Significance of Gender in Badminton Lunge Classification

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Abstract. Most badminton lunge studies considered only the male players. No study has investigated the effect of gender on the badminton lunge movement. Past researches presented the statistical analysis approach on badminton lunge motion study. However, no study has classified lunge motion specifically by gender segregation. This paper investigates the gender effects in distinguishing the five lunge directions; center-forward (CF), left-forward (LF), right-forward (RF), left-lateral (L) and right-lateral (R) lunges using classification approach. The case study involved video captures of five-male and six-female university-level players lunging in the badminton 21-point singles. A total of 23 attributes of 10894 instances were extracted to classify lunges into CF, LF, RF, L and R lunges using 21 classification algorithms of the WEKA tool. Lunge direction classifications were performed on unsegregated and segregated genders datasets. Lunge classification on segregated gender datasets showed improvement over the unsegregated gender on 17 out of 21 classification algorithms. The notable improvements were on Trees-Hoeffding Tree (+8.67% on male, +3.08% on female) and Functions-Multilayer Perceptron algorithms (+4.35% on male, +9.37% on female). The study shows that gender segregation improves the lunge classification accuracies.

Keywords: attribute, badminton, classification, gender, lunge direction

1. Introduction

The badminton lunge is a frequently performed footwork skill accounting for 15% of the entire movement in the badminton singles [1]. Good lunging skills enable efficient shot execution with good body posture balancing within minimum time and effort.

Cronin et al. [2] investigated the power determinants for a good lunge performance. Lunge attributes were reviewed in the design of conditional training programs for improving lunge skills [3]. Lunge motion can be categorised based on the movement direction, namely the center-forward (CF), left-forward (LF), right-forward (RF), left-lateral (L), right-lateral (R), left-backward (LB) and right-backward (RB) lunges. The single lunge [1] [4-8] and multi-directional lunges [9-12] had also been considered in past studies.

Ahlawat et al. [13] and Fernandez-Fernandez et al. [14] reported the difference in badminton sports performances by male and female players. However, case studies involving both the male and female players are limited. Majority case studies merely considered the male players [1][4-9][12]. The effect of gender factor on badminton lunge performances had not been investigated, especially for the lunge motion classification. Thus, this study contributes the novel idea on examining the gender attributes in distinguishing the CF, LF, RF, L and R lunges using the data classification approach.

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The experimental case study involved five-male and six-female players in the 21-point badminton singles. The spontaneously performed lunge movement attributes values were extracted from video-image-numeric transformation using the Kinovea V0.7.10 software. The data were classified into five lunge directional classes using 21 classification algorithms aided by the Waikato Environment for Knowledge Analysis (WEKA) tool. The lunge classifications were performed on both genders (un segregated gender) followed by the segregated gender dataset. The difference in classification performance (measured in percentage accuracy) was evaluated.

2. Methodology
Data mining analysis was performed on an experimental case study concerning the badminton lunge motion in 21-point singles. Lunge classification was performed on (i) unsegregated genders and (ii) segregated gender. The entire study framework is shown in figure 1.

![Flowchart of the study](image-url)

**Figure 1.** Flowchart of the study.
2.1. Participants
Eleven right-handed badminton players (5M, 6F, 22.3±1.1 years old; 166.6±7.5 cm; 56.1±6.7 kg) of Universiti Sains Malaysia (USM) were recruited for this study. The players have at least five years’ experience in badminton tournaments and are free from lower extremity injuries. The players received a detailed explanation of the experimental procedure and provided their consents to participate in the experiment.

2.2. Experiment
The experiments were conducted at the indoor badminton court of Azman Hashim USM Sports Arena, USM. Prior permission was obtained from the Sports and Recreation Center, USM. A five-camera recording system was set up as shown in figure 2. The players were required to play the standard 21-point badminton singles spontaneously without specific restrictions. The natural spontaneous lunge motions were performed at five identified directions: 0° (center-forward, CF), 0° < lunge angle ≤ 45° (left-forward, LF or right-forward, RF) and 45° < lunge degree ≤ 90° (left-lateral, L or right-lateral, R) based on the players’ foot orientations (lunge angle) (figure 2).

