Analysis and Evaluation of Human Movement based on Laban Movement Analysis

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Abstract

In the past, in the domain of human movement, athletes, dancers and rehabilitation relied heavily on experts to judge whether or not learners' movements were correct, and offered suggestions for improvement. By way of modern science and technology, analyses via sensors can determine the motion of each body region. Our research is based on the Laban Movement Analysis (LMA) of dance, where data from several sensors are analyzed. According to the aforementioned sensor data, we can examine the efforts made by learners' movements. In this paper, we use LMA sudden and sustained efforts to analyze these movements and construct a guiding language system in accordance with expert guiding language already available. This system will provide suggestions for students even in the absence of expert advice. In this way, learners can learn in such a self-taught way.

Key Words: Human Movement, Effort, Laban Movement Analysis (LMA), E-Learning, Sensor

1. Introduction

As previously mentioned, past efforts in the domain of human movement were dominated by expert judgment. However, it is impossible for an expert to remain at the side of a learner at all times. Thus, a system is needed to help learners continue in the absence of expert "guidance." To date, the use of sensors has proven useful, though limited.

This paper is based on a project by the Ministry of Economic Affairs, numbered 97-EC-17-A-02-S1-052. Our research is based on using Laban Movement Analysis (LMA) for analyzing dance, with data being analyzed by several different sensors and motion catchers. According to the data, we can examine learners' movement efforts, such as sudden and sustained motions, and so on. Also, constructed is a guiding language system in accordance with guiding language offered by experts.

Moreover, a method is needed to analysis the movements of learners for a real-time guiding language system. Because the time complexity of the Ramer-Douglas-Peucker algorithm (RDPA) is O(nlogn)~O(n2), it cannot be used reliably in real-time. Thus, we propose a Triangle Smoothing Algorithm (TSA) for discarding noise collected by sensors. The time complexity of TSA is O(n), and as a result of the TSA, learners can receive guiding language in real time. We had technology transferred to Fitness Authority Industrial Co., Ltd. a manufacturer of fitness equipment in Taiwan.

2. Related Works

Some relevant research is referenced in this paper. In this section, we introduce the Laban Movement Analysis (LMA) theory and the Ramer-Douglas-Peuker algorithm (RDPA) for smoothing curves.

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Rudolf Laban, a German dancer, proposed the Laban Movement Analysis (LMA) theory in 1928 [1,2]. It is a system that observes and describes all forms of bodily motion. By using LMA theory, the movements of the human body can be explained. This includes the movements of dancers, athletes, physical therapists, and so on. In addition, the above includes five categories: body, space, shape, effort, and relationship [3].

- **Body**: the parts of the body that are used and the initiation and sequencing of a particular motion.
- **Space**: the locale(s), direction(s), and path(s) of a movement.
- **Shape**: the changing forms that the body makes in space.
- **Effort** [4–7]: how the body concentrates its exertion while performing movements.
- **Relationship** [8]: the modes of interaction with oneself, others, and the environment.

The Ramer-Douglas-Peuker algorithm [9–11] (RDPA) is an algorithm for smoothing curves. It was suggested by Urs Ramer, David Douglas, and Thomas Peucker. RDPA uses the method of divide-and-conquer for reducing the number of points in a curve.

However, RDPA's time complexity is not good enough for a real-time e-learning system. As such, we use another algorithm in its place.

3. System Architecture

The system architecture of this paper is divided into three major components: data collection, data processing, and the guiding language system.

The purpose of data collection is to collect sensor data for analysis, with experts then providing their professional suggestions and producing a guiding language for self-learning.

For e-learning, the system uses algorithms in the "data processing" component to analyze the real-time data collected by sensors. At the same time, feedback is immediately relayed.

3.1 Data Collection

For collecting human movement date, we placed 45 optical sensors on the body of a dancer as shown in Figure 1.

Afterward, the sensor data is collected from the Optical Motion Capture System. This includes 8 Vicon devices for optical sensors, 2 digital video cameras, 3 data storage boxes, 1 data storage station, 1 Biopac system, and 2 computers.

Human movement data is collected by this system and then discussed by experts. The experts evaluate the efforts made when a dancer moved according to the film. After obtaining evaluation results from these experts, a module is constructed for analyzing the efforts of movements.

3.2 Data Processing

In this paper, we use speed and acceleration measures to analyze the time effort of human movement.

$$\text{Speed } \upsilon = \frac{\Delta s}{\Delta t} \tag{1}$$

$$\text{Acceleration a} = \frac{\Delta \upsilon}{\Delta t} \tag{2}$$

υ is the measure of rate of change in position with respect to time; it is equal to the magnitude $|v|$ of its velocity. Δs is an infinitesimal displacement and Δt is an infinitesimal interval of time. a is the rate of change of velocity over time.

