MULTI-CAMERA MOTION CAPTURE SYSTEMS AND LUNGES POSITION ANALYSIS OF MEN'S SINGLE BADMINTON PLAYER BY KINEMATICS AND KINETICS ANALYSIS

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INTRODUCTION

Badminton is a sport that requires fast, sudden movement, and repetitive movements. To achieve maximum performance, a badminton athlete needs to perform movements that are considered to result in various types of injuries. Injury in badminton players due to excessive muscle use as a percentage of up to 36% [1]. In badminton, the spine is a part of the body that is potentially injured by up to 21% [2]. However, there is rarely research on back pain injuries in badminton. Two of the extreme movement to receive shuttlecock are lunges and overhead. The repetition of these movements in single' category reaches up to more than 80 times for each match in a tournament. This study aimed to analyse the lunges position mechanism and use to predict the likelihood of back pain injury caused by fatigue.

To prevent injury, a comprehensive evaluation of the movements made by athletes during training and competition is needed. One of the tools that we can use is sport science with biomechanical approach [3]. Biomechanics is a highly developed domain. In this field, changes in research methodology occur very rapidly along with the advancement of technology and computing systems. Motion capture is one system that can be used to evaluate human movements. In this paper, we will design a multi-camera motion capture system that will use consumer grade cameras and evaluate the implementation on capturing the motion of badminton movement.

There are two sub-system that make-up the multi-camera system; hardware, digitizing, and analysis. The hardware sub-systems discuss about the camera setting (resolution and fps) and LED marker. In the digitizing sub-system has several parts such as camera calibration and three-dimension point reconstruction. The cameras get calibrated to obtain the extrinsic and intrinsic parameter. These parameters are the projection matrix that projects the real coordinate into the cameras coordinate. For reconstruction, we will use the Direct Linear Transformation to do the linear algebra to obtain the 3D coordinates [4]. The third sub-system will be the analysis sub-system. This section of the system will produce the kinematic parameter of the athlete.

Keywords: Motion Capture, Biomechanics, Lunge, Badminton

METHODS

Participants

8 single men's badminton players (Mean ± SD; age = 16-21 years; height (cm) = 174.5 ± 4.85 ; weight (kg) = 68.27 ± 10.53; body fat (kg) = 16.53 ± 4.22) from Sangkuriang Graha Sarana (SGS) PLN Badminton Club who actively compete in national and international tournament participate in this study.

Equipment Used

The movement of lunges captured using multi-camera motion capture consists of 5 GoPro cameras (2 GoPro Hero 7 cameras and 3 GoPro Hero 6 cameras) and active LED markers. The location of the markers for analysing back movement is the thoracolumbar part, the pelvis, and the femoral [5].

Procedures

a. Camera Placement

Camera placement has three components to consider: angle between cameras (θ), camera distance, and camera angle (α) & height[6]. These three parameters are determinants of the quality of 3D reconstruction later. Because the position of the marker can be viewed from a side, that is on the back of the athlete's body and the athlete's movements are mostly done in the three coordinates (x, y, and z), then the camera formation in figure 1 (left) is the most optimal choice. The greater the angle, the higher the error value [7] . The angle between the cameras together with the distance between the cameras also determines the recorded area. The ideal angle between cameras (θ) on multicamera system is around 25 to 40 degrees. To obtain all the markers, we put the cameras as the picture shown in figure 1 (right) . The cameras used are GoPro 7 Hero Black and GoPro 6 Hero Black. Each camera is set to 1920x1080 resolution and fps of 240. Camera's exposure is reduced for tracking constrain.

