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Research article

Recognition of TaeKwonDo kicking techniques based on accelerometer sensors

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ABSTRACT

TaeKwonDo (TKD) is a worldwide sport in both competitive among athletes and physical exercise among the public scenarios. Measuring TKD kicks have been studied a lot in a laboratory setting but rarely in a free-living situation. Machine learning algorithm combined with accelerometer data was used to study some martial art styles, e.g., Chinese KungFu but little in TKD. The purpose of this study was to discover a method to recognize different kicking techniques in TKD. A total of 20 participants (35 % male) were recruited to perform front kick, roundhouse kick, side kick and back kick 6 times on each side with three accelerometers wore on waist, right ankle and left ankle. SVM and decision tree were used to analyze data and classify kicking movements. The usage of different combination of accelerometers were also compared. The result showed that using accelerometers on waist and both ankles, on waist and only right ankle, on only waist and combined with SVM model could have at least 0.96 accuracy of classification, while decision tree had the accuracies around 0.8. It was concluded that using SVM model on only waist data is the optimal choice because of the high accuracy and less accelerometers used.

1. Introduction

TaeKwonDo (TKD) is a worldwide sport of combat, as well as a popular physical exercise among children, youth and adults to improve physical fitness and will power [1]. It was originated form peninsula of Korea, geographically, and from Karate, technically [2]. TaeKwonDo has two major federations: World TaeKwonDo (WT, originally World TKD Federation, WTF) and International TaeKwonDo Federation (ITF). Since 1960s, TKD started to have its unique kicking techniques and combat rules [3].

As a style of martial arts, TKD has its specific characteristic: kicking techniques occupy most proportion in the overall TKD training. Fig. 1 illustrates the kicking movements of front kick (lift leg up an kick upward to the front), roundhouse kick (turn the hip and whip the target from the side), side kick (push-strike the target while facing the target by your side) and back kick (rotate backwards and make the push-strike). The biomechanics between different kicks, e.g., roundhouse kick and side kick, in TKD varies. While roundhouse kick requires the practitioner to hit the target with their back of the foot, i.e., instep, with hip straight before the strike and leg extending during the strike, the sidekick asks the practitioners to strike with the bottom of the foot while extending hip and leg simultaneously. Making one is to "swing" strike and another one is "thrust" strike. The "swing" kicks, e.g., roundhouse kick and spin hook kick, were found faster than the "thrust" kicks, e.g., side kick, axe kick [4]. Same kick in different martial art styles could also

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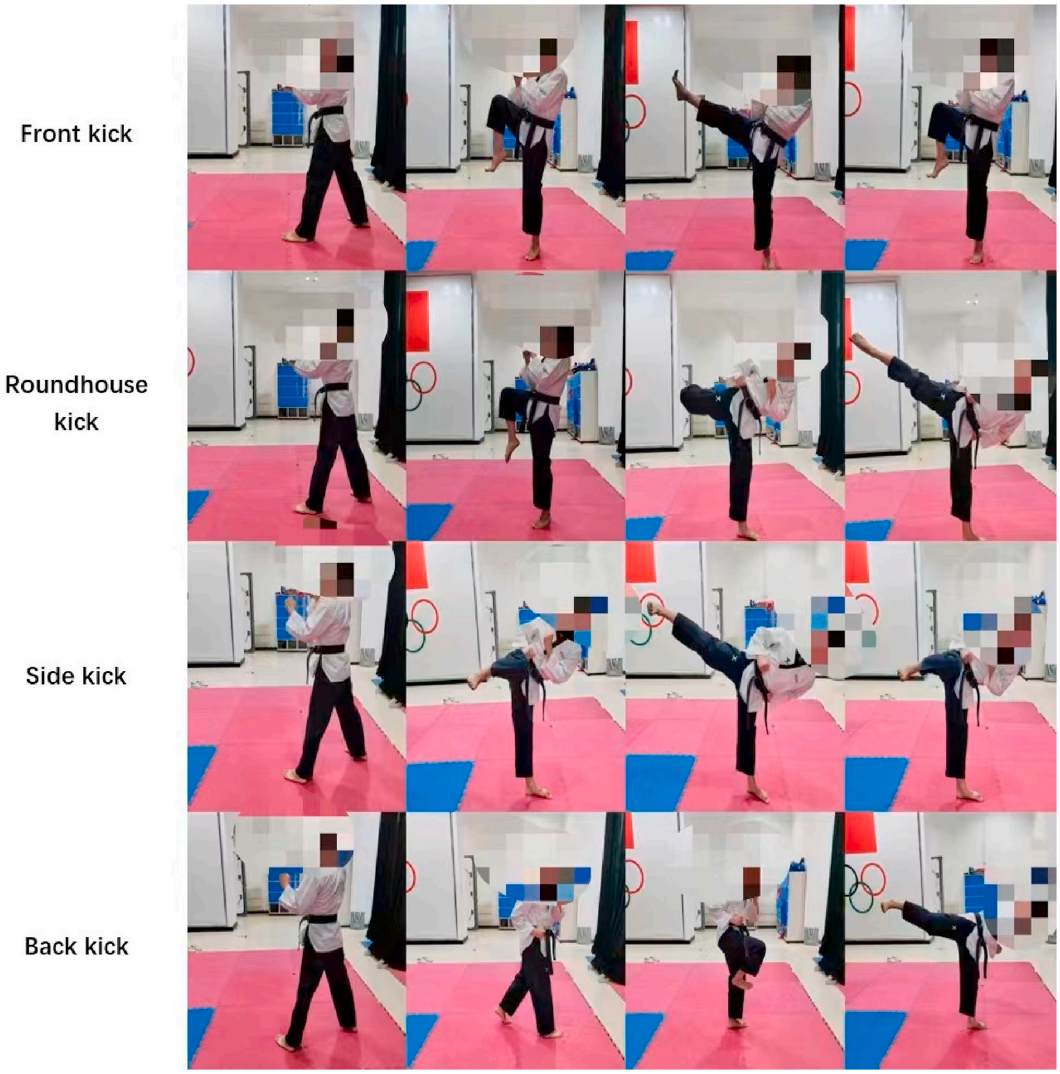