By using these formulae, we can calculate each sensor node's position during a specified period of time. Also, we can calculate the relations between different nodes, or the same node at different times. Figure 2 shows translation between speed and acceleration of a sample node in an interval of time.

In this paper, we analyze motion based on LMA. We

Figure 1. Dancer with optical sensors.

use speed and acceleration to determine the time efforts of LMA. There are two components in time efforts: "sustained" and "sudden." "Sustained" is used to describe leisurely, simple, and slow movements. Usually this indulges in time, such when a person strokes a baby. Examples of sustained efforts are shown in Figures 3(a) and 4(a). Figure 3(a) is a single sustained motion and Figure 4(a) is a series of sustained motions. "Sudden" is used to describe hurried and urgent movements. This type of motion is usually performed quickly, like swatting a fly. Examples of sudden efforts are shown in Figures 5(a) and 6(a). Both are examples of a human left arm during the act of swimming.

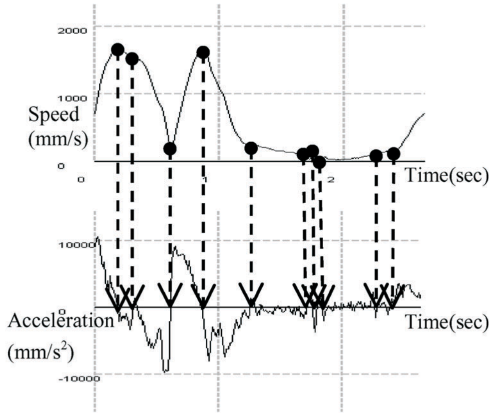
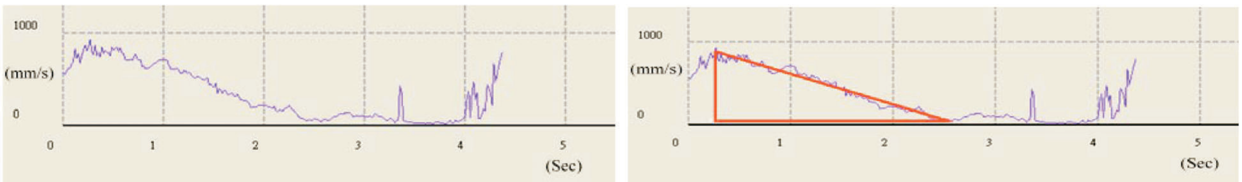


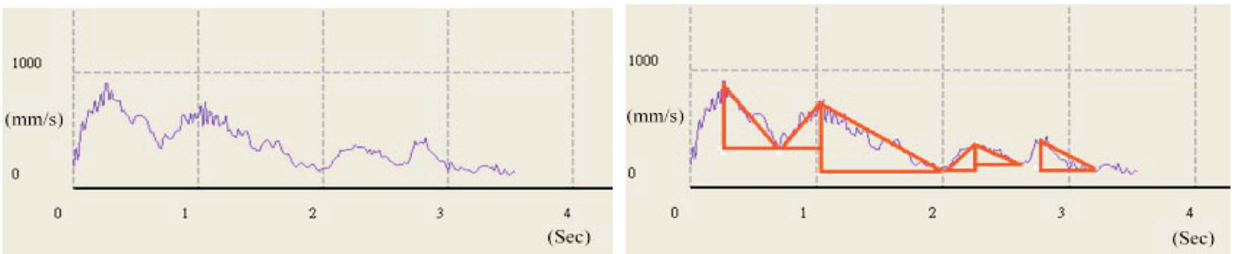
Figure 2. Translation between speed and acceleration.

When we analyze sustained and sudden efforts, we define M, δ, and T where M is the slope of speed variation, δ is a speed constant, and T is a period of time. If M > δ and T > ΔT, it is called "sustained" (Figures 3(b) and 4(b)). If M > δ, T ≦ ΔT, it is called "sudden" (Figures 5(b) and 6(b)). If neither, it is considered motionlessness.



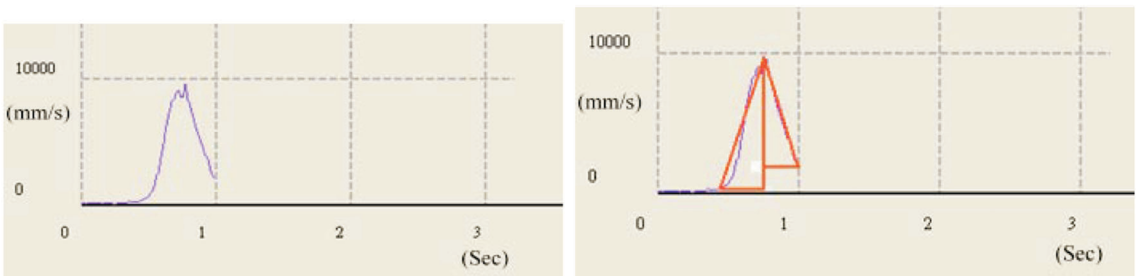
(a) (b)

Figure 3. (a) Single sustained motion. (b) Sustained motion analysis of Figure 3.3(a).