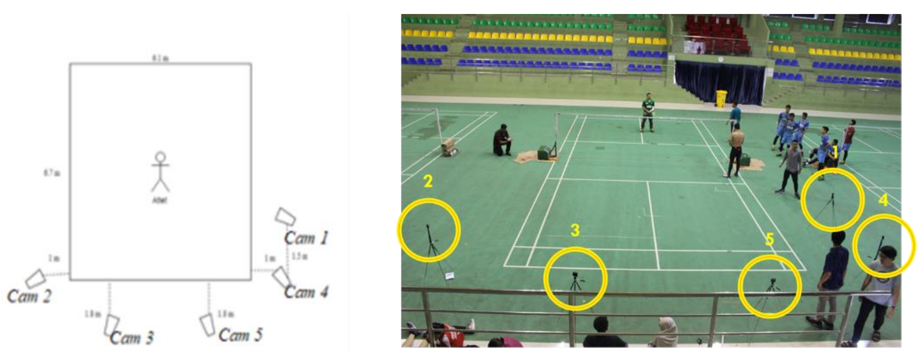

Figure 1 : Camera position for data acquisition

b. Markers

The marker used is active markers made with 12mm LEDs supplied by 3V coin battery. The 12mm LED was chosen because it has enough size to be seen on the camera and does not interfere with the performance of the athlete. Coin battery was chosen because it has a light weight and is small in size. The LED is attached to the coin battery holder and connected to the V + and V- pins, then the coin battery is installed in the slot that is already available on the holder. The markers do not use a switch, battery must be detached in order to turn it off. The switch is not used because it is considered to be able to increase the dimensions and weight of the marker. The marker is attached to the player's body by using double-sided foam tape. Figure 2 Active markers used.

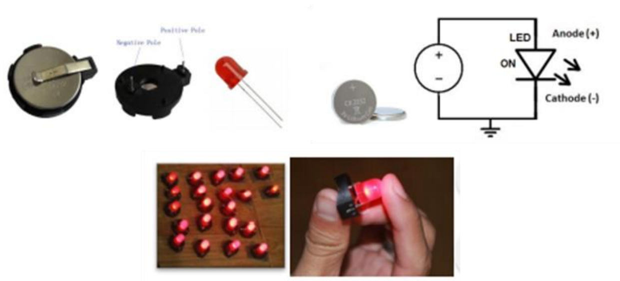

Figure 2 : Active marker used

Analysis of the possibility of back injury is based on the extension and flexion movements of the spine. Based on Tojima et.al (2018), the location of markers for analysing back movements are the thoracolumbar part (T10, T12, and right and left side T11), the pelvis (posterior superior right and left iliac spines and S3), and the femoral (greater trochanter, medial epicondyle, and lateral epicondyle). We attached the total of 12 markers to implement the theory. The marker placement can be seen in figure 3. The clothing worn by badminton players when recording data is to use tight black sports suits. This is done to get maximum recording results; markers can be seen on the camera in red and black background. These special clothes and markers used by badminton players are expected not to disturb the player's movements.

Figure 3 : Location of the markers on athlete's body

c. Camera Synchronization

Camera synchronization is an effort to get video files that are truly synchronous. This system uses audio tracks from each video to get the offset value. At the time of recording procedures performed by issuing audio (high frequency, high intensity). This motion capture system uses cross-correlation of audio signals to find offset between camera videos. This system will compare two videos, one video being the other video benchmark. Computation carried out in this case is to use Fast Fourier Transform (FFT).

d. Camera Matrix

To do calculations related to the relationship of the position of an object in real coordinates and the position of its representation in the image, which is the basis of this essay, mathematical modelling is done on the optical device in this case the camera. The camera model used is the pinhole model[8]. The technique to record a camera is to map the coordinates of O (x y z) ∈ R 3 in real coordinates on a planar image that has coordinates (u v). We can directly connect the coordinates of the projected image and real coordinates linearly. In the figure 4 we can see that there are two parts that are defined as: object-space reference frame (XYZ system) and image-plane reference frame (UV system). The optical system on the camera maps the O point in the object space in the image space. Space (x, y, z) is the object space coordinate (different from the real XYZ space) points O and (u, v) are the planar coordinates of the image at point I image. Point N (xo, yo, zo) is the projection centre point. The relationship between O, I and N is collinear. That will be the basis for calculating 3D reconstruction using the DLT method.

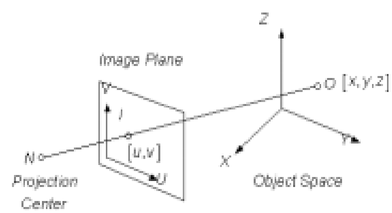

Figure 4: Camera projection of a point

e. Camera Calibration

Intrinsic calibration is carried out to determine the innate characteristics of the camera and is part of the P projection matrix. If we do intrinsic calibration on each camera, then no camera has rotational and translational parameters so that the equation of the camera model can be write it down with the equation

$$\boldsymbol{K} = \begin{bmatrix} \boldsymbol{f} & \mathbf{0} & \boldsymbol{Cx} \\ \mathbf{0} & \boldsymbol{f} & \boldsymbol{Cy} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} \end{bmatrix}$$

$$\mathbf{x} = \mathbf{KX}$$

by recording a pattern (such as a dot pattern) on media that has a value of z = 0 with known physical coordinates such as the distance between and shape of the pattern, we can estimate the K matrix.