Fig. 1. Demonstration of front kick, roundhouse kick, side kick and back kick.

have different biomechanical differences. Gavagan and Sayers [5] discovered that Muay Thai has significant higher relative impact force (the force divided by body weight) than TKD and Karate. Muay Thai has significant longer execution time than TKD. The center of mass of practitioners in Muay Thai has also higher uplift and forward shift than TKD and Karate [5]. Even in the same style of martial art, same kick movement demonstrated different biomechanical performance among different athletes. In roundhouse kick in TKD, athletes with higher impact force had a smaller plantarflexion angle and higher muscle activation on bicep femoris [6]. The differences in joint angle, direction, speed and execution time lead to the differences of acceleration on body parts. Recognizing the pattern of acceleration could be used to recognize the type of kick.

Measuring TKD movements, as well as other physical activities and exercises, is challengeable but efforts have been made on various of sensors and devices. Force plate was widely used to measure the ground reaction force in previous studies of TKD. Estevan et al. used force plate and camera-motion capture system to measure the relationship between ground reaction force, angle of feet in stance and execution time [7]. The ground reaction force was discovered to have negative correlation with execution time and positive with thigh as well as with shank. At the same time the stance with 90° between feet provides the longest execution time comparing to 0 and 45°. Force plate was also used to discover optimal landing positions to prevent injury and wider angle was correlated to lower ground reaction force therefore the lower risk of getting injured [8]. Force plates have the benefits of measuring force in a highly controlled settings, e.g., laboratory. Motion capturing camera was also widely used to examine the relationship between joint angle and target distance [9], building scoring system [10], detecting position of athletes in combat [11], etc. Benefiting from the convenience of non-wearing and fixed environment, e.g., laboratory or real TKD stadium, the usage of camera was adopted in the past decades to analysis kinematic performance. Combining force plate and camera provides researchers both kinetic and kinematic information of TKD kick performance, but the data collection environment is limited to laboratory settings instead of free-living settings, e.g., playground, backyard, gym, campus, etc.

Accelerometer, on the contrary, is light in weight, wearable and fits all the scenarios of physical exercises, including TKD. In free-living physical activity recognition, accelerometer, together with gyroscope, could have a high accuracy (>95 %) on walking, going upstairs, downstairs, standing, sitting and lying [12]. Combat sport also uses inertial sensors, i.e., accelerometer, gyroscope and magnetometer, to measure and evaluate sport performance [13]. For a specific sport, accelerometer could also have high validity on recognizing different movements, i.e., in swimming [14]. Chen et al. [15] and Li et al. [16] used wearable inertial sensors to detect fall. This study took the advantage of the convenience of accelerometers to develop a method of TKD kicking recognition that feasible in non-laboratory settings.

Artificial intelligence techniques, i.e., machine learning and deep learning algorithms, has been used to process sport performance data in physical exercises especially martial arts. Qin et al. [14] used accelerometer data and support vector machine (SVM) to classify, breaststroke, butterfly, front crawl and back strokes and signal processing to count the number of strokes. Zhou [17] used visual image combined with signal processing and Hidden Markov Model (HMM) and SVM to recognize Wushu (known also as Chinese KungFu) movements. Pei et al. [18] used K-nearest neighbors (KNN) to recognize combat moves, e.g., punch, block, kicks. Li et al. [19] used inertial sensors combined with SVM to recognize Baduanjin exercise, a traditional Chinese sport. Comparing to other classification methods, SVM shows high validity and generalizability and saves time, comparing to neural networks that costs multiple hours to fit a model. However, SVM was never used to do the pattern recognition of basic TKD kicks.