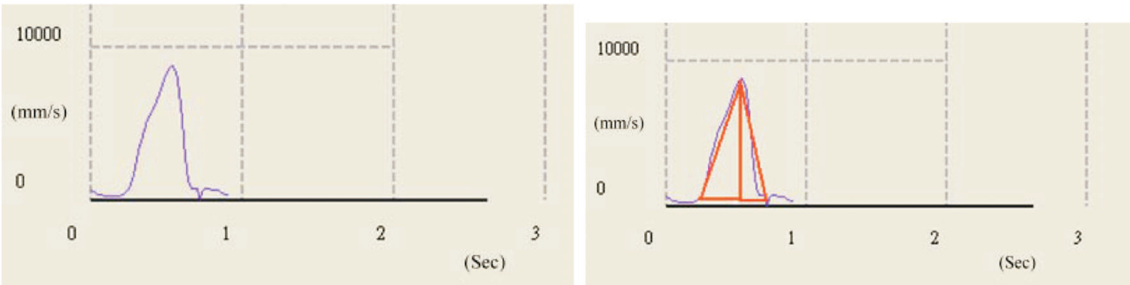
(a) (b)

Figure 4. (a) Series of sustained motion. (b) Sustained motion analysis of Figure 3.4(a).



(a) (b)

Figure 5. (a) Single sudden motion. (b) Sudden motion analysis of Figure 3.5(a).

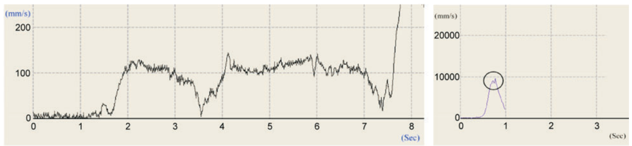


(a) (b)

Figure 6. (a) A sudden motion. (b) Sudden motion analysis of Figure 3.6(a).

The shaking of people's limbs will cause noise in measurement data (Figures 7(a) and (b)). In this paper, we proposed an algorithm, the Triangle Smoothing Algorithm (TSA), for reducing the number of points in a curve in order to discard noise. The traditional algorithm, RDPA, takes O(nlogn)~O(n^2) time complexity. It is not efficient enough for real-time environments because it spends too much time deducing which point should be reduced. The TSA simplifies the RDPA and provides a similar result. It takes O(n) time complexity and makes our system more efficient.

The algorithm of the TSA method is shown in Table 1.



(a) (b)

Figure 7. (a) Sustain effort with lots of noise. (b) Sudden effort with noise.

So, how does the TSA work? First, we assume there to be a threshold value. If the area of a triangle is less than the threshold, it is regarded as noise and discarded. An example is shown in Figure 8.

After analyzing a series of triangles, we can deter-

Table 1. TSA algorithm

TAS Algorithm	cost
Procedure TAS_algorithm(Threshold)	
{	
for(int i=Ta;i<Tb;i++)	
{	
//To compute_trialgle_area(i);	
Compute_TA (i);	c1
if(Area_List[i]<Threshold)	
{	
//To compute merge triangle area	c2
Compute_MTA();	
}	
//To sift and record Base_Point	c3
Sift_base_point();	
}	
}	

<Proof>
Compute_TA (i) is a function to calculate the area of a triangular, the running time is constant c1.
Compute_MTA() is a function to calculate the sum of two triangular areas, the running time is constant c2.
Sift_base_point() is a function to sift and record Base_Point, the running time is constant c2.
Compute_TA (i) and Compute_MTA() must be repeated from time Ta to time Tb,
The time complexity

$$T(n) = \sum_{i=Ta}^{Tb} (c1 + c2) + c3 = |Tb - Ta| \times (c1 + c2) + c3 \leq O(n) + c3 = O(n)$$

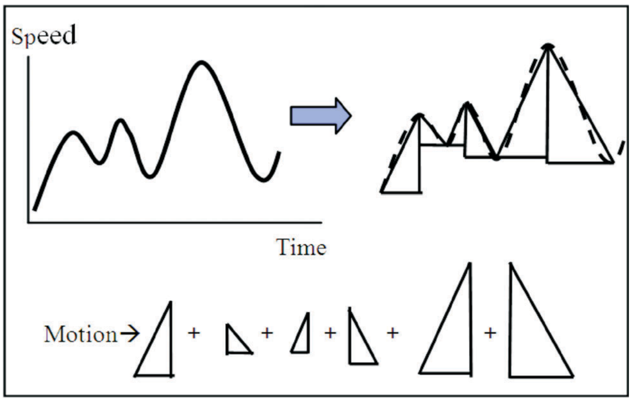


Figure 8. Dividing motion into small parts by the TSA.

mine significant motions. Meanwhile, useless noises are skipped. The data structure of the TSA is shown in Table 2.