The wand method uses two points whose distance is known in real space and compares with the reprojection distance in the planar image. To get an accurate estimate, the wand method selects the projection factor by determining the error modeled by $E_{alg} = \sum_{ij} | \boldsymbol{\lambda} u_{ij} - \mathbf{P}_{ixj} |$ in other words, we calculate the error from the difference in Euclidian distance between the two points mapped to the camera and those that are projected with P. Hartley's projection factor (4) states that minimizing the error with the equation above for the two cameras is considered sufficient to determine the P projection factor. Initial estimation of matrix P is used a linear relationship matrix between two projections on two different cameras, a matrix called the fundamental matrix F. This matrix has the following equation

$$F = K^{T}{}_{1} \, \mathbf{R} \, [\mu \mathbf{t}] \, \mathbf{K}_{2}$$

where K1 and K2 are the matrix of each camera. Camera 1 will always be used as a reference camera that has no matrix R | t. Matrix P is obtained from the operation of matrix F using the SVD method [8].

f. Three-Dimensional Reconstruction
To get the results of 3D reconstruction, we use frames recorded by markers on athletes from 2 or more cameras. From the previous method we have obtained the projection matrix P = K [R | t] on each camera used and represent it in 11 DLT coefficients for each of the cameras above. The next process is how to implement this coefficient with coordinates (u, v) markers on each camera to get 3D coordinates.

Analysis Method

The lunges movement in this study is divided into five stages; stage 1 is when the player starts the lunges movement, stage 2 is when the players move 1 step to the front, stage 3 is the maximum position of lunges movement while the player performs lowest neck position and knee angle at 90 degrees, stage 4 is when the player performs balance position, and stage 5 is when player steps back to the initial position.

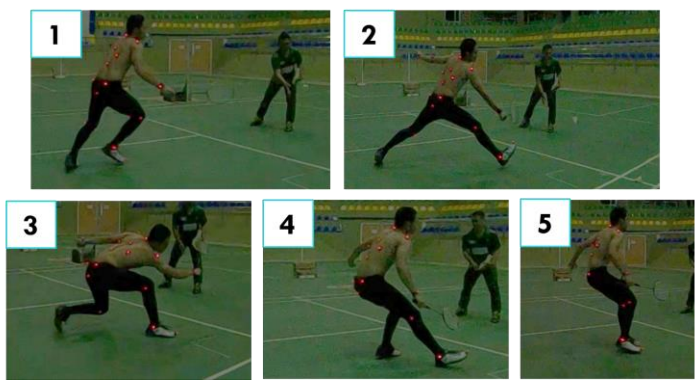

Figure 5 : 5 stage of lunge movement

a. Kinematics Analysis
The basis of mechanics related to Newton's Law is used in the analysis of the movements to be performed. The kinematics aspects to be investigated are linear displacement, velocity and acceleration. Displacement is the movement of the marker position represented in global cartesian coordinates x, y, z. Velocity is defined as the change in movement with time. Acceleration is obtained from data changes in velocity with time. Scalar velocity and acceleration values are obtained from the square root of velocity and acceleration in the x, y, and z coordinates. Information on these three kinematic variables is used to understand movement characteristics and compare movements of two different subjects.

Frequency is an important component of a signal. Each signal has its own frequency value. In this case, a fast fourier transform (FFT) operation is performed on the signal to determine the frequency value from the biomechanical data obtained.

Noise is an unwanted component in a signal. To get meaningful information, it is necessary to filter data. Eliminating noise is done before conducting further data analysis. In this case, a low pass filter is used to pass signals with low values. The cut-off value is determined by looking at the frequency value of the obtained biomechanical signal. There are several types of digital filters that can be used, one of which is Butterworth.

The duration of the subject when doing the movements can be different for each repetition. Normalization is done to see the pattern of movement and get the average value of n-movement. In this case, the pulmonary movement cycle is represented as a percentage, with a maximum of 100%. The kinematic value obtained per time is transformed into per percentage. The movement cycle is divided into five stages and each stage of the movement has a range of their respective percentage values.

b. Kinetics Analysis

Kinetic analysis is obtained from kinematics data processing results. To get the force, the linear acceleration obtained is multiplied by the mass of the segment on the corresponding marker. Each physical segment of the body needs to be determined. One relevant characteristic is the mass segment of a subject's body parts. In this study, the determination of segment mass is done based on Dempster parameters (1955).