The data collected by accelerometers usually exists in the form of information streams, and most of the research is based on time series action recognition. In recent years, the research on action recognition based on accelerometer sensor data at home and abroad has gradually increased, and researchers have actively explored methods and technologies for action recognition using accelerometer data.

Commonly used data preprocessing methods include missing value processing, denoising and smoothing, normalization processing, and subsequence division [20]. British engineer Stephen Butterworth first proposed the Butterworth filter in 1930 [21]. Atrsaei et al. [22] designed an adaptive scented Kalman filter. The collected time series data is typically sliced, most commonly using a sliding window algorithm. The length of the sliding window is critical and dynamic sliding window method was proposed, dynamically adjusting the window size and offset at each step, using fewer instances to achieve better results [23,24]. The feature extraction method can be divided into two types: time domain analysis method and frequency domain analysis method. Commonly used time domain characteristics include mean, variance, standard deviation, kurtosis, skewness, percentile, etc. Common frequency domain features include Fourier coefficient, frequency domain entropy, etc. Ferhat Attal et al. used time-frequency hybrid analysis to classify major daily life human activities based on three wearable accelerometers, and achieved substantial results [25]. In this study, time domain features such as mean, variance, skewness, kurtosis, root mean square, and frequency domain features such as fast Fourier transform (FFT) coefficient, spectral density (PSD), and frequency domain entropy (FDE) are used.To avoid the problem of too high feature space dimensionality, feature selection is required, and the common ones are principal component analysis method, Boosting algorithm and linear decision analysis method.

Given the specificity of TKD sport and the advantages of accelerometers, the aim of this study was to develop a statistical model using the time series data recorded by accelerometers to recognize four basic TKD kicks: front kick, roundhouse kick, side kick and back kick. Specifically, the purposes of this study were to compare the performance of different classification models, i.e., SVM and decision tree, and to compare the optimal combination of site of wearing accelerometer: waist with left and right ankle, waist with right ankle, waist. It was hypothesized that SVM have a higher validity, e.g., accuracy, and the combination of three accelerometers on waist and left and right ankle has the highest validity.

2. Methods

2.1. Experimental design

2.1.1. Participants

A total of 20 participants (7 male, 35 %; (M±SD) height = 169.35 ± 7.82, weight = 61.84 ± 14.22, BMI = 21.40 ± 3.50) were recruited from Beijing Sport University (BSU) with 10 professional TKD athletes and 10 practitioners. There were 10 professional practitioners and 10 amateurs. Among professional practitioners, 4 were first degree black belt, 6 were level-1 athlete, 3 were level-2 athletes, two of them were both black belt and level-1 athlete and one of them was both black belt and level-1 athlete (Level-1 is higher than level-2; some professional TKD athletes don't do belt test). Among amateur practitioners, none of them have gone through belt test. The participants were recruited by Wechat posts and had to be able to perform front kick, roundhouse kick, side kick and back kick.

2.1.2. Device and software

The devices used in the experiment were accelerometers, ActiGraph GT3X, with the sampling frequency 30Hz. The software used was ActiLife [26].

A pacer was also used to play "beep" sound every 4 s to remind the participant about the correct time of making a kick.

This study used Python 3.8.8 to process the data. The integrated development environment (IDE), i.e., the software used for code execution, was Jupiter Notebook. The packages used in coding were numpy 1.21.5, pandas, tsfresh, sklearn 1.0.2 and RFECV. The system used was Windows 10 x64, 8G memory. The code is not available to the public due to the institute's policy.

2.1.3. Data collection procedure

Three ActiGraph GT3X accelerometer units were initialized by using USB to link to a laptop. On the laptop, ActiLife software was used to initialize the accelerometers. The clock, i.e., time axis, of three accelerometers were calibrated with the clock of the laptop. The ActiLife software specified the exact start time of the accelerometers. For example, if we are doing the initialization process at 9:45am and we want to start to collect acceleration data at 9:50am, we just need to put "9:50am" in the "start at" blank in ActiLife while initializing the three accelerometers.

After initialization, the accelerometers were put and worn on the participant's waist, left ankle and right ankle (see Fig. 2). Participants were asked to perform front kick, roundhouse kick, sidekick and back kick, 6 repetitions each. Each repetition was asked to be performed in a fixed time interval of 4 s, marked by the beeps from a pacer. The start time was recorded.

The specific procedure is shown below.