The flow of the TSA is as follows:

■ Initial:

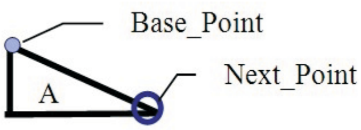
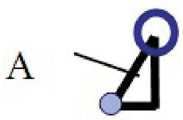
The first point is chosen from *Top_Bottom_Point_List*, and then set as *Base_Point*. At the same time, the sum of the series of triangle areas calculated and added to *Area_List*.

■ Step 1:

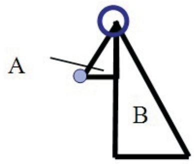
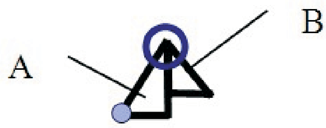
Add a node of *Smooth_List to Base_Point*.

■ Step 2:

Measure the area of a triangle and decide whether it is less than *threshold* or not. Threshold must to be based on the actual application and expert opinion to manual adjustment its value.

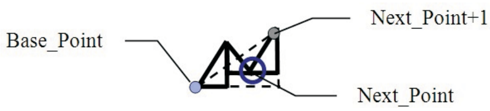
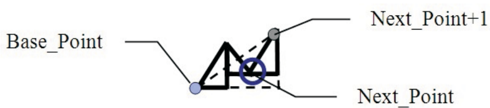
Condition	Case 1: Area A ≧ Threshold
Graph	
Action	(1) Setting Next_Point as Base_Point. (2) Returning to and continuing Step 1.
Condition	Case 2: Area A < Threshold
Graph	
Action	Continuing Step 3. (Checking the next triangle area)

■ Step 3:

Condition	Case 1: Area B ≧ Threshold
Graph	
Action	(1) Setting Next_Point as Base_Point. (2) Returning to and continuing Step 1.
Condition	Case 2: Area B < Threshold
Graph	
Action	Continuing Step 4. (Checking the next triangle area)

■ Step 4:

If the sum of a series of triangle areas is less than *threshold*, it is discarded.

Condition	Case 1: Triangle area (dotted-line) ≧ Threshold
Graph	
Action	(1) Setting Next_Point+1 into Base_Point. (2) Returning to and continuing Step 1.
Condition	Case 2: Triangle area (dotted-line) < Threshold
Graph	
Action	Continuing and checking the next triangle area.

An example of waveform graphs is shown in Figure 9. By following these steps, a waveform graph can be obtained and all noise can be discarded.

Afterward, the results of the TSA are used to analyze effort time. The LMA time effort analysis definition is shown in Table 3.

The rules of the LMA time effort analysis are defined as follows:

- If $S_a < S_{Motionless}$ and $S_b < S_{Motionless}$, the interval between A and B is motionlessness.

Table 2. Data structure of the TSA

Data Name	Data Type	Comment
Node	Frame (int), Speed (double)	Recording a relative velocity for each frame.
Top_Bottom_Point_List	List of Nodes (array)	Recording a series of nodes for a waveform graph's highest and lowest points.
Area_List	Value (double)	Recording an area for a series of triangles.
Smooth_List	List of Nodes (array)	Recording a series of nodes.
Base_Point	Value (int)	Recording a node of current base point.
Next_Point	Value (int)	Recording a node of next point which may become the next Base_Point.
Threshold	Value (double)	An amount of the area of a triangle. When the threshold is reached, a node is added to the Smooth_List.

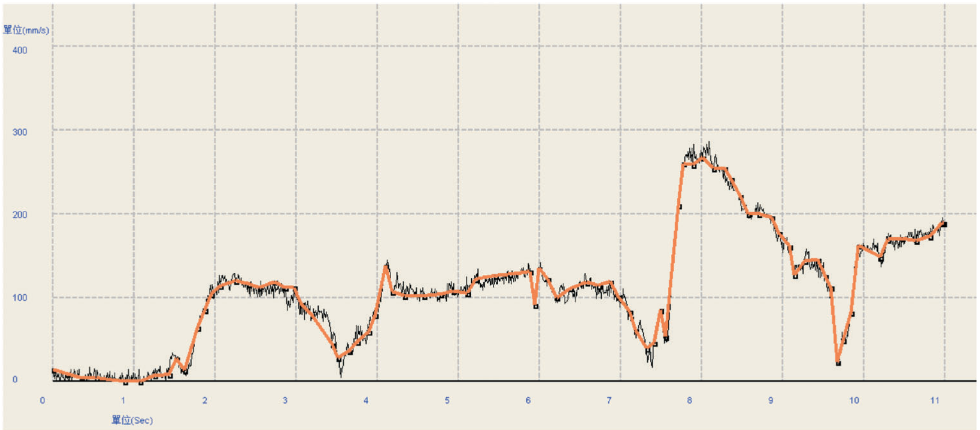


Figure 9. Discarded TSA noise.

