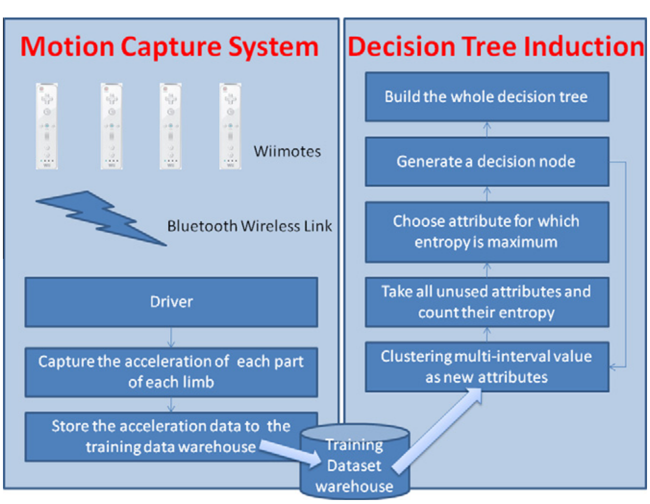

Fig. 2. The flow chart of the proposed system.

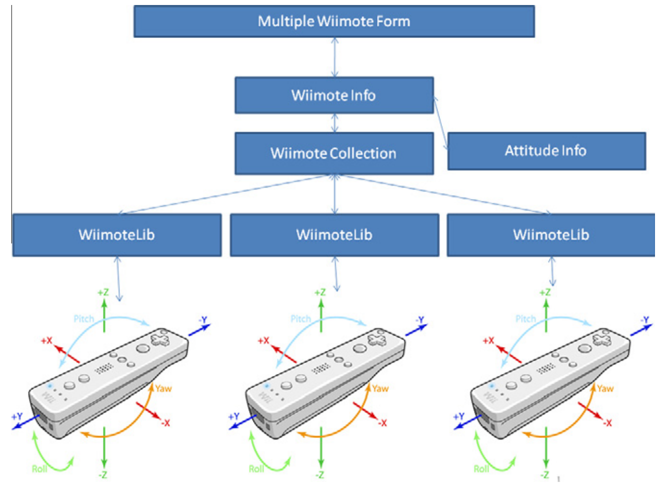

Fig. 3. The architecture of motion capture subsystem.

In the process of capturing motion dataset, the user presses button A to start the capture motion. After the presetting duration, the recorded acceleration data of the motion will store into the data warehouse. These motion dataset should be used by ID3 inductive learning as detailed in the next section.

3.2. Decision tree model

The decision tree subsystem uses ID3 inductive learning. The algorithm of ID3 inductive learning is described as follows:

ID3 (Examples, Target_Attribute, Attributes)
Create a root node for the tree
If all examples are positive, Return the single-node tree Root, with label = +.
If all examples are negative, Return the single-node tree Root, with label = −.
If number of predicting attributes is empty, then Return the single-node tree Root, with label = most common value of the target attribute in the examples.
Otherwise Begin
  A = The Attribute that best classifies examples.
  Decision Tree attribute for Root = A.
  For each possible value, vi, of A,
  Add a new tree branch below Root, corresponding to the test A = vi.
  Let Examples(vi), be the subset of examples that have the value vi for A
  If Examples(vi) is empty
  Then below this new branch add a leaf node with label = most common target value in the examples
  Else below this new branch add the subtree ID3 (Examples(vi), Target_Attribute, Attributes − {A})
  End
  Return Root

Table 1
Categories of motion dataset.