1. Participants, wearing the initialized accelerometers, standing in a fighting stance (right foot on the back, left foot on the front, shoulder width);
2. The participants were asked to perform all the kicks by their backfoot, i.e., right foot, before switching the stance;
3. The first beep of the pacer played, and beep is reoccurred every 4 s automatically;
4. The participant heard the beep and perform a front kick, then pull back to the fighting stance immediately (this was before the second beep played);
5. Four seconds after the first beep played, the second beep played and the participant perform another front kick;
6. The participant repetitively perform 6 front kicks
7. After the 6th front kick was performed, the participant took rest for a 4-s- interval, while was reminded about the next kick, i.e., roundhouse kick.
8. Roundhouse kick was performed in the same protocol as in front kick (steps 3 to 7);
9. Six sidekicks was performed after the 4-s rest after roundhouse kick, in the same protocol, then the back kicks;
10. After the 6th back kick was performed by right foot, the participant use the upcoming 4-s interval to switch the stance, i.e., right foot in the front and left foot on the back after switch, and take the rest.
11. After hearing the next beep, the participant started to perform the first front kick by left foot.
12. The participant performed all the 4 kicks with 6 repetition each with left foot in the exact same protocol as they did with right foot (steps 3 to 9).
13. After one participant completed the whole procedure, the accelerometer was removed and the data was downloaded;
14. Execute the same procedure (steps 1 to 13) with all 20 participants.

When a beep is played, the participant can start to perform one repetition of a kick and wait for the next beep to kick again. After the 6th repetition of one type of kick, the participant was asked to stay still doing nothing in an empty interval to prepare for the next type of kick. The next kick would be performed in the next interval after the empty one. Each participants used right leg to perform all four types of kicks first then switch to the left leg. During the kicking procedure.

2.1.4. Data download

The accelerometer was connected to the laptop again after the participant finishes the experiment protocol. The raw data was downloaded from the accelerometer device to the laptop using ActiLife software. The time-series data of acceleration was recorded in a sampling rate of 30Hz and were downloaded as a spreadsheet, i.e., .csv, file. The data was recorded in the unit of "g", i.e., the gravity 9.8 m/s^2. For example, 2 in the acceleration data corresponds to 19.62 m/s^2.

2.1.5. Data analysis

Fig. 3 illustrated the procedure of experiment and data analysis.

Fig. 2. The sites placing accelerometers.

2.1.6. Data cleaning and preprocessing

Since the purpose of the study was to recognize the type of kicks, an observation is defined as a repetition of kick. In the time-series data, one repetition of kick corresponds to a 4-seocnd signal, i.e., a time-series data with the length of 120 time points (30Hz is 30 points per second and 4 s corresponds to 120 time points). In raw data, each time point has 9 acceleration measures (channels of signal): x-axis of accelerometer on the waist (x-waist), y-waist, z-waist, x-right ankle, y-right ankle, z-right ankle, x-left ankle, y-left ankle, z-left ankle. Besides, the resultant vector of accelerometers on waist, right ankle and left angle was also computed. As a result, one accelerometer corresponds to 4 channels, i.e., x, y, z and/resultant. a total of 12 (9 original +3 resultant) channels with length 120 time points served as one observation, i.e., one kick repetition. Fig. 5 illustrated the signal of one observation.

The data was cut into segments of 120 timepoints to separate different repetitions. For each participant, data from waist, left ankle and right ankle were merged based on timestamp. The timestamp between different accelerometers were already synchronized with the laptop during the initialization phase. The time-series data of acceleration was segmented into 4-s, i.e., 120 (4 s* 30Hz) timepoints of acceleration numbers, and the starting point of the first segment was chosen based on experiment record.

2.1.7. Feature extraction

Features of each accelerometer (4 channels) were extracted from each segment by tsfresh, a Python package designed to extract features from time-series data. For each channel, more than 1000 features were extracted. The classic features, i.e., mean, standard deviation, skewness, kurtosis, Fast Fourier Transformation (FFT)-main frequency, power, etc., were already included in the set of features of tsfresh. The features were selected by the Python package Recursive feature elimination cross-validation (RFECV) and 42 features of each accelerometer were finally selected to fit the models.

Data matrix was assembled by the features of repetitions of kicks where each repetition served as an observation and features served as independent variables (IV). Type of this repetition (i.e., front kick, round-house kick, side kick or back kick), another variable, was also added based on the experimental journal and served as dependent variable (DV). The label variable of the leg method was added to the data matrix, such as ‘Left front kick _1_0’ represents the first action of the second person doing the left front kick.

2.1.8. Statistical and machine learning analysis

Two types of classifiers, decision tree and support vector machine (SVM), were used to predict the type of each repetition. All observations of the dataset were split into train data (70 %) and test data (30 %). The model was fitted using training data and cross-validated by the test data [27].

Three combinations of accelerometers, waist + right ankle + left ankle, waist + right ankle and solely waist, were compared to find the least number of devices to use and still having substantial classification quality. For the combination of waist and both ankles, a total of 126 features (42*3) were used and for the combination of waist + right ankle, 84 features were used while for solely waist, 42 features were used.