RESULT AND DISCUSSION

1. Motion Capture

a. System Implementation

The system implemented using GoPro cameras and LED markers. The camera position shown in Figure 1. Active markers were chosen because they are easier to filter with cameras like GoPro with exposure level on gopro reduced to have an ISO range of 100-400. It is done so that the marker image can be easily distinguished during the tracking process. Exposure settings too low can also make the marker not captured by the camera when the position is far from the camera (Figure 6). Then it is necessary to determine the appropriate range, the exposure numbers above do not have standards, but are obtained from trial and error.

Figure 6: Video frame taken with GoPro and active marker

Camera synchronization cannot be implemented. This is due to the amount of noise around the court. We tested our algorithm in the studio and we didn’t anticipate when there is large amount of unwanted noises. However, we need to synchronize the videos in order to perform calibration and reconstruction. And the synchronization was done manually by looking at the frame one by one to get the exact amount of offset each take. The software that carry out the digitizing and kinematic analysis was supported by a user interface system

b. Camera Calibration

The variable f in table represents the focal length in pixels. The focal length has a different value because it is an estimate, but from the 5 cameras we can determine that the focal length of the camera (the same) is 910-920px. Cx and cy represent the midpoint of the image, because the image is recorded in 1920x1080px resolution, we get the same results, 960px and 540px. Distortion coefficients (k1, k2 k3) also have different values because they are estimates.

Table 1 : Intrinsic calibration result

Cam	f (px)	Cx (px)	Cy (px)	k1	k2	rmse (px)
1	913.9085	959.5	539.5	-0.271	0.0769	436.0
2	915.1048	959.5	539.5	-0.276	0.0826	436.2
3	923.6370	959.5	539.5	-0.280	0.0857	436.2
4	914.4561	959.5	539.5	-0.271	0.0777	436.4
5	913.7887	959.5	539.5	-0.271	0.0776	439.2

In the next process, the coefficients obtained from intrinsic calibration will be used in the K camera matrix for each camera. This process also issues an error in the form of rms. Error is calculated by reprojection frame coordinates which are not used as operations during calibration, and compared with real coordinates. All cameras get an error of around 436px, the number represents all the pixel differences in the circle pattern. When using the 12x9 pattern, there are 108 circles, so the resulting reprojection has a difference of around 4px per circle. This error is also generated due to the distortion owned by the GoPro camera.

With the input in the form of camera intrinsic parameters, or matrix K on each camera, the coordinates of the two wand points (u, v) x total frame, the real wand length, the results of the calculation of the projection factor are carried out and issue an error shown in Table 2.

Table 2 : Projection factor error

Data acqusition number	Wand Length (cm)	Camera	Error (px)
2 (3500 frame)	100	1	18.3000
		2	16.6963
		3	13.0105
		4	6.7159
		5	8.8048
1 (4175 frame)	80	1	38.6597
		2	8.5800
		3	5.4259
		4	91.8591
		5	5.3337

The above error represents the difference in average wand length in the coordinate image (u, v) of the reprojection and wand length in the tracking results. Errors can also increase from intrinsic calibration and imperfect tracking, therefore camera-1 also raises an error even though it is used as a reference camera. If there are outliers in the length difference data, then we can repeat the calibration by removing the frame that has the data that causes the outliers to occur. If the errors on the five cameras have a value <100, then the determination of the projection matrix is considered accurate [9]. Because we have an error value <100, the second extrinsic calibration of data retrieval is considered successful.

c. Three-Dimensional Reconstruction

From the DLT efficiencies from the calibration, we can reconstruct the markers recorded on the 5 cameras. The accuracy of reconstruction is certainly influenced by the quality of intrinsic and extrinsic calibration. So, we can find out the intrinsic and extrinsic calibration accuracy by reconstructing the wand point and calculating the difference in distance with the real length. Reconstruction results are obtained from the distance of the Euclidian 2-point 3D coordinates and calculate the total error with the number of verification frames in the form of rms.