2.3. Data pre-processing
Two-level data transformations: video-image and image-numeric were performed using the Kinovea V0.7.10 software: “Track Path” function at default 24 frames per second (fps) setting. From the images, 23 attributes were extracted as shown in table 1. The numeric data were presented in comma-separated values (CSV) file format readable by the Waikato Environment for Knowledge Analysis (WEKA) tool for data classification.

Qualitative data inspection was performed by investigating the potential outliers and extreme values following equations (1) and (2). The detected outliers and extreme values will be discarded from the datasets.
\[ Q_1 - 6 \times IQR \leq \text{Outlier} < Q_1 - 3 \times IQR \]
\[ Q_3 + 3 \times IQR < \text{Outlier} \leq Q_3 + 6 \times IQR \]
\[ \text{Extreme value} < Q_1 - 6 \times IQR \]
\[ \text{Extreme value} > Q_3 + 6 \times IQR \]

where
\[ Q_1 = \text{first quartile} \]
\[ Q_3 = \text{third quartile} \]
\[ IQR = \text{interquartile range}, Q_3 - Q_1 \]

The demographic (age and gender) and anthropometric (height, weight, true leg length and apparent leg length) factors, along with the lower extremity kinematics were considered (table 1). The lunge directions (CF, LF, RF, L and R) were assigned as the class attributes for classification analysis aided by the WEKA tool.

| No. | Attribute: Description | Unit |
|-----|------------------------|------|
| 1   | A: Age                 | years|
| 2   | G: Gender              | -    |
| 3   | H: Height              | cm   |
| 4   | W: Weight              | kg   |
| 5   | TLL: True leg length, the distance between the pelvis and the bottom of the heel [15] | cm |
| 6   | ALL: Apparent leg length, the distance from the umbilicus to the medial malleolus [15] | cm |
| 7   | LT: Lunge time, the time with respect to the beginning of the lunge movement | s |
| 8   | GP: Game phase, the time expressed in percentage with respect to the overall duration of the match | % |
| 9   | xL: x-coordinate of left ankle | m |
| 10  | yL: y-coordinate of left ankle | m |
| 11  | dxL: Change in x-coordinate of left ankle with respect to previous frame | m |
| 12  | dyL: Change in y-coordinate of left ankle with respect to previous frame | m |
| 13  | dL: Distance by left ankle with respect to previous frame (equation (3)) | m |
| 14  | sL: Speed of left ankle (equation (4)) | m \(s^{-1}\) |
| 15  | xR: x-coordinate of right ankle | m |
| 16  | yR: y-coordinate of right ankle | m |
| 17  | dxR: Change in x-coordinate of right ankle with respect to previous frame | m |
| 18  | dyR: Change in y-coordinate of right ankle with respect to previous frame | m |
| 19  | dR: Distance by right ankle with respect to previous frame (equation (3)) | m |
| 20  | sR: Speed of right ankle (equation (4)) | m \(s^{-1}\) |
| 21  | NOS: Number of steps performed from start until completion of the lunge movement (Figure 2) | - |
| 22  | Sc: Score point of player at that point of time | - |
| 23  | LD: Lunge direction | - |
\[
\text{Distance}, D_i = \sqrt{(dx_i)^2 + (dy_i)^2}
\]

where

\[
dx_i = x_i - x_{i-1}
\]
\[
dy_i = y_i - y_{i-1}
\]

\[
\text{Speed}, s_i = \frac{D_i}{FD_i}
\]

where

\[D_i = \text{lunge distance}\]

\[FD_i = \frac{1}{\text{Frame per second (fps)}}\]