The metrics of the classification model, i.e., accuracy, precision, recall and F1 score were examined on both training data and test data. Higher recall correlated with lower precision so both are necessary. The metrics were calculated by the formulae:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad \text{(Formula-1)}$$

$$Precision = \frac{TP}{TP + FP} \quad \text{(Formula-2)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{(Formula-3)}$$

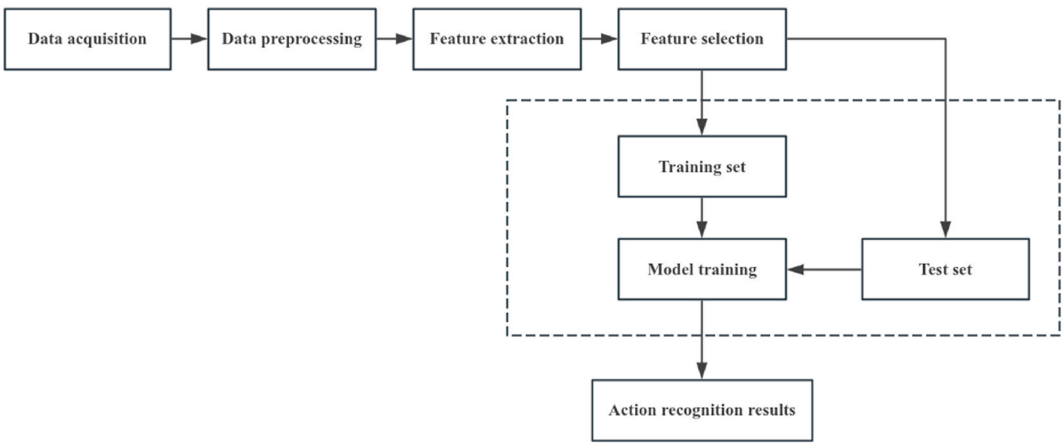

Fig. 3. Data analysis procedure.

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad \text{(Formula-4)}$$

where true positive (TP), False positive (FP), true negative (TN) and false negative (FN) were defined as in Tables 1 and 2.

The confusion matrix can be used to calculate multiple performance metrics such as accuracy, precision, recall, F1 score, and more to evaluate the performance of a classification model[28–30].

3. Results

Table 3 illustrates the descriptive statistics of accelerometer data on all 12 channels, including mean (M), standard deviation (SD), variance (Var), skewness, kurtosis, minimum value (min), maximum value (max), 25th percentile (X.25), 50th percentile or median (X.50), 75th percentile (X.75). In addition, Fig. 4 visualizes the distribution of the magnitude of the resultant vector of accelerations.

Since the data is in time-series format not only the distribution but also the timestamp contains the information of each kick. Fig. 5 visualizes the time-series data as signal.

Fig. 6 illustrates the format of data matrix used for machine learning algorithms. The features served as independent variables and the "label" variable served as dependent variables.

Table 4 summarizes the performance of SVM and decision tree in three combinations of accelerometers: waist + right ankle + left ankle, waist + right ankle and solely waist. Although in train data, decision tree gives 100 % accuracy in all three combinations, the accuracies in test data were around 0.8. On the contrary, SVM provided extremely high accuracies (0.98 and above) in train data, and also very high accuracies (0.96 and above) in test data. SVM shows less overfit than decision tree.

Under the condition of SVM, different combinations of accelerometers provides similar accuracy in both train data and test data. However, since the waist accelerometer solely could already achieve accuracy of 0.98, the other two, i.e., accelerometers on left and right ankle made the accuracy lower. As a result, SVM + waist accelerometer is the optimal combination.

Table 5 summarizes the precision, recall and F1 score of the optimal model chosen, i.e., SVM + waist accelerometer. In test data, all the precisions were higher than 0.95 except for right back kick on right side (0.88). Right back kick also has the lowest recall (0.91) while other kick had the recall at least 0.94. Fig. 7 illustrated the detailed information about the predicted kicking types and true kicking types by confusion matrix.

4. Discussion

This study investigated the methods of recognizing TKD kicks, i.e., front kick, roundhouse kick, side kick and back kick, using accelerometer and combined with machine learning techniques. The comparison of different machine learning models showed that SVM (accuracy 0.96 or above) performed far better than decision tree (accuracy around 0.8). The comparison between different combinations conveyed that only one accelerometer on waist is accurate enough to classify the four kicks. Introducing additional accelerometers are unnecessary and might increase the noise and therefore affect undermine the validity of classification model. As a result, the best way was to use waist accelerometer data and combined with SVM model.