Table 3 : Reconstruction error of wand

Data acqusition number	Total Frame	Wand Length (cm)	rmse (cm)
1	4,000	80	7.295
2	2,700	100	6.932

The reconstruction was carried out on 12 markers attached to the athlete's body. Two markers T11r and T11l are averaged to get the midpoint that represents T11. T10-T11-T12-S3 markers are connected by lines at the time of visualization to represent the spine. The left hip-left knee-left ankle marker is connected to represent the left foot, and the right hip-right knee-right ankle is connected to represent the right foot (figure 7).

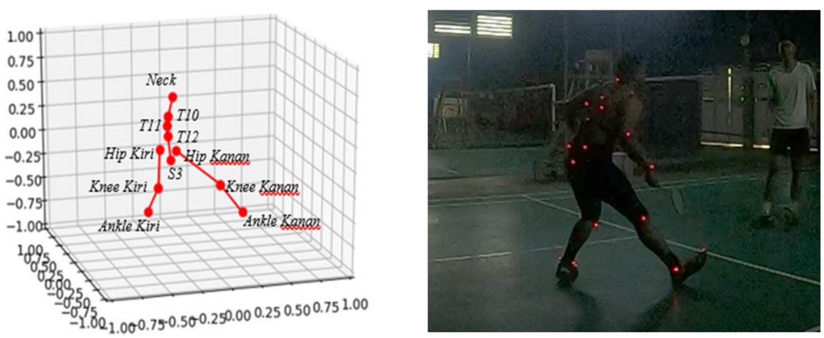

Figure 7: 3-D plot of human model (left) in its reference frame (right)

3D points for each marker are stored in the form (X, Y, Z) in a .csv file. These 3D points will be used as a representation of the athlete's movements to be processed. From this position point we can find kinematics parameters and kinetics of other athletes' movements such as speed and acceleration of motion, angles, etc. To verify the results of reconstruction on the athlete's marker, we take one line, the hip-knee point. Rms errors are calculated from differences in reconstruction length and hip-knee length measured at the time of data collection (table 4).

Table 4: Reconstruction error of athlete limb

Participant	Hip-Knee Distance (cm)	rmse (cm)
1	48.0	4.2
2	45.0	5.1
3	42.0	1.8
4	42.0	4.8
5	45.0	1.7
6	46.0	1.5
7	46.0	3.4
8	42.0	2.6

2. Kinematics and Kinetics Analysis

Position data in cartesian coordinates (x, y, z) are obtained from digitalization blocks of simple motion capture systems. Retrieval of data using 5 cameras consisting of GoPro Hero 7 Black and GoPro Hero 6 Black with 1920x1080px settings with 240fps. Reconstruction of the video is done with the Python library (figure 8)

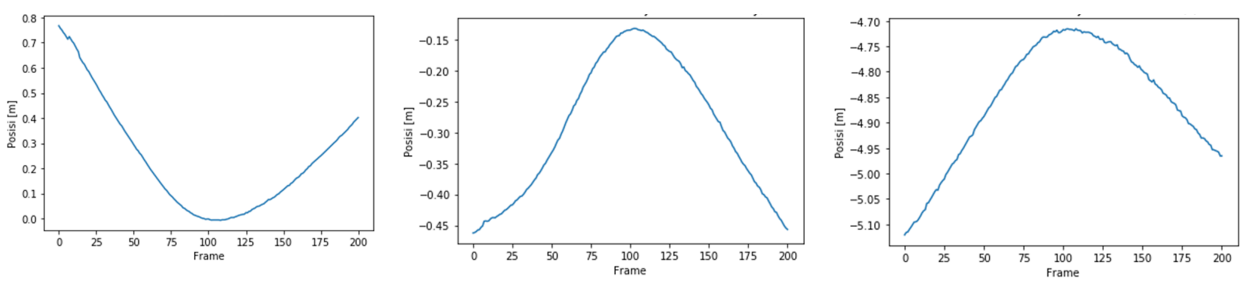

Figure 8: Neck marker position in x-axis (left), y-axis (middle), z-axis (right)

Instantaneous velocity is obtained from the displacement that occurs for each frame. In the position data, we calculate the instantaneous velocity data for each frame (figure 9). From the results of visualization, it appears that the marker velocity data still looks irregular. Therefore, smoothing needs to be done for better analysis. In this case, smoothing can be done by applying a filter for each velocity data.

