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Badminton Stroke Movement Comparison Using Kinect-Based Adaptive Range of Movement Index Technique

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Abstract

Objectives: In this paper, we extended our previous novel lossless compact view invariant compression technique, namely Range of Movement Index (RoMI) by fusing an adaptive module. **Methods:** An adaptive module is proposed to fuse with the RoMI to elevate the technique to become left-right handed invariant. The module will firstly identify the label of the normalized RoMI value from a particular range in order to determine left or right side. Subsequently, the adaptive mapping functions are utilized to perform left to right or right to left mappings using the identified label. **Findings:** Generally, badminton players can be categorized into three different handed: mainly right-handed players and left handed-players and rarely the ambidextrous players. In our previous technique, the RoMI can only benchmark or perform computerized badminton movement quality comparison based on the handedness of a badminton player. In specific, the benchmarking mechanism is left-right handed variant, i.e., left-handed player with left-handed player and right-handed player with right-handed player. This limitation will increase the effort to benchmark badminton players' movement quality with different handedness of badminton player. The proposed adaptive module enables the comparison of computerized stroke movements between different players with different handedness. As such, this new method will identify the labels of the normalized RoMI and performs adaptive mapping to match with the reference handedness to produce a more consistent benchmarking of different handedness badminton players. **Improvement:** The ability to benchmark different handedness badminton players enables the system to be adopted by a larger range of badminton players and further simplify data collection and analysis procedures.

Keywords: Adaptive, Badminton Stroke, Kinect, Movement Comparison, Range of Movement Index (RoMI)

1. Introduction

Badminton, the racquet sport starts its origins in ancient civilization of Asia and Europe more than 2000 years ago. The sport, was also known as battledore and shuttlecock in ancient time, where a paddle was used to hit the shuttlecock back and forth, already gained its popularity in several regions, such as India, China, Japan, and Greece[1]. In the 1800s, British military officers revolutionized the game (a contemporary form of badminton), namely Poona where the players hit the shuttlecock across the net. Later, the sport became popular when the British officers took the game back to England[2]. Today, badminton is one of the most popular racquet sports in Malaysia, as well as in other countries. The game is generally played by two opposing players in singles match or opposing pairs in doubles match within a center netted rectangular court. Moreover, badminton is the fastest racquet sport in accordance with shuttlecock speed along with tennis and squash[3].

A common method in sport science to analyze and evaluate body movements is to film the athletes using a video digitization system. The footage is later annotated in an offline mode manually. Such popular method, however, requires system expert to annotate the videos in order to extract essential contents. Besides, motion cap-

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ture and tracking system can be served as an alternative to extract athlete's skeleton model automatically using physical body markers and perform manual motion analysis later in an offline mode. Although such technology produces a more precise human body in 3D representation, but it involves cumbersome placement of body markers. Also, the method is laborious and is inconvenient particularly to the athlete. On the other hand, marker less motion capture and tracking system overcomes the limitation of physical body makers. The system also offers valuable information to the experts through illustrating the movement of athlete from different view angles, access of hidden parameters that cannot be detected by human naked eyes, and quantify of the motion parameters, such as speed, angle, distance, etc. As such, coaches and sports scientists can customize a tailored training rather than pushing futile training programmed in order to further enhance the athlete's performance.

In recent years, one of the markers less depth motion capture technology which is inexpensive and reliable, namely Microsoft Kinect sensor has gained enormous attention amongst the sports research community[4]. The Kinect sensor is getting prevalent due to its cost-effective solution for expensive motion capture systems. Moreover, the accuracy and validation of the skeleton tracking of the Kinect sensor using depth map sequences have already been validated[5-7]. There is numerous motion analysis researches, specifically applied on badminton have been conducted using the Kinect sensor.

In[8] proposed a badminton movement recognition system based on log-covariance quaternion framework. The framework capable to recognizes 10 badminton movements with an average recognition accuracy of 92%. Besides, the similar authors evolved the badminton motion analysis algorithm by proposing a new lossless compression technique where the technique can recover the compressed spherical coordination information which is deemed to be beneficial to sports scientists and coaches[9-10]. Furthermore, auxiliary badminton training system, which aims to assist trainer to monitor movement and obtain motion parameters was developed by in[11] using the Kinect sensor. Apart from marker less badminton motion analysis, the combination of the Kinect sensor technology with Inertial Measurement Unit (IMU) has been studied. In[12] developed a geometric method to recover self-occlusion body joint information by adopting IMU and Kinect sensor. The experimental results which were tested on badminton swing motion demonstrated that the distorted animation was successfully repaired. Moreover[13] utilizes unscented Kalman filter to merge IMU and depth sequences data to rectify the accumulated errors of IMU and minimize the noise of the Kinect. Additionally, in[14] performed a comparison between IMU and Kinect sensor for acceleration quantification. The preliminary results revealed that the readings and patterns of graph are comparable to the data generated by IMU.

