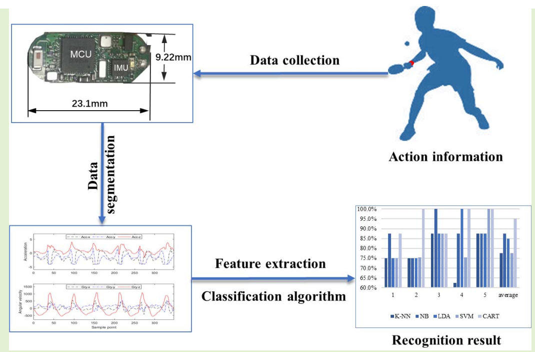
Accurate Recognition of Player Identity and Stroke Performance in Table Tennis Using a Smart Wristband

Xiaopeng Sha, Guanghua Wei, Xueliang Zhang, Xianshou Ren, Shuyu Wang, Zhonghai He, and Yuliang Zhao, *Member, IEEE*

***Abstract*—In table tennis, a 40 mm in diameter table tennis ball weighing 2.7g can reach the opponent's table in a very short time when it travels at a speed of 17m/s. That is difficult for new players to hit accurately. The purpose of this work is to recognize hits and misses by distinguishing the action difference between hitting and missing table tennis. The result of recognition can be used to figure out a small deviation from the correct posture and improve the hitting accuracy. Six volunteers participated in the experiment. The volunteers wore wristband sensors on the wrist on which they held the table tennis bat. Each volunteer played the ball 100 times and collected the information through a wristband sensor. The collected information was analyzed by support vector machine (SVM), decision tree (CART), linear discriminant analysis (LDA), K nearest neighbor (KNN), and Naive Bayes (NB) to identify the identities of volunteers and the hit or miss of the ball. The accuracy rate of volunteers' identity recognition is 99%, and the accuracy rate of hits and misses is 95%. The results show that the wristband sensor can accurately identify the volunteers' identities and missing cases through appropriate classification methods. This shows that we can find out the nuances between the stroke postures by hitting or missing the ball, and then use the results to correct the movement of the players, and thus improve the players' skill.**



***Index Terms*— Wearable sensor, IMU, sports analysis, table tennis stroke, stroke performance.**

I. Introduction

TABLE tennis is small and generally runs at a high speed, which requires quick reactions from athletes, so it is difficult to assess whether the players' movements are accurate [1]. In addition, the grip posture, hitting angle, impact strength are also important factors affecting the correct movements [2]. Athletes always need a lot of training to improve their skills. However, without scientific, accurate and proper movement guidance, too much training may be futile and even harmful to the body [3]. A recognition system is urgently needed to accurately measure the rapid movement and performance of players. And the system can play a role in evaluating the effect of sports and guiding the action of playing ball [4]. At present, the main research technologies of motion recognition include video analysis technology, wireless signal technology, and wearable sensor technology.

Video analysis technology has developed rapidly in recent years, and has given rise to a lot of action recognition practices intended to achieve auxiliary training through data analysis [5], [6]. Martin *et al.* [7] proposed a new Siamese Spatio-Temporal Convolutional neural network (SSTC), which can detect and identify 20 table tennis movements in videos with a recognition accuracy of 91.4%. Wu *et al.* [8] used the Radial Basis Function Neural Network (RBFNN) motion recognition method trained by the Local Generalized Error Model (L-GEM) to divide the motion in 599 videos into six types with the accuracy of 98.61%. Tu *et al.* [9] collected motion features in videos through adaptive video feature segmentation and adaptive segmentation, and introduced flow warping technology to detect and discard redundant feature maps, thus realizing action recognition. Saad Ali *et al.* [10] proposed a kinematics feature based on optical flow, and used the nearest neighbor algorithm to recognize human motion in

Manuscript received January 15, 2021; revised January 29, 2021; accepted February 9, 2021. Date of publication March 1, 2021; date of current version April 5, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 61873307 and Grant 61673278, in part by the Natural Science Foundation of Hebei Province under Grant F2020501033, in part by the Qinhuangdao Science and Technology Planning under Project 201901B013, in part by the Scientific Research Project of Colleges and Universities in Hebei Province under Grant ZD2019305, in part by the Hebei Natural Science Foundation under Grant F2020501040, and in part by the Fundamental Research Funds for the Central Universities under Grant N2023015. The associate editor coordinating the review of this article and approving it for publication was Prof. Aime Lay-Ekuakille. *(Corresponding author: Yuliang Zhao.)*

The authors are with the School of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China (e-mail: zhaoyuliang@neuq.edu.cn).