Table 3. Definition of a time effort analysis

Variable	Comment
S_a	The initial speed (position A) of a motion interval
S_b	The final speed (position B) of a motion interval
$S_{Motionless}$	The motionlessness threshold
T_{Sudden}	The decision to make a sudden effort in an infinitesimal interval of time
λ	A variable for deciding whether a motion is sudden or sustained effort

- If the slope between A and B $\geqq \lambda$ and $\Delta t < T_{Sudden}$, the interval between A and B is a sudden effort.
- If the slope between A and B $< \lambda$, the interval between A and B is a sustained effort.

The result of the time effort analysis is shown in Figure 10.

3.3. Guiding Language System

After data processing that analyzes the efforts of human movement, sudden effort, sustained effort, and motionlessness are used to evaluate learners' motions. Also, time effort analyses are combined with expert opinions in order to construct a guiding language system.

For this system, we built many motion patterns. (See Figure 11(a)) A pattern means "a part of a continuous motion." Each pattern may include a sudden effort, sustained effort, or motionlessness. The Context-Free Grammar for these is shown in Figure 11(b).

Moreover, we can construct a decision tree for parsing patterns (Figure 12) by this grammar.

According to sequential patterns, a guiding language

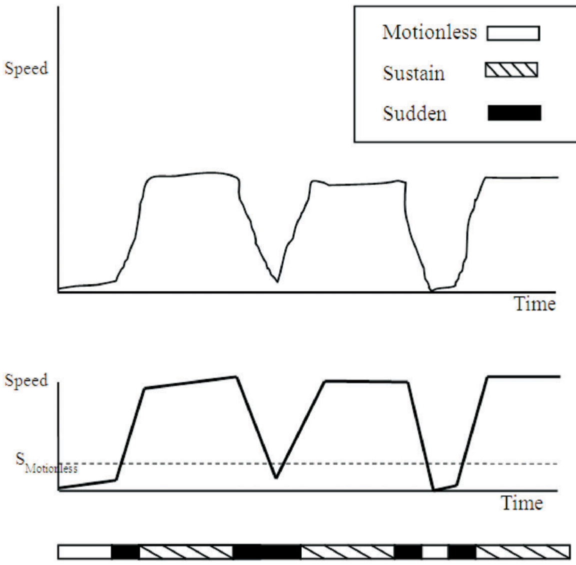
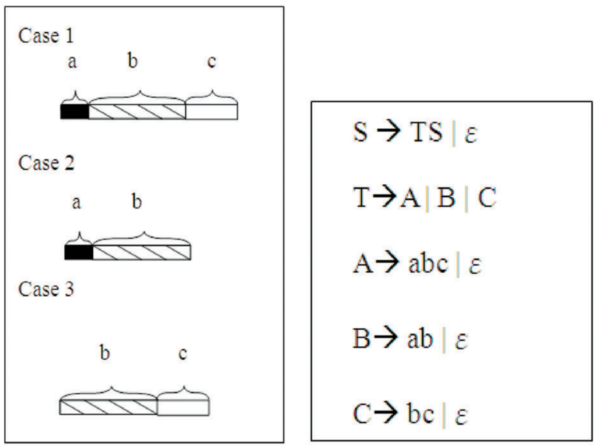


Figure 10. The result of the time effort analysis.



(a) (b)

Figure 11. (a) Standard motion patterns. (b) Context-free grammar for motion patterns.

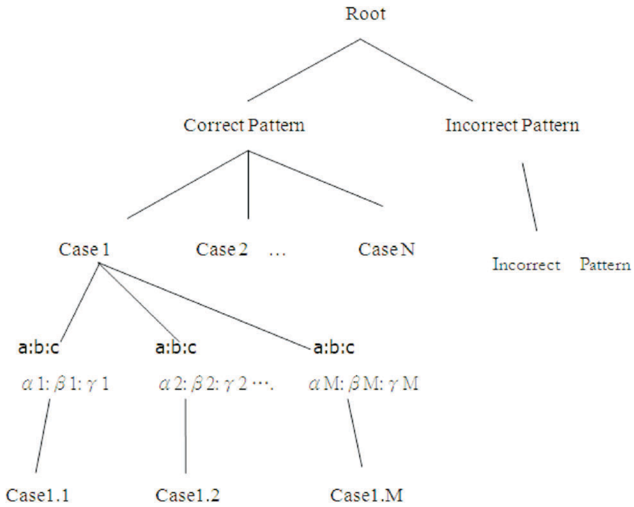


Figure 12. Decision tree for motion patterns.

