Kinect-Based Badminton Motion Analysis Using Intelligent Adaptive Range of Movement Index

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Abstract. Badminton is a type of racquet sport that is played using racquets to strike a shuttlecock within a netted rectangular court, and it is one of the most popular sport in Malaysia. In this paper, the team expanded their previous adaptive novel lossless compact view invariant compression technique, named adaptive range of movement index (RoMI) by embedding an intelligent mapping algorithm. Badminton players are broadly classified into two handedness groups, which are left-handed players and right-handed players. The adaptive RoMI technique in the previous module is capable of identifying the labels of normalized RoMI and perform adaptive mapping for badminton players of different handedness. However, the mechanism requires manual judgement from humans to select the type of handedness. This technique will increase the error rate and effort of importing data properties with incorrect manual handedness input or data stream from different handedness datasets of badminton players. Thus, the proposed intelligent adaptive RoMI technique enables the analyzing system to outperform the previous module by detecting the labels of normalized RoMI automatically and by performing intelligent mapping. The motion analysis system will then become much more efficient, intelligent hence simplifying data collection and the handedness invariant benchmarking approach.

1. Introduction

In recent years, human motion analysis has gained much attention in sport science and other third-party applications such as console entertainment, surveillance system and so forth. A common human motion analysis is to record and film the motion of athletes by utilizing monocular RGB (red, green, and blue) camera. The methodology, however, must be done manually under offline condition as the key features from the footages need to be annotated by an expert of the system. There is another methodology that involves attaching the markers onto an athlete’s physical body in order to define body-fixed coordinate systems or skeleton model of athlete’s motion and generates precise 3D representation of human body during marker processing. However, the placement of markers is usually cumbersome and inconvenient for athletes, especially in badminton sessions. The marker-based motion analysis module is also performed separately under offline mode. Elsewhere, a marker-less motion capturing system is generally better than marker-based motion tracking system in terms of efficiency as it tackles every limitation occurred in a marker-based system. The marker-less system is gaining popularity in recent scientific research and sport science training system development as it is able to generate a series of properties in different motion parameters that can be quantified and analyzed such as distance, angle and speed.
With the advances in sensor technology in this decade, there is a well-known inexpensive markerless depth motion capture system, namely, Microsoft Kinect sensor that has gained a lot of interests and recognition by researchers to be a cost-friendly sensor that could help in the discussion of collected measurements and data [1]. Besides, this sensor has been validated as being used for accuracy determination of skeleton tracking using depth map sequences [2-4], and the sensor would have substantial utilization for sport science analysis [3]. There are numerous Kinect motion analysis research in badminton in recent years, such as [5] that developed an auxiliary badminton training system for assisting trainers in terms of badminton movement analysis.

In year 2014, a badminton movement recognition system was proposed in [6] based on log-covariance quaternions framework which can recognize 10 badminton movements with the accuracy rate of 92%. Apart from that, [7-8] proposed a badminton motion analysis algorithm that can perform lossless compression and viewpoint invariant, in which the algorithm can compress, normalize and recover the spherical coordinate system into more distinctive and descriptive information that can aid the training process of players and coaches. Moreover, there are some researchers [9-10] that utilized the inertial measurement unit (IMU) technology by merging with Kinect sensor technology. In [9], authors were investigating on Unscented Kalman filter (UKF) by fusing data from internal sensors of IMU with Kinect which can overcome the limitation of the sensors and achieve better results in both accuracy and robustness. Meanwhile in [10], badminton athlete performance evaluation was conducted in order to investigate the acceleration differences between Kinect motion tracking and IMU by mathematical operations that compare the acceleration reading of IMU and Kinect motion tracking.

In this paper, the team improved their previous work [11] by implementing new embedded intelligent handedness adaptive module. The handedness badminton motion data is important for analysis as the performance of badminton players can be compared or benchmarked quantitatively and a consistency test can be performed among the players themselves regardless of handedness. Through this module, the manual handedness invariant selection process can be overcome by intelligent handedness automated decision and further reduce the error rate of human input.