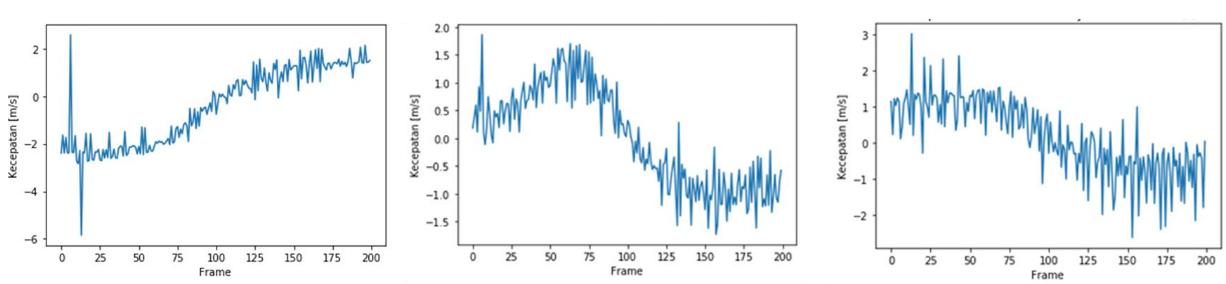

Figure 9 : Velocity of neck marker in x-axis (left), y-axis (middle), z-axis (right)

Noise is an unwanted component in the signal. To get meaningful information, it is necessary to filter data. Eliminating noise is done before conducting further data analysis. In this case, LPF is used to pass signals with low values. The cut-off value is determined by looking at the frequency value of the obtained biomechanical signal. There are several types of digital filters that can be used, one of which is Butterworth. In this case, the type of filter used is Butterworth order 1 (figure 10).

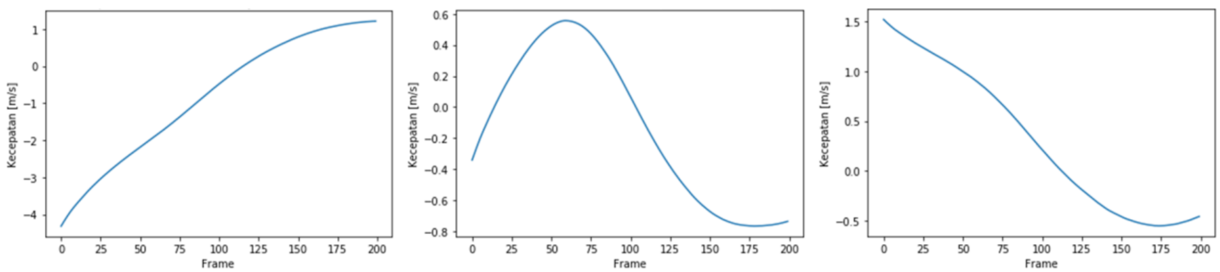

Figure 10 : Velocity of neck marker with filtering in x-axis (left), y-axis (middle), z-axis (right)

To complement linear kinematics data, marker acceleration data is needed. In accordance with the formula, instantaneous acceleration is obtained from the velocity that occurs for each frame. In this case, the velocity data used is the result of the filter.

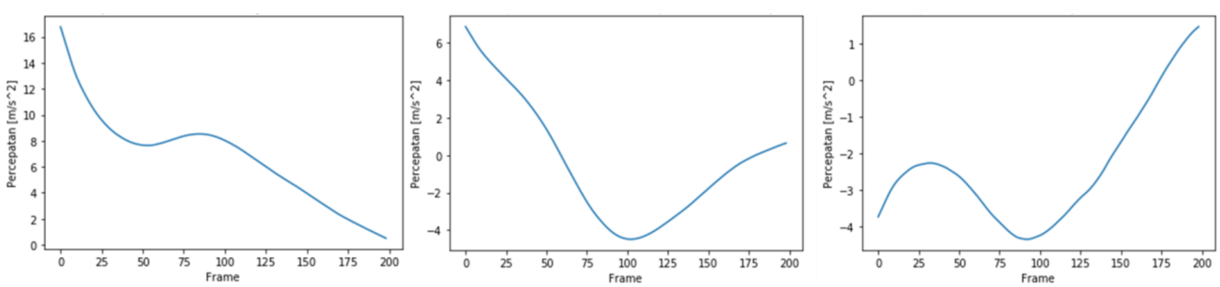

Figure 11 : Acceleration of neck marker with filtering in x-axis (left), y-axis (middle), z-axis (right)

The same movement was repeated several times to get an average value of velocity and acceleration. The duration of the subject when doing the movements can be different for each repetition. Normalization is done to see the pattern of movement and get the average value of n-movement. The movement cycle is represented as a percentage, with a maximum of 100%. The kinematic value obtained per time is transformed into per percentage. Normalization is applied for velocity and acceleration data. In this experiment, the x-axis normalization is done using the Python library. Figure 12, 13, and 14 shows the acceleration from neck, thoracolumbar 12 (T12) and sacrum 3 (S3) from each athlete.