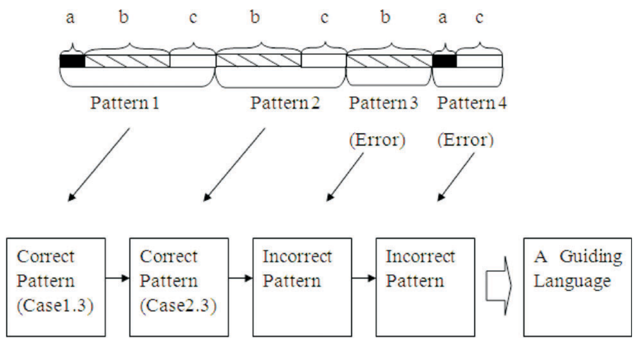


Figure 13. The relationship between learners' motions and the guiding language system.

for e-learning is constructed. We then use said guiding language system to check learners' motions. For example, when a learner's motion is received it needs to be checked, as shown in Figure 13. Some patterns match the patterns shown in Figure 11(a), which are correct patterns. If they do not match, they are incorrect patterns. Therefore, Pattern 1 and Pattern 2 are correct patterns. Conversely, Pattern 3 and Pattern 4 are incorrect patterns.

Meanwhile, learners' motions may be too fast or slow, so the guiding language system has another rule to check conditions. This rule includes slow, fast, unstable, and matched conditions.

4. Implementation

In this section, we use the healthy chair (Figure 1) offered by the Fitness Authority Industrial Co. to commence numerous experiments. We will discuss the experiment results.

4.1 The RDPA and the TSA

To compare the RDPA to the TSA, we chose a body motion (the swinging of the left arm) for the experiment. Figures 14 and 15 are the same data, with a segment length of 11 seconds and including 1,100 frames. The threshold of the RDPA is a perpendicular bisector and the threshold of the TSA is the area of a triangle. (Figure 14 is the RDPA results and Figure 15 is the TSA results)

The cost means the number of algorithm calculations. Because the threshold of the RDPA is a perpendicular bisector of two points and the threshold of the

TSA is the area of a triangle, they do not have the same threshold base, but similar results. For instance, Figures 14(a) and 15(a) are similar, and Figures 14(b) and 15(b) have similar results. In Figure 14(a) the threshold is 10, so it needs 8,059 calculations; however, the TSA only needs to 1,363 computations. Consequently, contrasts can be discerned. When the threshold of the RDPA is equal to 20, it costs 5,745. If the threshold of the TSA is equal to 750, it costs 1,378. When the time complexity of RDPA is O(nlogn)~O(n^2), it means RDPA needs more time to discern noise than TSA. RDPA has a serious shortcoming: if the threshold is too loose, it will cause the result and original figure to be different (Figure 14(d)). So, TSA is a better choice for a real-time e-learning environment. Figure 16 shows the two algorithms' relationships between costs and frame numbers. The condition of RDPA is poorer when frame numbers are increased.

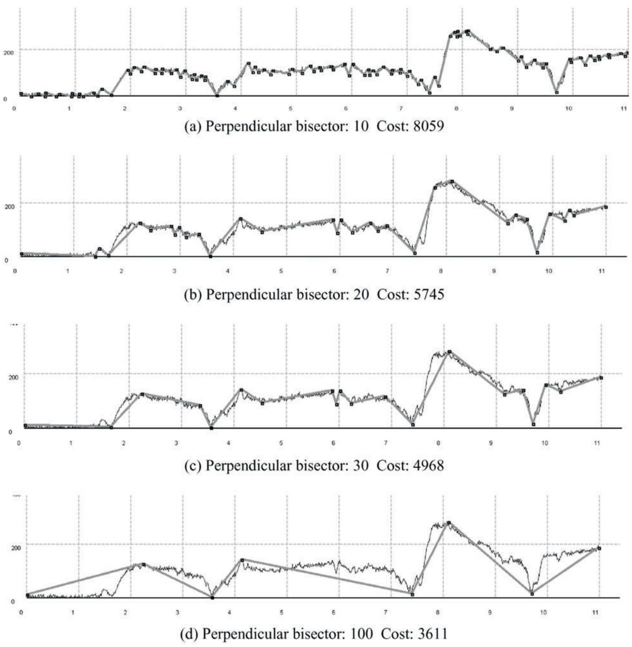


Figure 14. RDPA results.