2. Problem and Contribution

In the previous work [11], a combination of novel lossless compact view invariant compression technique, namely range of movement index (RoMI) and the use of an adaptive module was proposed to utilize the inexpensive and reliable Microsoft Kinect sensor. The RoMI technique has the ability to represent the spherical coordinate in compact form and normalize by adding the label in the predefined range to have a distinctive representation. The added label, however, was predefined based on upper and lower body region, as well as left and right body region. Consequently, the feature that is extracted from the badminton motion data via RoMI was handedness variant. Though, the badminton motion analysis or benchmarking can still be conducted with the same handedness badminton motion data. In order to reduce the effort in data collection and tackle the handedness variant, the adaptive module was introduced to fuse with the RoMI by manually trigger the region mapping from left to right or vice versa. In doing so, the selection of handedness of data stream was needed to be made by human manually, in which both the error rate and effort of incorrect data stream importing will be increased. Thus, an embedded intelligent handedness adaptive module is introduced in this research to overcome the manual limitations as mentioned.

The rest of the paper is structured as follows: First, the team presents an overview of the proposed embedded intelligent handedness adaptive module, RoMI and adaptive mapping module. Next, the team presents the result and discussions of the proposed module by using the data collected via Microsoft Kinect sensor. Lastly, the conclusion and future works will be presented to end this paper.

3. Proposed Method

3.1. Embedded Intelligent Handedness Adaptive Module
In this section, an embedded intelligent handedness adaptive module is proposed in order to overcome the manual badminton handedness data selection. To do so, both handedness travel distances are compared using extracted handedness hand joint feature via skeletal model as shown in Figure 1.

The distance of frames is calculated using (1).

\[ D_n = \left| P_{f(n)}P_{f(n)+1} \right| = \sqrt{\left(x_{f(n)+1} - x_{f(n)}\right)^2 + \left(y_{f(n)+1} - y_{f(n)}\right)^2 + \left(z_{f(n)+1} - z_{f(n)}\right)^2} \]  

(1)

where \( D_n \) is the number of distance, \( P \) is the hand joint and \( f(n) \) is the number of frame. Meanwhile, \( x \), \( y \), and \( z \) are the coordination of hand joint. Subsequently, the total distance of both handedness hand joints is calculated and compared using the following equation, where (2) and (3) are utilized to combine all the travel distances of each frame for both left hand joint and right hand joint.

\[ T_{\text{LH}} = \sum_{n=1}^{N} D_n \]  

(2)

\[ T_{\text{RH}} = \sum_{n=1}^{N} D_n \]  

(3)

where \( T \) is total travel distance and \( N \) is total number of distances. After calculating total travel distance for both left and right hand joint, the comparison is identified as follows.

If \( T_{\text{LH}} > T_{\text{RH}} \) \( \therefore \) left-handed;  
Else if \( T_{\text{RH}} > T_{\text{LH}} \) \( \therefore \) right-handed.

After verifying handedness, the data of verified handedness is fused with the RoMI and adaptive mapping module.

3.2. Review of Range of Movement Index

In [8], a novel lossless compact view invariant compression technique, namely range of movement index (RoMI), was proposed in order to define the three axes at the spine joint of tracked depth map sequences and divides the body parts into eight regions for body joint coordinate estimation. The range of movement is constructed to establish the body joints to the spine joint respectively. Figure 2 shows the eight divided regions with label for upper part body (Figure 2(a)) and lower part body (Figure 2(b)).
A compact spherical coordinate system is established for each region in order to provide information such as radius, inclination and azimuth angles between spine joint and other body joints. The equations are shown as follows.

\[ r = \sqrt{x^2 + y^2 + z^2}; \quad r \geq 0 \]  

\[ \theta = \arccos\left(\frac{y}{r}\right) \]  

\[ \phi = \arctan\left(\frac{x}{z}\right) \]  

where \( x, y, \) and \( z \) are the coordinates of the 3D human body joint. The RoMI, \( I \) is denoted as follows to represent spherical coordinate of regions in a simplified form.

\[ I = (r \times \theta_{\text{max}} \times \phi_{\text{max}}) + (\theta \times \phi_{\text{max}}) + \phi \]  

where \( \theta_{\text{max}} \) and \( \phi_{\text{max}} \) are maximum angle of inclination and azimuth of regions respectively. The normalized RoMI is then added with label, \( R \) that provide distinctive RoMI notation in every region, whereas \( M \) is denoted as normalized RoMI body joints in a single frame of depth map as follows.

\[ M = R + \text{normalized}\{I\} \]  

3.3. Review of Adaptive Module

In [11], an adaptive mapping module is proposed in order to provide handedness invariant mapping via RoMI. Figure 3 illustrates the flowchart of proposed adaptive mapping module.
The verified handedness from embedded intelligent handedness adaptive module is normalized as shown in Figure 2. Then, the adaptive mapping functions are shown in (9) and (10) which demonstrate left to right mapping and vice versa, with the uses of identified label, m as normalized RoMI of body joints.

\[
f_{L\rightarrow R}(m) = \begin{cases} 
  m - 3 & \text{for } m = 3,7 \\
  m - 1 & \text{for } m = 2,6 
\end{cases}
\]

\[
f_{R\rightarrow L}(m) = \begin{cases} 
  m + 3 & \text{for } m = 0,4 \\
  m + 1 & \text{for } m = 1,5 
\end{cases}
\]

4. Results

On the previous badminton motion benchmark using adaptive RoMI, the handedness determination of badminton players has to be identified by human manually in order to trigger the adaptive mapping module, which in turn increases the rate of incorrect handedness identification and human error.