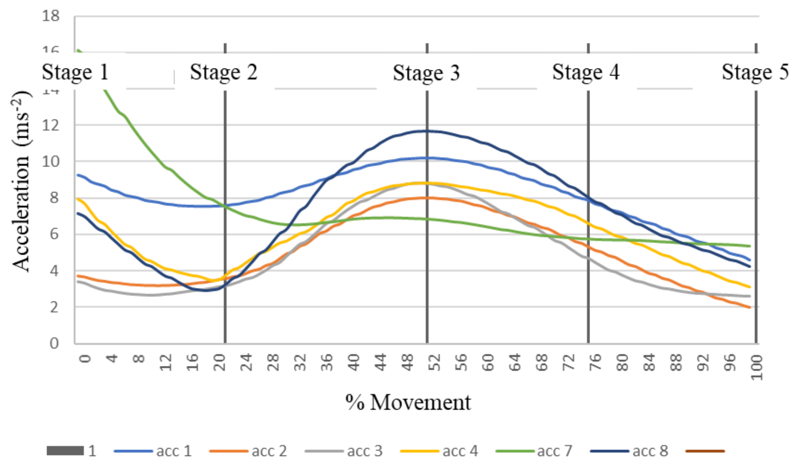

Figure 12: Acceleration on neck

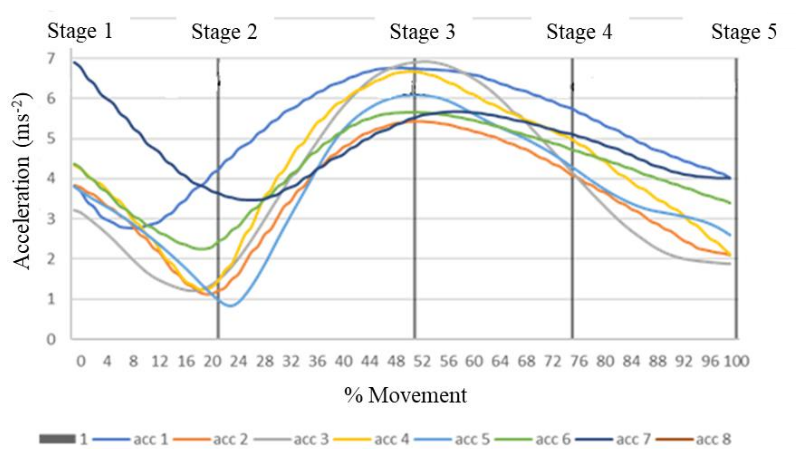

Figure 13 : Acceleration on T12

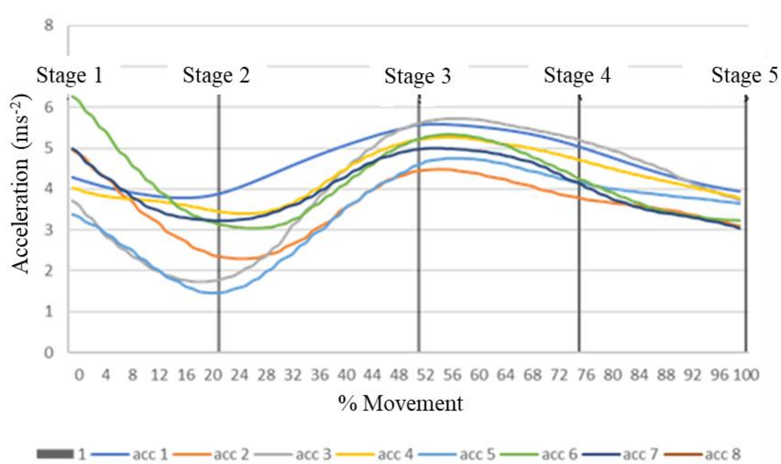

Figure 14 : Acceleration on S3

From the acceleration data per position obtained, we find the value of the external force by multiplying the acceleration and mass of the body segment (Table 5,6,7).