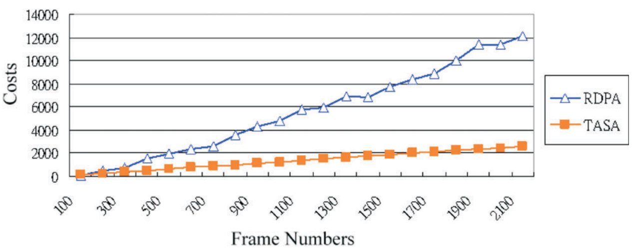


Figure 16. RDPA vs. TSA.

4.2 Guiding Language System

The device used in our experiment for a guiding language system is a healthy chair. Its motion is fixed between turning left and right. Other device specifications are listed in Table 4.

Figure 17 shows variations on angle and angle velocity. Normally, the angles for the healthy chair are between 80° and 180°.

Figure 18 shows standard motion resulting from an expert utilizing the healthy chair. Depending on the difference of the λ value, the system responds with different effort results. When λ is greater, the result is stricter. However, λ cannot be too great or its pattern cannot be analyzed. The range of λ in this exercise should be between 250 and 500. Otherwise, the guiding language system may not function correctly.

Figure 19 shows a learner's motion in the healthy chair. Figure 19(a) shows a regular user motion and Figure 19(b) shows an irregular user motion. Based on LMA

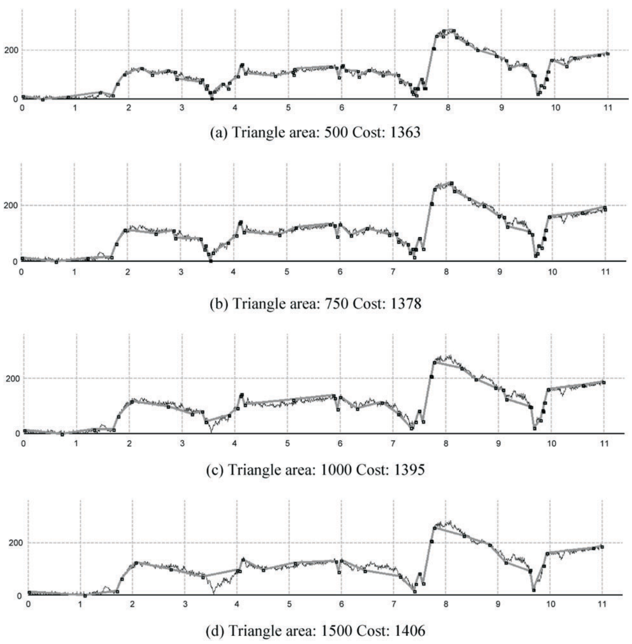


Figure 15. TSA results.

Table 4. The environment of the healthy chair

CPU	Intel® Pentium® 4 3.0 GHz
RAM	DDR400 RAM 1.0 GB
OS	Microsoft Windows XP SP3
Toolkit	Microsoft Visual Studio C#
Sensor	Motion Capture Sensors, Angle Sensor
Equipment	Healthy Chair

time effort analysis, the learner's motion has been analyzed to have several efforts, such as sudden effort, sustained effort and motionlessness. Furthermore, according to the guiding language system, these effort patterns should be compared. After calculations are completed using a user's motions, the system can determine and report on which part of an exercise is done correctly or incorrectly.

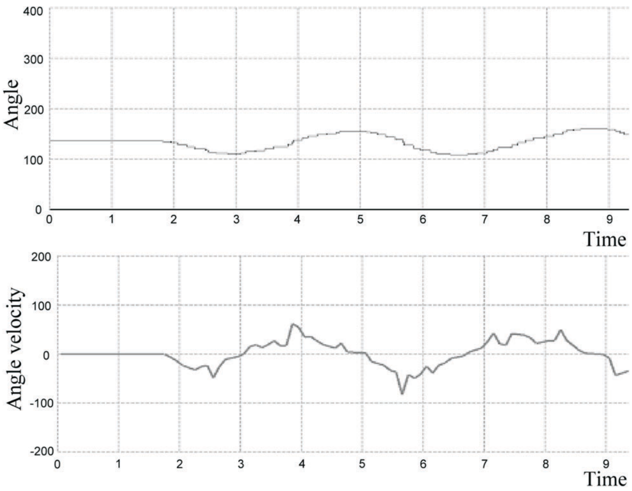


Figure 17. Angle and angle velocity of the healthy chair.

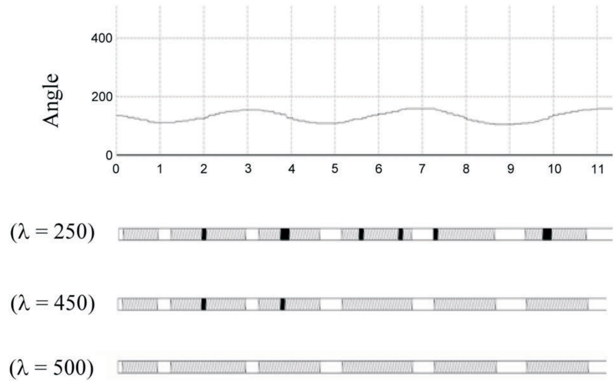


Figure 18. The relationship between λ and effort.