The results agreed with the original hypothesis and the literature that SVM has a good performance on classification missions [14, 19]. However, more accelerometer seems to be redundant since waist accelerometer solely could have a very high validity (accuracy >0.95). Practically, using less devices and achieve higher accuracy, as well as higher precision, recall of each category, is desirable but there are always trade-offs between conveniency and validity. Fortunately, these four basic kicks in TKD have significant biomechanical differences so the kinetic information from waist is sufficient to differentiate them.

However, TKD has a great number of kicking techniques and some of them are not easy to recognize even with eye balls. For example, there was one type of roundhouse kick using not instep but the ball of foot to strike the target. The difference only happens on foot but the kinetical features are exactly same as normal roundhouse kick. To further recognize more kicks, additional sensors are needed to be embedded in to wearable devices.

When using the data of the waist and the left and right ankle for action recognition, the effect of using the SVM model for classification is better than that of using the decision tree model, and the identification accuracy is higher. Using RFE has similar effects to RFECV for feature selection for action recognition. Based on feature extraction, different feature selection methods were compared, and different leg movements were classified using SVM and decision tree as classifiers. Overfit exists in decision tree models but not obvious in SVM.

Taken together, the experimental results show that reducing the number of accelerometers can effectively reduce costs, and usually does not result in a significant loss of accuracy. Therefore, using only a single accelerometer sensor on the waist for action recognition is an ideal placement that enables accurate action recognition while saving costs and resources. This conclusion has important guiding

Table 1
Basic information of participants (M±SD).

	Age(years)	Weight(kg)	Height(cm)	BMI	Years of training
Total	21.45 ± 1.73	61.84 ± 14.22	169.35 ± 7.82	21.40 ± 3.50	5.30 ± 3.37
Male	22.40 ± 1.82	77.80 ± 18.91	178.00 ± 6.60	24.33 ± 4.11	5.60 ± 2.70
Female	21.13 ± 1.65	55.87 ± 6.49	166.67 ± 5.74	20.11 ± 2.21	5.20 ± 3.65

Table 2
Confusion matrix of binary classification.

	Actual positive category	Actual negative category
Predict positive categories	TP	FP
Predict negative categories	FN	TN

Table 3
Descriptive statistics of the acceleration data on 12 channels.

	M	SD	Var	Skewness	Kurtosis	Min	X.25	X.50	X.75	Max
x_W	0.94	0.25	0.06	−0.03	9.21	−1.72	0.86	0.97	1.01	4.07
y_W	0.06	0.39	0.15	−0.11	4.42	−4.88	−0.14	0.05	0.27	4.29
z_W	0.01	0.25	0.06	−0.77	6.76	−3.01	−0.11	0	0.15	2.3
x_rL	1.06	0.6	0.36	3.59	30.14	−5.52	0.93	0.99	1.04	8
y_rL	−0.06	0.66	0.43	−1.77	18.24	−7.38	−0.23	−0.02	0.19	7.43
z_rL	0.09	0.52	0.27	1.53	16.59	−6	−0.08	0.06	0.22	7
x_lL	1.06	0.6	0.35	3.66	28.5	−3.61	0.94	0.99	1.05	8
y_lL	0.07	0.66	0.44	1.58	17.34	−6.79	−0.17	0.04	0.23	7.63
z_lL	0.04	0.5	0.25	1.31	14.95	−5.41	−0.11	0.04	0.18	6.93
v_W	1.05	0.22	0.05	3.09	21.87	0.06	0.97	1.01	1.08	5.08
v_rL	1.28	0.74	0.55	4.35	25.19	0.02	1	1.02	1.2	10.44
v_lL	1.28	0.73	0.54	4.18	22.86	0.07	1	1.02	1.2	11.28

Note: x_W = x-axis of the Waist accelerometer(x-waist); y_W = y-waist; z_W = z-waist; x_rL = x-right ankle; y_rL = y-right ankle; z_rL = z-ankle; x_lL = x-left ankle; y_lL = y-ankle; z_lL = z-ankle; v_W = magnitude of resultant vector of acceleration on x, y, z axis (v-waist); v_rl = v-right ankle; v_lL = v-left ankle.