Categories	Feedback	The number of samples
Correct forehand swing	Excellent	80
Only swing wrist	Swing the whole arm	50
Arm unstretch	Stretch out the arm	50
Racquet is not vertical	Grip the racquet horizontally	50

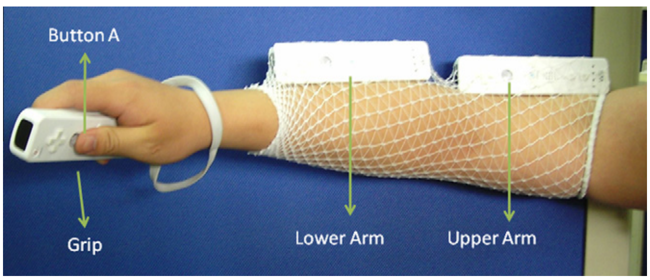

Fig. 4. The position of the Wiimote.

Information gain is calculated from the entropy of the subtree and collection of the object

$$E[C] = \sum_j p_j \log_2 p_j \quad (1)$$

Table 2
Accuracy of motion dataset.

Categories	Feedback	Accuracy (%)
Correct forehand swing	Excellent	83
Only swing wrist	Swing the whole arm	75
Arm unstretch	Stretch out the arm	78
Racquet is not vertical	Grip the racquet horizontally	74

The largest information gain attribute will be selected as test attribute in this node.

4. Experiment

To assess the performance of the proposed motion-training system, an evaluation of the tentative tennis motion-training system has been carried out. The experiment chooses forehand swing motion as the training sample data set. There are four categories as the output of the decision tree induction. Table 1 presents the detail of the four categories. Each motion returns a unique feedback. The system has been a collection of 230 sample datasets. With a coach labeling, the classifiers are able to classify the motion with ID3 algorithms. The system is written in a C# language by using WiimoteLib.

Fig. 4 is the gadget which the user required in the experiment. Two Wiimotes are fastened on a user's upper arm and lower arm. One Wiimote is gripped in user's hand. The user swings forehand after pressing button A. The acceleration will be recorded and then send back to the laptop immediately.