In this paper, we enhance our previous badminton motion analysis algorithm, namely range of movement index[10] by fusing an adaptive module. With such module, the motion analysis algorithm becomes left-right handed invariant and further simplifies data collection and analysis procedures.

2. Problem and Contribution

In our previous technique[10], a novel lossless compact view invariant compression technique, namely Range of Movement Index (RoMI) was proposed. Generally, the technique capable to represents the acquired spherical coordinate compactly. Subsequently, the RoMI is normalized and added with a label in order to provide a distinctive representation in each predefined range. However, the label was defined based on upper and lower body parts, as well as the left and right of the body. As such, the collected badminton motion sample is left-right handed variant. The badminton motion comparison or benchmarking, however, can only be applied on specific group of badminton players, i.e., left-handed player with left-handed player and right-handed player with right-handed player. As a result, the effort on data collection is two-fold as well. Thus, in this research, the existing technique is fused with an adaptive module in order to overcome the limitations abovementioned.

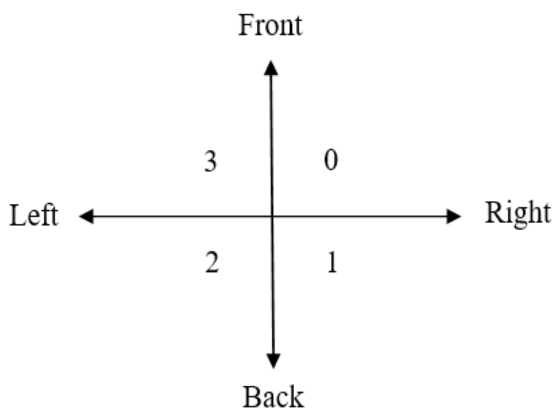
The rest of the paper is organized as follows: First, we provide an overview of the RoMI and the proposed adaptive module. Next, we present the results and discussions of the proposed method using Microsoft Kinect sensor. Lastly, a conclusive remark and possible future works end this technical paper.

3. Proposed Method

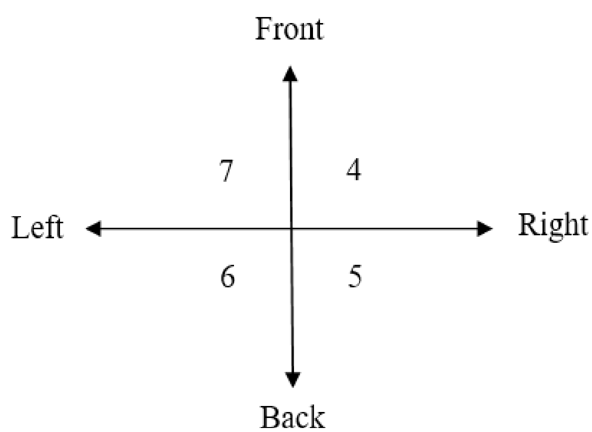
3.1 Review of Range of Movement Index (RoMI)

Previously, a novel lossless compact viewpoint invariant compression technique, namely RoMI was proposed[10].

Technically, three axes (orthogonal) are defined at spine joint, which is tracked depth map sequences and divides human body into eight distinct ranges. Figure 1 illustrates the defined eight distinct ranges with labels for upper (Figure 1(a)) and lower body (Figure 1(b)).



(a) Upper body



(b) Lower body

Figure 1. Eight distinct ranges.