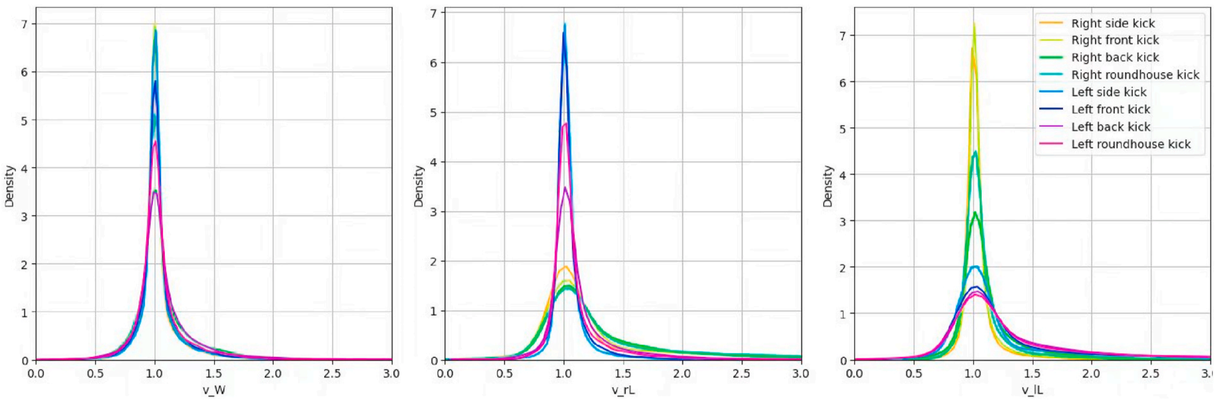

Fig. 4. Distribution of magnitude of the resultant vectors of accelerations.

significance for the design and practical application of action recognition systems, especially in the case of limited budget and resources.

In the study of action recognition based on accelerometer sensor, the key to accurate identification of TKD leg movements is to capture the core characteristics of motion. In leg movements, the movement patterns of the legs and waist are usually closely related, and the differences in leg movements can usually be assisted by the overall dynamics of the waist. Thus, even placing only one accelerometer in the waist captures enough critical information to keep the identification results within an acceptable accuracy range. Moreover, with suitable feature extraction and classification algorithms, representative features can be extracted from the data of the waist sensor and further improve the accuracy of identification.

The limitation of this study includes the limited number of participants and kicking types. Spin hook kick is one of the most useful kicks but rare people could perform is well. The later recruitment process needs to target on wider range of populations instead of just one university. The future researches need to focus on more wearable sensors, e.g., gyroscope, and doing the pattern recognition using hand-movement data since most people wear the trackers on wrist instead of waist.

Ethics and consent

All participants knew the experiment procedure and consented to participate. This study was reviewed and approved by Sport Science Experiment Ethics Committee of Beijing Sport University with the approval number 2024121H, dated Nov. 1st, 2023.