2.4. Data classification
Data classification was performed at three levels using five classifiers’ algorithms: Bayes (Bayes Net, Naïve Bayes, Naïve Bayes Multinomial Text, Naïve Bayes Updateable), Functions (Logistic, Multilayer Perceptron, Simple Logistic), Lazy (IBk, Kstar, LWL), Rules (Decision Table, JRip, Part, ZeroR as baseline classifier) and Trees (Decision Stump, Hoeffding Tree, J48, LMT, Random Forest, REP Tree) on ten-fold cross-validation mode in WEKA. At the first level, lunge direction classification was performed on the study attributes and instances considering both genders (unsegregated gender).

At the second level analysis, the effect of gender on lunge direction classification was investigated with the gender being defined as the class attribute. The demographic (age) and anthropometric (height, weight, true leg length and apparent leg length) measurable attributes were excluded for gender classification to avoid biases due to their possible correlational relationship with gender. This was to investigate the interaction between lunge kinematics and gender classification, without the influence of demographic and anthropometric factors.

At the third level analysis, lunge direction classification was segregated by gender and executed separately for male and female players. The lunge classification accuracies were compared between the segregated and the unsegregated gender dataset.

At all levels, the classification accuracies resulted from the five classifiers algorithms were also compared with the ZeroR (baseline classifier) for benchmarking purpose. The ZeroR algorithm is commonly used as the standard baseline classifier for cross-validation classifications [16]–[19]. The classification accuracy was deemed reliable if the classification accuracies are above the ZeroR accuracy.

3. Results and discussion
There were 23 attributes of 10894 instances extracted from the video-image-numeric transformation at data pre-processing stage for the data classification analysis. Following outliers and extreme values inspections, no outliers or extreme values were detected from the datasets.

For the first level lunge classification, Bayes, Functions, Lazy, Rules and Trees algorithms showed accuracies of at least equal to or above the baseline classifier, ZeroR (36.2585\%). The best-performed algorithms for each classifier were: Bayes-Bayes Net (83.4863\%), Functions-Multilayer Perceptron (81.2282\%), Lazy-IBk (95.8693\%), Rules-Decision Table (99.1004\%) and Trees-Random Forest (98.0632\%) (figure 3). The top range of accuracies were 81.2282 - 99.1004\% indicating that the lunge motions were well segregated into five directions (CF, LF, RF, L and R) with an average minimal 8.4505\% error.
There were only 18 attributes of 10894 instances considered for the gender classification. The gender classification accuracies were equal or higher than ZeroR (58.6929%) (figure 3). The best-performed algorithms for each classifier were Bayes-Bayes Net (87.3692%), Functions-Multilayer Perceptron (96.5118%), Lazy-IBk (98.4303%), Rules-Part (98.6231%) and Trees-Random Forest (99.7246%) (figure 5). These results observe that the lunge kinematics attributes efficiently segregated the gender, suggesting an important role of the gender factor contribution to lunge classification.

![Figure 3](image-url)

**Figure 3.** Classification accuracy by lunge direction and gender on Bayes, Functions, Lazy, Rules and Trees classifiers.

On subsequent segregation by gender, a total of 22 attributes of 6394 instances and 4500 instances were considered for the male and female respectively. There were improvements in lunge classification...
accuracies in 17 out of 21 classifier algorithms by segregated gender (figure 4). The notable accuracy improvements were on Trees-Hoeffding Tree (+8.67% on male, +3.08% on female) and Functions-Multilayer Perceptron (+4.35% on male, +9.37% on female). On the other hand, Lazy-Ibk and Kstar showed minimal decrease of 0.4361 and 0.8347% respectively for the male segregated dataset. Lazy-LWL and Bayes-Multinomial Text whereas, showed a decrease of 0.0361 and 2.2585% respectively for the female segregated dataset. Aside for Lazy-Ibk, Kstar, LWL and Bayes-Multinomial Text, the findings suggested that executing lunge classification with gender segregation yields a better classification performance for the majority algorithms.