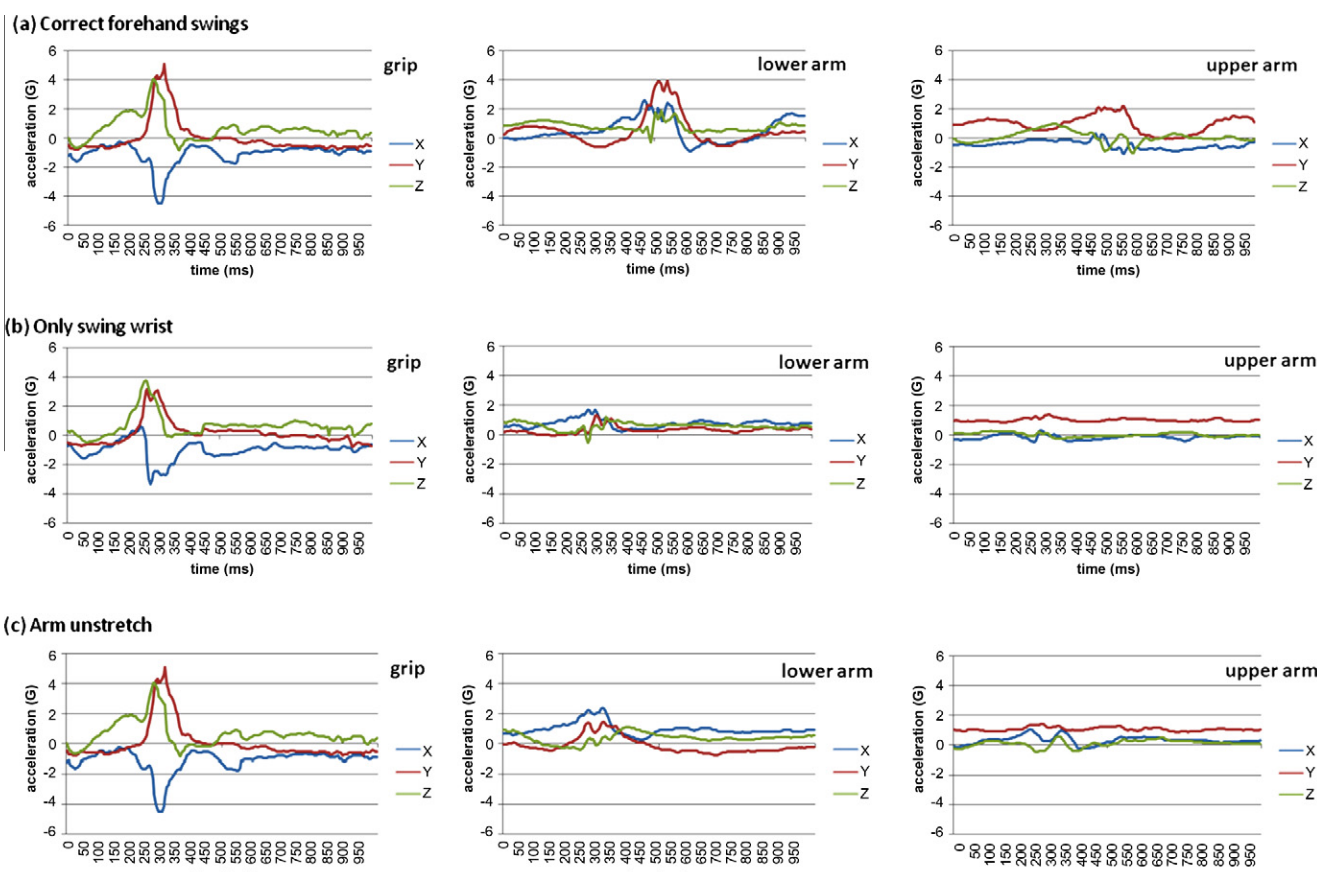

Fig. 5. (a) The correct forehand swings. The motion of a standard forehand shot of a coach. (b) The coach swings the racquet using the wrist. (c) The coach swings a racquet without stretching her arm.

Fig. 5 is the acceleration data measured in three motion types. We measure the acceleration in G. The duration of measurement is one second. Each motion sample contains 600 attributes. There are three lines in each graph. The blue[1] line is acceleration on *X*-axis. The red line is acceleration on *Y*-axis. The green line is acceleration on *Z*-axis. Fig. 5(a) is the graph of correct forehand swings. All the accelerometers in three positions measure significant acceleration. Fig. 5(b) is the motion which only swings the wrist. The beginners often do this wrong swing. The figure shows that accelerometer on upper arm measures low acceleration value. Fig. 5(c) is the motion at which the user swings without stretching the arms. This is also an another mistake that the beginners often do. This figure is similar to Fig. 5(b). However, the acceleration of *X* on upper arm is larger than that of the previous motion. This feature can be used in the classifier.

In the final experiment we check the accuracy of classifier. In this experiment, 50% samples are used in training the decision tree. Fifty percent samples are used to be classified by the decision tree. As Table 2, the correct swing motion is most accurate. It may be caused by the large number of training sample. The accuracy of motion at which the user's racquet is not vertical is lowest.

5. Conclusion and future work

Along with the development of the motion-training system, it creates the opportunity of enhancing physical education. In our experiment, the computer-assisted motion-training suits with tennis swing training. Since learning these skills requires drills and practices, this system aids the students with motion recording and advice. On the other hand, the efficiency of motion classifiers is our concern. In this research, the classifier applies a multi-interval decision rule on continuous value to reduce the size of the decision tree.

This research conducts a set of experiments to quantify the benefits of combining classification and body sensor data for motion training. We believe that our motion-training system provides significant improvement over conventional motion training. In our motion-training system, accelerometer data are used as a feedback to the user allowing him to coarsely adjust his motion. In addition, our system evaluates the motion in real-time and provides the appropriate advice.

In the further research, other training scenario will be investigated. Martial art or other acute body movement will measure high acceleration. These scenarios will need a more sophisticated accelerometer. We expect to design a specific suit for intense movement. Applying this protocol in a different application is also an interesting research point.

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[1] For interpretation of color in Figs. 1–5, the reader is referred to the web version of this article.