In each range, a spherical coordinate system is constructed to describe radius, inclination, and azimuth angles of body joint with respect to spine joint using the following equations.

$$r = \sqrt{x^2 + y^2 + z^2} \; ; r \geq 0 \tag{1}$$

$$\theta = \arccos(\frac{y}{r}) \tag{2}$$

$$\varphi = \arctan(\frac{x}{z}) \tag{3}$$

Where x, y, and z are the 3D human body joint coordinates. In order to represent the spherical coordinate in a specific range more compactly, RoMI is formed. The RoMI, I am denoted as:

$$I = (r \times \theta_{\max} \times \varphi_{\max}) + (\theta \times \varphi_{\max}) + \varphi \tag{4}$$

Where $\theta_{\max}$ and $\varphi_{\max}$ is the maximum angle of inclination and azimuth in each range respectively. Then, RoMI is normalized and added with label, R which is shown in Equation (5) to provide a distinctive representation of ROMI in each range for each joint.

$$M = R + normalized\{I\} \tag{5}$$

3.2 An Adaptive Module

In this section, an adaptive module is proposed to fuse with the RoMI to elevate the technique to become left-right handed invariant. Figure 2 shows the flowchart of the proposed adaptive module.

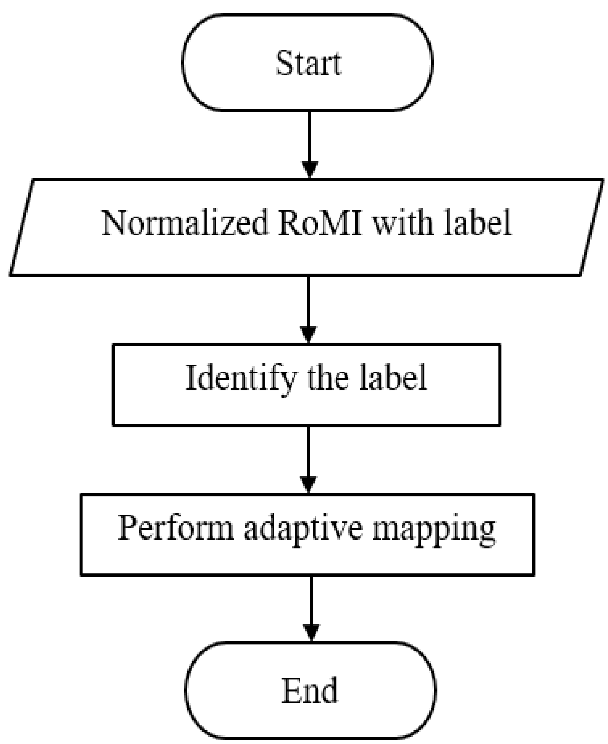


Figure 2. Flow chart of the proposed adaptive module.

The label of the normalized RoMI value from a particular range is identified in order to determine left or right side. For instance, label 3, 2, 7, and 6 indicate left side, while label 0, 1, 4, and 5 indicate right side as shown in

Figure 1. Subsequently, the adaptive mapping functions as exhibited in Equation (6) and (7) are utilized to perform left to right and right to left mappings using the identified label, m, respectively.

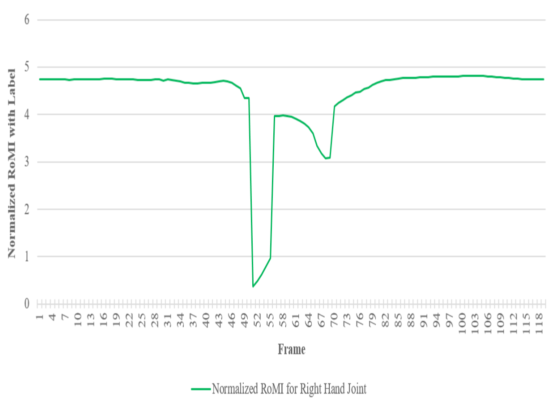
$$f_{L\to R}(m) = \begin{cases} m-3 \text{ ; for } m = 3,7 \\ m-1 \text{ ; for } m = 2,6 \end{cases} \tag{6}$$

$$f_{R\to L}(m) = \begin{cases} m+3 \text{ ; for } m = 0,4 \\ m+1 \text{ ; for } m = 1,5 \end{cases} \tag{7}$$

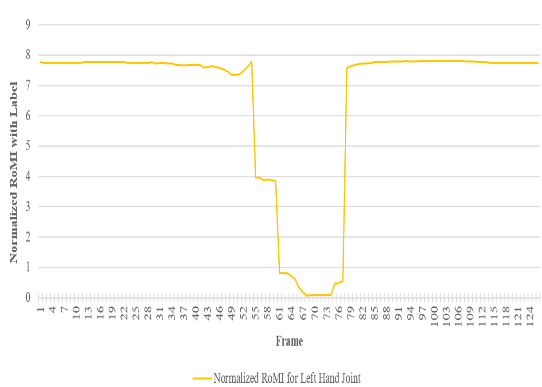
Equation (6) and (7) demonstrate the mapping from left to right and right to left, respectively.