Digital Object Identifier 10.1109/JSEN.2021.3060914

videos, with a recognition rate of 87.7%. Using video methods to recognize actions has problems such as high cost, complex equipment, and inconvenience to carry. In addition, blind spots in the continuous motion of athletes will inevitably appear in the field of view, which reduces the accuracy of motion recognition.

Wireless signals have developed from a simple communication medium to a tool capable of sensing the surrounding environment. Since human behavior affects Wi-Fi signals, different motions and positions introduce different multipath distortions in Wi-Fi signals, and human behavior can be captured by using channel state information (CSI) [11]–[13]. Yao *et al.* [14] combined Wi-Fi with an accelerometer to collect motion information and adopted the BP neural network to identify seven basic movements of table tennis, with a recognition rate of 97.43%. Chen *et al.* [15] proposed a Wi-Fi signal-based table tennis action recognition system that uses the support vector machine (SVM) to identify six table tennis actions. In Chen's experiment, the average accuracy of motion recognition was only 90.33%. However, there are many wireless signals in life, resulting in a large amount of noise in the received data, which also brings great difficulties to the data analysis and reduces the accuracy of action recognition. Moreover, this method is seriously affected by the location and the surrounding environment.

Wearable sensors provide another technology that uses sensors worn on the body to collect human motion information and recognize human motion. Ruichen *et al.* [16] proposed a table tennis sport recognition system based on a wearable sensors network. The sensors were placed in the upper arm, lower arm, and the back of the body respectively. In their research, only different movements were distinguished, but no nuances of the same movement were studied. Wang *et al.* [17] used a two-layer Hidden Markov Model (HMM) to identify the movement information of badminton, and adopted four sensors to collect the movement information of the left wrist, right wrist, waist, and right ankle for data processing. In their work, it was necessary to collect movement information of multiple parts of the human body, which complicated the process for users, affected their comfort level, and increased economic costs. Wang *et al.* designed a wearable inertial motion sensor with a recognition accuracy rate of 94% to track athletes' movements, monitor their performance, and help them in training [18]. Huang *et al.* [19] designed a new wearable sensor based on triboelectric charging, used a k-nearest neighbor (KNN) clustering algorithm to identify daily activities, and realized the recognition of walking, sitting and standing activities, but the accuracy rate is only 80 %.

Compared with the three motion recognition technologies, sensor-based technology has the characteristics of portability, low cost, and easy promotion. However, in the motion recognition of wearable sensors, the portability and the difference recognition of the same movement are still limited.

This paper analyzes the difference of movement information by using various recognition algorithms to identify the slight difference between hitting and missing in table tennis. By analyzing the movement differences that are difficult to distinguish with the naked eye, we can correct the movement posture to help training. The number of strokes and results of table tennis players can provide a basis for evaluating the performance of players.

TABLE I
MEASUREMENT RANGE OF EACH PARAMETER

Sensor type	Project	Measuring range
MPU9250	Three-axis magnetic field [μT]	±4900
	Three-axis acceleration [G]	±16
	Three-axis angular velocity [dps]	±2000

II. EXPERIMENTAL METHOD

A. Hardware Model

In this experiment, the MPU9250 is mainly used for data collection. The MPU9250 includes a 6-DOF inertial measurement unit (IMU) and a 3-DOF magnetometer sensor. Roth, K showed that in a laboratory to establish a pre-cueing experiment, table tennis requires about 370 milliseconds of movement time ((from start of swing to bat-ball contact) [20]. This article studies the stroke movement from the start to the end, which takes about 700 to 1000 milliseconds. Through the test of a variety of sampling frequencies, it is found that when selecting a sampling frequency of 50 Hz to satisfy the collection of motion information, it is also convenient for data analysis. The range of each parameter is shown in Table I. MCU is built on a 32-bit ARM Cortex-M4F CPU with 512 kB + 64 kB RAM. The overall volume is as small as a one-yuan coin RMB, so players would not feel discomfort when moving with the sensor. It has the advantages of small size (23.05 mm×9.24 mm×5.5 mm), high accuracy, and low power consumption. The wearing method and schematic diagram of the wristband sensor are shown in Figure 1 (a), (b), and (c).