With the implementation of embedded intelligent handedness adaptive module, the system has identified the handedness of input depth map sequence automatically. Experimental results with different performers and movements revealed that there is a 100% average handedness adaptive accuracy as shown in Table 1, thereafter, the RoMI technique and adaptive mapping is performed.

| Handedness | Performer | 1st Attempt | 2nd Attempt | 3rd Attempt | 1st Attempt | 2nd Attempt | 3rd Attempt | 1st Attempt | 2nd Attempt | 3rd Attempt |
|------------|-----------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Right      | Coach 1   | Right       | Right       | Right       | Right       | Right       | Right       | Right       | Right       | 100         |
| Left       | Player 1  | Left        | Left        | Left        | Left        | Left        | Left        | Left        | Left        | 100         |
| Right      | Player 2  | Right       | Right       | Right       | Right       | Right       | Right       | Right       | Right       | 100         |
| Right      | Player 3  | Right       | Right       | Right       | Right       | Right       | Right       | Right       | Right       | 100         |
| Left       | Player 4  | Left        | Left        | Left        | Left        | Left        | Left        | Left        | Left        | 100         |
| Right      | Player 5  | Right       | Right       | Right       | Right       | Right       | Right       | Right       | Right       | 100         |
| Right      | Player 6  | Right       | Right       | Right       | Right       | Right       | Right       | Right       | Right       | 100         |
| Right      | Player 7  | Right       | Right       | Right       | Right       | Right       | Right       | Right       | Right       | 100         |
| Left       | Player 8  | Left        | Left        | Left        | Left        | Left        | Left        | Left        | Left        | 100         |
| Right      | Player 9  | Right       | Right       | Right       | Right       | Right       | Right       | Right       | Right       | 100         |

Table 1. Average Intelligent Handedness Adaptive Accuracy.
Figure 4 illustrates the normalized RoMI of handedness backhand lift movement in the labelled graphs. Figure 4(a) shows the normalized motion performed by a right-handed badminton coach, while Figure 4(b) is performed by a left-handed badminton player. (10) and (11) are applied and shown in Figure 4(b) as the system determined that the motion is performed by a person that is left-handed.

![Normalized RoMI of handedness backhand lift movement performed by (a) right-handed badminton coach and (b) left-handed badminton player](image)

**Figure 4.** Normalized RoMI of handedness backhand lift movement performed by (a) right-handed badminton coach and (b) left-handed badminton player

In Figure 5, the benchmarking result of a backhand lift movement is shown for both the right-handed badminton coach and left-handed badminton player. Similarity index formula was utilized from [8] in order to compute the benchmark similarity index of 99.23%.
5. Discussions
In this experiment, a dataset was collected from 10 different handedness of badminton coaches and players, which consists of 3 attempts of each of the 3 badminton movements to justify the accuracy of the handedness adaptive module. The predefined badminton movements are: backhand lift, forehand lift and overhead forehand clear. All of the movements were collected using Microsoft Kinect v2 sensor with the depth ranging within three meters. Figure 6 illustrates the experimental setup outline for badminton movement data collection via Microsoft Kinect sensor.

6. Conclusions
In this paper, the proposed embedded intelligent handedness adaptive module can be served in precise handedness determination automatically during depth map sequence entry in order to reduce effort of data entry and human error. This new module is able to identify the handedness of racket handling precisely and perform adaptive mapping by fusing with normalized RoMI to benchmark motion regardless of handedness of badminton players. The ability of intelligent handedness determination based on decision rules allows the system to have an automated flow and precise identification on the use of handedness to improve overall system efficiency. For further study, a survey will be conducted to gather professional opinion from certified professional badminton coaches to identify benchmarking
legitimacy on different handedness of players using the similar base reference. Moreover, the system will be optimized with a more simplified lossless compression and mapping technique that can increase the efficiency of system performance.

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Acknowledgments

This work was supported by University College of Technology Sarawak research grant.