Figure 4. Lunge direction classification accuracy difference between the segregated and unsegregated gender dataset.
The confusion matrix for Functions-Multiplayer Perceptron algorithm, which showed notable accuracy improvement in segregated gender datasets was presented in figure 5. The i-th row, j-th column element of confusion matrix show the percentage instances of i-th class (mis)classified as j-th class. The shaded diagonal elements presented the correctly classified percentage instances. The difference in percentage instances for the male and female segregated dataset respectively was calculated from equation (5).

\[
\Delta \%_G = \%_G - \%_U
\]

where
\( G = \) male or female
\( \%_G = \) percentage instances for gender segregated dataset
\( \%_U = \) percentage instances for unsegregated dataset

For the unsegregated dataset, the highest error contribution of 4.36% was due to the misclassification of RF instances as CF. Classification with gender segregation has reduced this error by 3.52% in male and 3.23% in female segregated data as shown in figure 5.

Overall findings show that segregating gender enhances the classification accuracy. This suggested the male and female performed different lunge postures [13]. Therefore, inclusive of both genders in the datasets could hardly distinguish the badminton lunge direction.

| CF       | L        | LF       | RF       | R        | \(<\) classified as |
|----------|----------|----------|----------|----------|-------------------|
| 32.37 (2.49) -0.77* | 0.58 (-0.12) 0.02* | 1.16 (1.17) -0.27* | 1.75 (-1.60) -1.02* | 0.40 (-0.29) -0.23* | CF     |
| 1.14 (0.32) -0.12* | 6.63 (8.53) 3.88* | 0.65 (0.46) -0.21* | 0.66 (-0.40) -0.64* | 0.34 (-0.07) -0.01* | L      |
| 2.34 (1.35) -1.41* | 0.48 (0.16) -0.14* | 14.96 (12.61) 3.55* | 0.93 (-0.61) -0.68* | 0.39 (-0.06) -0.12* | LF     |
| 4.36 (-3.52) -3.23* | 0.37 (-0.09) -0.23* | 0.96 (-0.07) -0.30* | 20.96 (-15.76) -3.56* | 0.49 (-0.33) -0.38* | RF     |
| 0.50 (-0.14) -0.16* | 0.37 (-0.34) -0.12* | 0.39 (0.23) -0.01* | 0.52 (-0.41) -0.35* | 6.32 (-3.45) 6.46* | R      |

*#unsegregated dataset (#changes for male segregated dataset) # changes for female segregated dataset*

**Figure 5.** Confusion matrix showing percentage instances classified into lunge direction using the Functions-Multilayer Perceptron.

4. Conclusion

This paper distinguishes lunge motion into five lunge directional classes, namely the CF, LF, RF, L and R using 21 classification algorithms of the WEKA tool. Particularly, the effect of gender attribute on lunge direction classification was investigated. Classifications were performed on three levels: lunge direction classification considering unsegregated gender, gender classification, and lunge direction classification on the segregated gender datasets.

The classification results were reliable with accuracies obtained above the ZeroR baseline classifier in all 21 classification algorithms. There were improvements in lunge classification accuracy with segregated gender dataset in the majority 17 out of 21 algorithms. Therefore, lunge classification is ought to be performed separately on male and female segregated dataset for improved accuracy.