B. Experimental Process

The whole process of the experiment includes data collection, data segmentation, data preprocessing, feature extraction and selection, dimensionality reduction, and data classification. The flow chart of the experimental process is shown in Figure 1 (d).

III. DATA PROCESSING

A. Data Collection

In this experiment, we invited six volunteers who have played table tennis before to participate in data collection. The basic information of these six volunteers is shown in Table II.

During the experiment, volunteers were asked to wear the wristband on the wrist of the player's hand to collect movement information by swinging a tennis ball. (Because the selection in this study was to be good at using the right hand, so the wristband was worn on the right wrist). The volunteers carried out a number of experiments, which were collected by sensors on their wristbands. After analyzing a large number

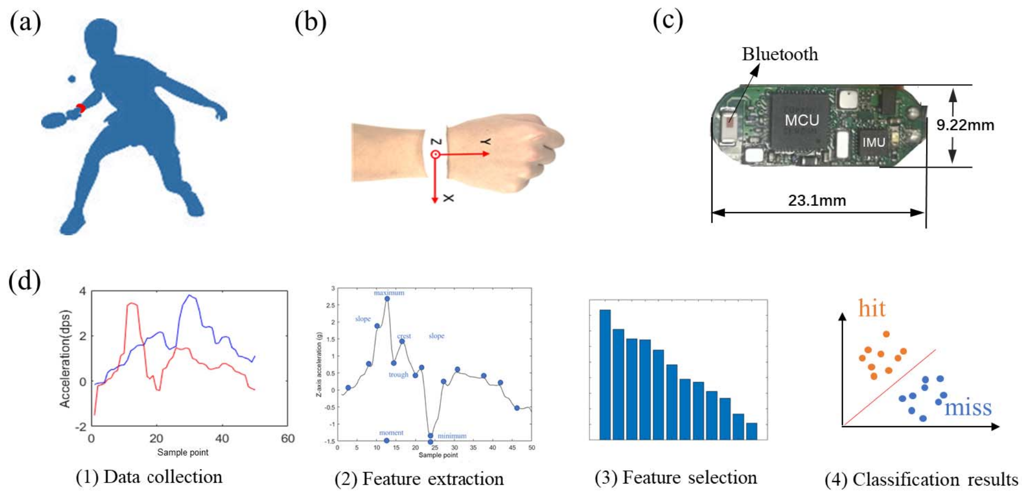


Fig. 1. (a) Schematic diagram of wearing the wristband sensor, (b) Sensor wearing real picture, (c) Schematic diagram of sensor hardware, (d) Schematic diagram of the experimental process.

TABLE II
BASIC INFORMATION OF VOLUNTEERS

Subject	Age	Height	Body Mass
Volunteer 1	24	177 cm	70 kg
Volunteer 2	28	178 cm	62 kg
Volunteer 3	39	173 cm	83 kg
Volunteer 4	24	162 cm	50 kg
Volunteer 5	25	170 cm	60 kg
Volunteer 6	19	153 cm	50 kg

of data, the result is approximately equal to the results of 100 data per person. In order to obtain the accuracy from the specific data, we selected 100 data per person as the datasets in the paper. A sports camera was used to record the volunteer's ball hitting action, and the hit or miss recorded by the sports camera was used as the actual value for identifying hits and misses.

As shown in Figure 2, the second and third cycles are data of missed table tennis balls, and the rest are data of hitting table tennis balls. By observing the oscillogram, it can be found that in the acceleration data, the profiles of the peaks in the X-axis and Y-axis are similar, but there are significant differences for the peaks on Z-axis. As for the oscillogram of angular velocities, the peaks are almost the same in the X, Y, and Z axes. Therefore, in the subsequent motion recognition and detection, we select the Z-axis acceleration data as the motion analysis data and subdivide it.

B. Data Segmentation and Data Preprocessing

After the above analysis, we chose the Z-axis acceleration data to analyze the action. Therefore, we need to segment the original data of the Z-axis acceleration to analyze the difference of each hitting action and extract its characteristics. The first step is to analyze the physical meaning of the original data, as shown in Figure 3. Based on the physical meaning of the Z-axis acceleration data collected when playing table tennis, a detailed analysis is performed.