Table 5: Force on neck for each stage

Participant	Force				
	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
1	51.20	41.81	56.35	44.10	25.39
2	22.43	21.28	48.09	33.19	12.11
3	17.85	16.38	46.52	25.25	13.61
4	45.39	19.89	50.42	38.87	17.62
5	12.44	8.23	36.14	25.12	15.69
7	108.91	52.11	46.44	38.99	36.25
8	33.12	14.08	53.93	38.33	19.69

Table 6: Force on T12 for each stage

Participant	Force				
	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
1	55.86	60.55	99.18	85.10	58.99
2	61.44	18.27	86.75	67.10	33.69
3	45.15	19.23	96.45	60.75	26.45
4	65.87	19.86	101.34	76.94	32.31
5	42.95	12.51	68.65	49.63	29.28
6	60.88	32.10	78.77	66.60	47.33
7	124.42	66.29	98.77	92.62	72.28
8	47.48	33.11	95.44	74.19	43.13

Table 7: Force on S3 for each stage

Participant	Force				
	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
1	40.63	36.47	52.64	48.19	37.40
2	51.15	24.63	45.68	39.38	32.09
3	33.58	15.89	50.42	47.52	33.69
4	39.36	33.99	50.59	46.55	36.86
5	24.51	10.51	33.02	30.32	26.43
6	56.15	28.66	46.49	38.88	29.01
7	58.03	37.51	57.69	48.82	35.23
8	51.01	25.86	43.98	41.07	32.35

This study focus on mechanics of the back bone in lunges movements. The maximum acceleration occurs in stage 3 of lunge movement where player at lowest position for neck (9.10 ± 1.37 ms^{-2}) . While the maximum acceleration for thoracolumbar 12 (T12) and sacral 3 (S3) was in stage 4 when player lift up his back to balance (6.36 ± 0.79 ms^{-2} and 5.06 ± 0.46 ms^{-2}. During the lunge's movements, there was no significant difference in neck and S3 in each stage. However, T12 acceleration was change 1.5 times bigger from stage 2 (4.2 ± 1.09 ms^{-2}) into stage 3 before it reduces back in stage 5 (4.96 ± 0.67 ms^{-2}). Acceleration on the neck, was the highest in all stages. In table 8, T12 and S3 has the highest force in all stages with the maximum forces is stage 4; 91.22 ± 12.08 N and 48.50 ± 7.04 N. Whilst, the maximum force in the neck at stage 3 is 49.00 ± 6.60 N.

Table 9 : Force of neck, T12, S3 in each stage

Part	Force (N)				
	Stage 1	**Stage 2**	**Stage 3**	**Stage 4**	**Stage 5**
Neck	41.62 ± 32.89	40.76 ± 32.26	49.00 ± 6.60	48.30 ± 6.52	34.84 ± 7.31
T12	63.01 ± 26.19	62.09 ± 25.64	90.29 ± 11.52	91.22 ± 12.08	71.62 ± 13.65
S3	44.30 ± 11.74	43.44 ± 11.46	47.02 ± 7.41	48.50 ± 7.04	42.59 ± 6.40

There are two phenomena showed in this study, the neck maximum acceleration and force appear in stage 3, while the maximum acceleration and force of T12 and S3 exist in stage 4. During the lunge movement from stage 1 to stage 3, the muscle and strength in upper extremities take major part since the player has to bend down to take the shuttlecock near the net area. After stage 3 movement, in stage 4, the player has to balance himself first before straighten his back and step back to get ready to receive the next shuttlecock. This transition required a good muscle strength in lower extremities. In agreement with this, the neck movement stop in the lowest position while T12 and S3 biggest role was in stage 4 as part of balancing force.

CONCLUSION

This research, were able to implement the multi-camera motion capture system using consumer grade cameras. With using active markers, we can easily filter out the unwanted object by lowering the camera's exposure. However, in some moment, the fully manual tracking procedure may fail to follow the correct marker, so correction by the user is required. This conclude that we need better automatic tracking system or use the current semi-manually. The calibration can also be performed with some errors. The reconstruction also can be performed with some difference with the real condition. The reconstruction accuracy can be improved by adding more cameras.

This study shows that men's single player required to have a good muscle strength both in upper and lower extremities while doing lunge movement. Additionally, with the repetition of almost reach 100 in each competitive match this could lead to fatigue.

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