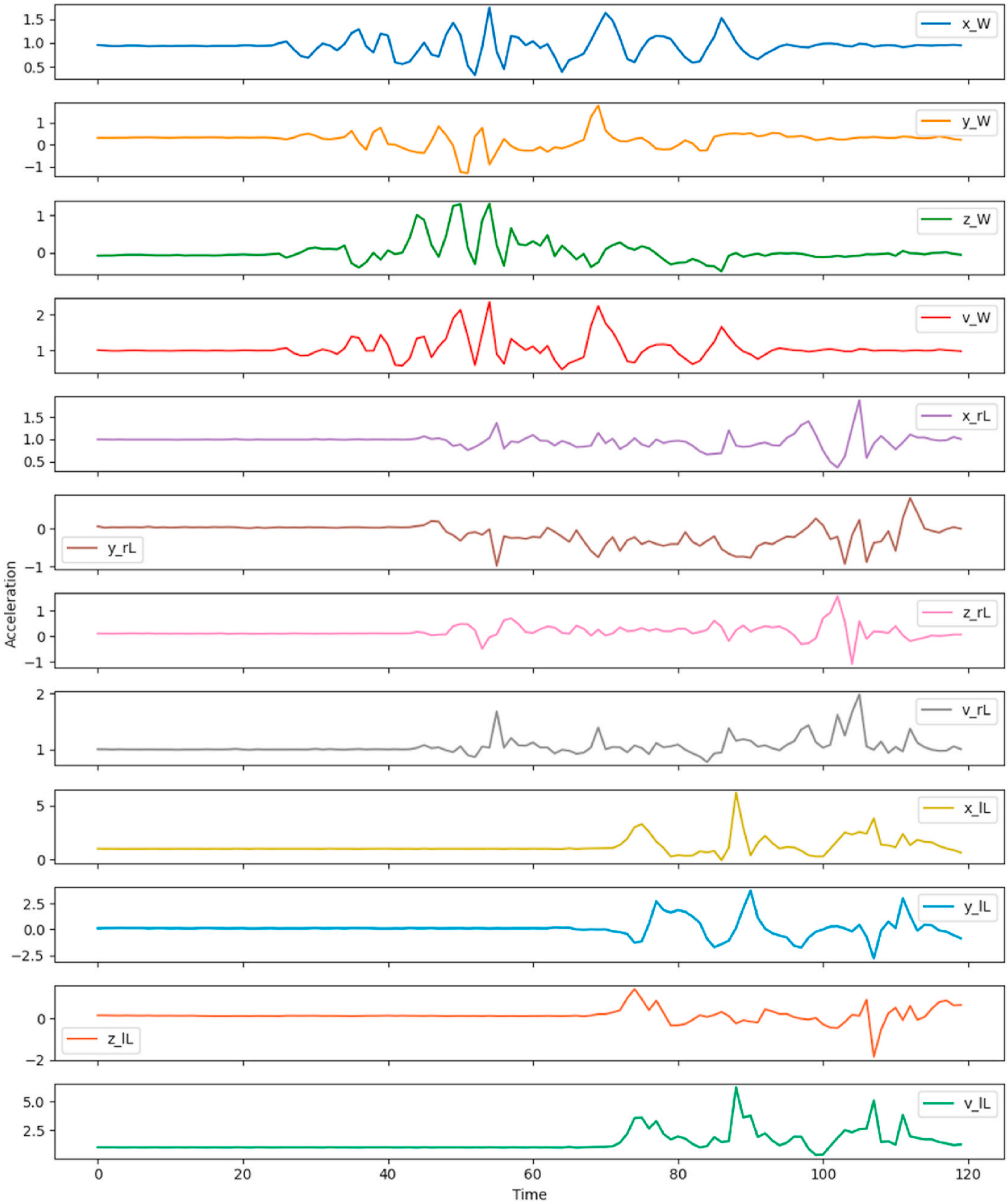

Fig. 5. Example of the signals from 12 channels of one kick (a 4-s segment; In plot: x-axis = time, unit = 0.033s; y-axis = acceleration, unit = g or 9.81 m/s^2).

Data availability statement

The data will be made available on request.

CRediT authorship contribution statement

Zeting Liu: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition. **Mengyuan Yang:** Writing – review & editing, Writing – original draft, Visualization, Software. **Kaihang Li:** Visualization, Software, Formal analysis, Data curation. **Xiong Qin:** Writing – review & editing, Writing – original draft, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

id	label	z_rL__count_above_mean	z_rL__ratio_value_number_to_time_series_length	z_rL__quantile__q_0.9	z_rL__autocorrelation__lag_2
Right side kick_10_0	Right side kick	0.925926	0.316667	0.069260	0.721638
Right side kick_10_1	Right side kick	0.888889	0.283333	0.088852	0.672847
Right side kick_10_2	Right side kick	0.864198	0.350000	0.102428	0.642462
Right side kick_10_3	Right side kick	0.913580	0.300000	0.079746	0.632124
Right side kick_10_4	Right side kick	0.851852	0.450000	0.116446	0.655218

Fig. 6. The format of data matrix (partial) of features (IV) and label (DV).

Table 4
Accuracy of SVM and Decision Tree in 3 accelerometer combinations.

	Accuracy of SVM		Accuracy of Decision Tree	
	Train	Test	Train	Test
Waist, Right ankle and Left ankle	0.98	0.97	1	0.82
Waist, Right ankle	0.99	0.96	1	0.79
Waist	0.99	0.98	1	0.82

Table 5
Precision, recall and F1 score of SVM model using waist accelerometer.

	Train			Test		
	Precision	Recall	F1-Score	Precision/%	Recall/%	F1-Score
Right side kick	0.91	1	0.95	1	0.97	0.99
Right front kick	0.99	0.99	0.99	1	0.97	0.99
Right back kick	0.98	0.98	0.98	0.88	0.91	0.89
Right roundhouse kick	1	1	1	0.97	1	0.98
Left side kick	1	0.97	0.99	1	0.96	0.98
Left front kick	0.99	0.99	0.99	0.97	0.94	0.96
Left back kick	0.96	0.99	0.97	0.97	1	0.98
Left roundhouse kick	1	0.9	0.95	0.97	1	0.98

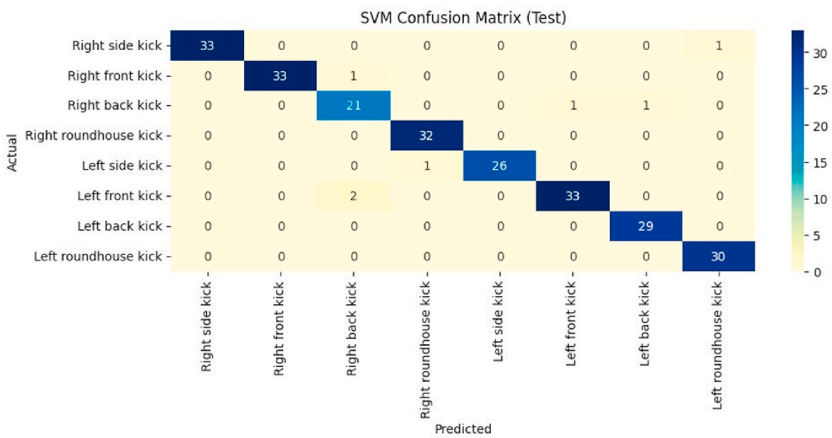

Fig. 7. Confusion matrix between predicted and true kicking types.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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