For example, Figure 20(a) shows a learner's un-

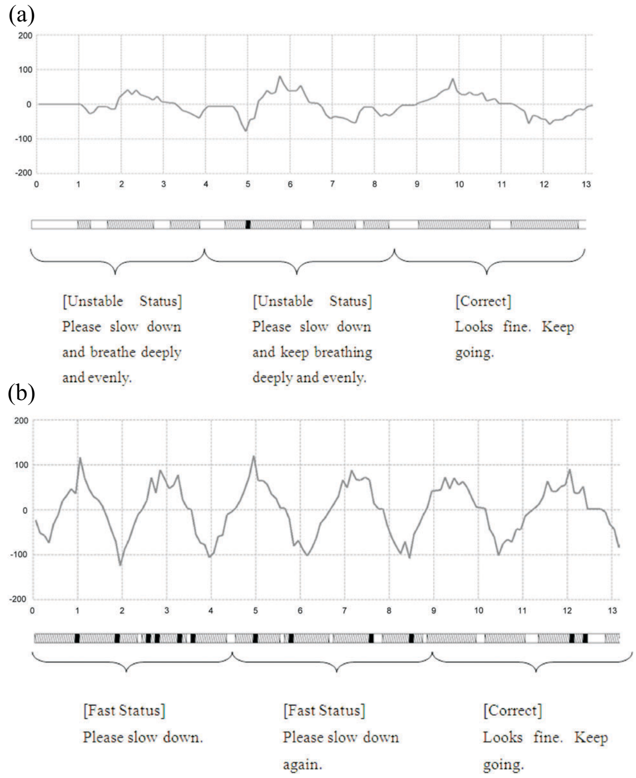


Figure 20. (a) A learner's motion with unstable status. (b) A learner's motion with fast status.

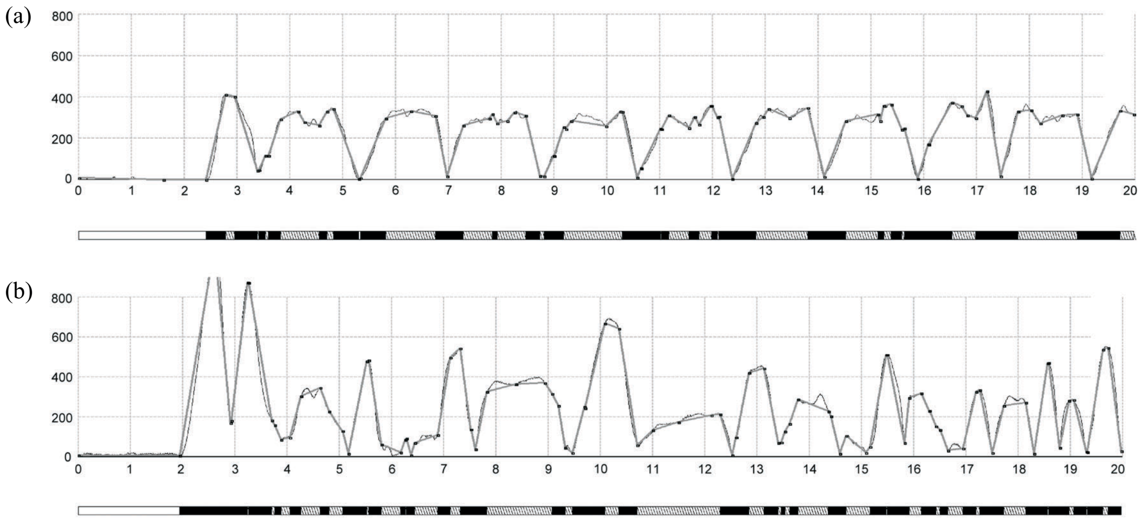


Figure 19. (a) The healthy chair with regular motion. (b) The healthy chair with irregular motion.

steady motion. Our e-learning system replies with comments telling the learner to slow down and breathe deeply and evenly. Figure 20(b) shows a learner's motion that is too fast. The guiding language system tells the learner to slow down.

5. Conclusion and Future Work

In summation, we proposed a new e-learning system for human movement. Based on the aforementioned guiding language system, learners can study by themselves. Also, they can receive experts' suggestions regardless of whether an expert is present. Moreover, we propose a TSA to discard the noise in a real-time system.

In this paper, we analyzed and evaluated sudden and sustained efforts, put forth by human movement, by way of LMA. However, in the area of body motion, there is much more to be done. We will continue research for other efforts and make our guiding language system more complete.

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