This study provides a guideline for conditional training programme design to improve the badminton lunging performance. Specifically, different conditional training has to be designed for the male and female players. The current study framework considered only the university-level badminton players, thus have limited potential for generalization. Future works could consider multiple case studies involving badminton players of different skills background.
References

[1] G Kuntze, N Mansfield, and W Sellers 2010 A biomechanical analysis of common lunge tasks in badminton J. Sports Sci. Vol 28 No 2 pp 183–191
[2] J Cronin, P J McNair and R N Marshall 2003 Lunge performance and its determinants J. Sports Sci. Vol 21 No 1 pp 49–57
[3] S J Maloney 2018 A Review of the Badminton Lunge and Specific Training Considerations Strength Cond. J. pp 1
[4] H -W Lin, K -S Huang, K -M Pan and C -L Tsai 2015 Biomechanical Analysis of Badminton Different Forward Steps ISBS - Conf. Proc. Arch. Vol 1 No 1 pp 1066–1069
[5] Q Mei, Y Gu, F Fu and J Fernandez 2017 A biomechanical investigation of right-forward lunging step among badminton players J. Sports Sci., Vol 35 No 5 pp 457–462
[6] W K Lam, J Ryue, K K Lee, S K Park, J T M Cheung and J Ryu 2017 Does shoe heel design influence ground reaction forces and knee moments during maximum lunges in elite and intermediate badminton players? PLoS One Vol 12 No 3 pp 1–13
[7] W K Lam, R Ding and Y Qu 2017 Ground reaction forces and knee kinetics during single and repeated badminton lunges J. Sports Sci. Vol 35 No 6 pp 587–592
[8] L Fu, F Ren and J S Baker 2017 Comparison of Joint Loading in Badminton Lunging between Professional and Amateur Badminton Players Appl. Bionics Biomech. Vol 2017
[9] Y Hong, S J Wang, W K Lam and J T -M Cheung 2014 Kinetics of Badminton Lunges in Four Directions J. Appl. Biomech. Vol 30 No 1 pp 113–118
[10] M T Huang, H H Lee, C F Lin, Y J Tsai and J C Liao 2014 How does knee pain affect trunk and knee motion during badminton forehand lunges? J. Sports Sci. Vol 32 No 7 pp 690–700
[11] C F Lin, S H Hua, M T Huang, H H Lee and J C Liao 2015 Biomechanical analysis of knee and trunk in badminton players with and without knee pain during backhand diagonal lunges J. Sports Sci. Vol 33, No 14 pp 1429–1439
[12] X Hu, J X Li, Y Hong and L Wang 2015 Characteristics of planter loads in maximum forward lunge tasks in badminton PLoS One Vol 10 No 9 pp 1–10
[13] U K R Ahlawat, N Yadav and D Shaw 2018 Kinematic differences among the players / repetitions and between the gender in regard to left ( subordinate ) leg lunges exercise for lower extremities with 15 RM load Int. J. Acad. Res. Dev. Vol 3 No 1 pp 167–173
[14] J Fernandez-Fernandez, J G De La Aleja Tellez, M Moya-Ramon, D Cabello-Manrique and A Mendez-Villanueva 2013 Gender differences in game responses during badminton match play J. Strength Cond. Res. Vol 27 No 9 pp 2396–2404
[15] S Sabharwal and A Kumar 2008 Methods for assessing leg length discrepancy Clin. Orthop. Relat. Res. Vol 466 No 12 pp 2910–2922
[16] R Sood, I Koprinska and V G Agelidis 2010 Electricity Load Forecasting Based on Autocorrelation Analysis The 2010 International Joint Conference on Neural Networks (IJCNN) pp 1–8
[17] N Lavesson, M Boldt, P Davidsson and A Jacobsson 2011 Learning to detect spyware using end user license agreements Knowl. Inf. Syst. Vol 26 No 2 pp 285–307
[18] K Palaniappan and S Mukherjee 2011 Predicting ‘essential’ genes across microbial genomes: a machine learning approach 10th International Conference on Machine Learning and Applications and Workshops pp 189–194
[19] M Schuchhardt, B Scholbrock, U Pamukszu, G Memik, P Dinda and R P Dick 2012 Understanding the Impact of Laptop Power Saving Options on User Satisfaction Using Physiological Sensors Proceedings of the 2012 ACM/IEEE international symposium on Low power electronics and design pp 291–296