4. Results and Discussions

Previously, visual badminton motion benchmarking is done based on handedness of the reference sample. Therefore, its uses are restricted on the handedness of badminton players; especially right-handed most of the experts or professional players are right-handed.



(a) badminton coach, right-handed



(b) player, left-handed

Figure 3. Normalized RoMI with label graphs for forehand lift movement that were performed.

Figure 3 illustrates the normalized RoMI with label graphs. Figure 3(a) shows the graph from a badminton coach who is right-handed, while Figure 3(b) shows the graph from a badminton player who is left-handed. We can clearly observe that both graphs demonstrate a different pattern. The transition range of the badminton coach is: 4-0-3-4; while the transition range of the badminton player is: 7-3-0-7. As such, it is difficult to measure the similarity of the both graphs quantitatively although both of the movement is similar.

In order to benchmark or compare the badminton player's forehand lifting movement (Figure 3(b) with the reference movement done by the coach (Figure 3(a), Equations (6) and (7) are applied on badminton player's normalized RoMI with label graph. Figure 4 exhibits the normalized RoMI with label graph after applying Equations (6) and (7). The transition range for badminton player's graph changed from 7-3-0-7 to 4-0-3-4 after adaptive mapping, which is the same pattern as the coach's one.

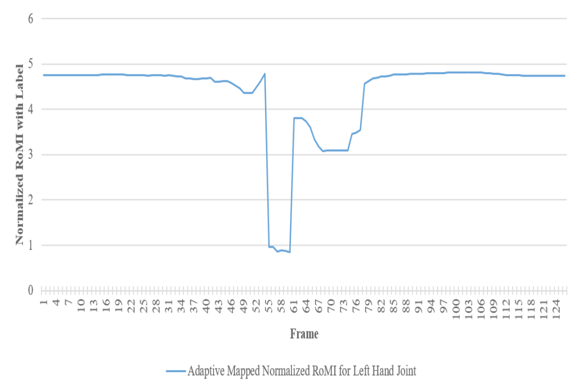


Figure 4. Normalized RoMI with label graph for forehand lift movement that was performed by left-handed badminton player after adaptive mapping.

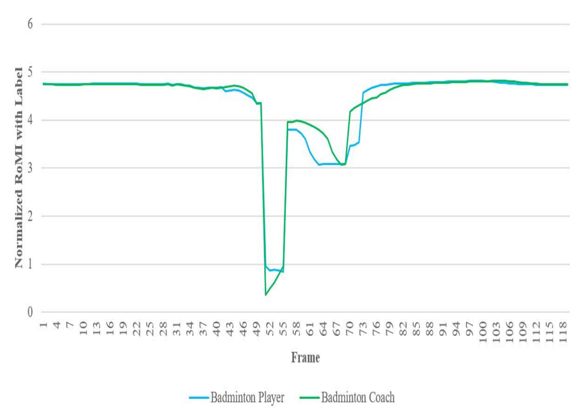


Figure 5. Badminton skill level benchmarking result between badminton coach and player for forehand lift movement.

In addition, Figure 5 demonstrates the badminton skill level benchmarking result between badminton coach (right-handed) and player (left-handed, after adaptive mapping) for forehand lift movement. The benchmarking similarity index was computed by using similarity index formula[10] with the result of 93.37%.

5. Conclusion

As a conclusion, the propose adaptive RoMI method can be used to benchmark badminton players' stroke motion irrespective of their handedness. This new method will identify the labels of the normalized RoMI and performs adaptive mapping to match with the reference handedness to produce a more consistent benchmarking of different handedness badminton players. The ability to benchmark different handedness badminton players enables the system to be adopted by a larger range of badminton players in a more efficient manner. In future works, a survey will be conveyed in order to gather professional badminton coaches' opinion regarding the usability of the system to determine whether different handed players can be benchmarked by a single base reference. In addition, the system will be embedded with an intelligent module where the module can compare different handedness badminton players effectively based on decision rules and provides comprehensive benchmarking results.

6. Acknowledgements

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