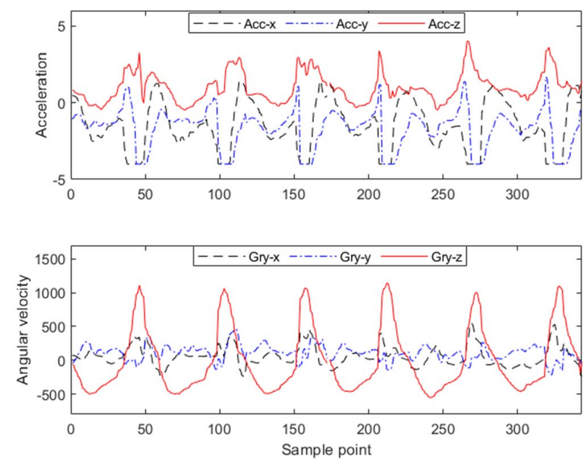


Fig. 2. X, Y, Z acceleration and angular velocity data of table tennis hitting.

As shown in Figure 3, the various stages of the hitting action. As shown in serial number 1, the preparation stage for hitting is performed. Due to the acceleration of gravity, the acceleration on the Z-axis is initially equal to 1. As shown in serial number 2, during the shot, the arm quickly stretches backward and generates a downward force, which causes the acceleration on the Z-axis to decrease. As shown in serial number 3, when the ball machine launches a ping-pong ball, our arms must be stretched forward to hit the ping-pong ball. At this time, upward acceleration is generated, and the acceleration on the Z-axis increases. As shown in serial number 4, when a volunteer is playing table tennis, due to inertia, the arm continues to move to the chest, so the angle of the Z-axis will continue to change. When the arm reaches the chest, the acceleration on the Z-axis will rise rapidly. Then, we control the arm to extend back and return to the initial state to wait for the next blow. The whole process constitutes the hitting action. As shown in Figure 4, we segment the original data according to this physical meaning.

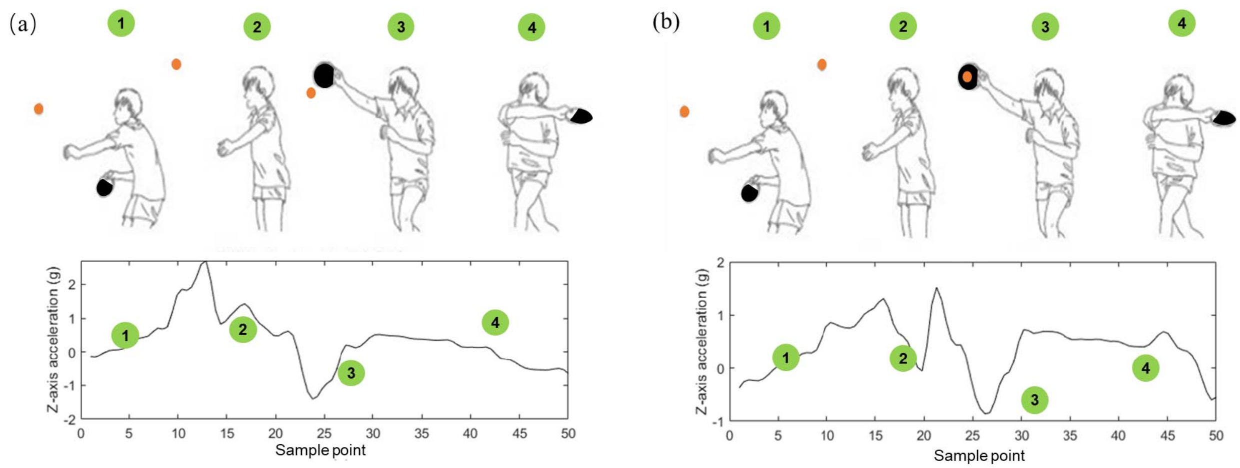


Fig. 3. Schematic diagram of data physical meaning analysis. (a) is an exploded view of the action of missing the table tennis; (b) is an exploded view of the action of hitting the table tennis. The serial number in the curves and the action serial number correspond one-to-one, and the data of the serial number in the graph is obtained under the action corresponding to the serial number.

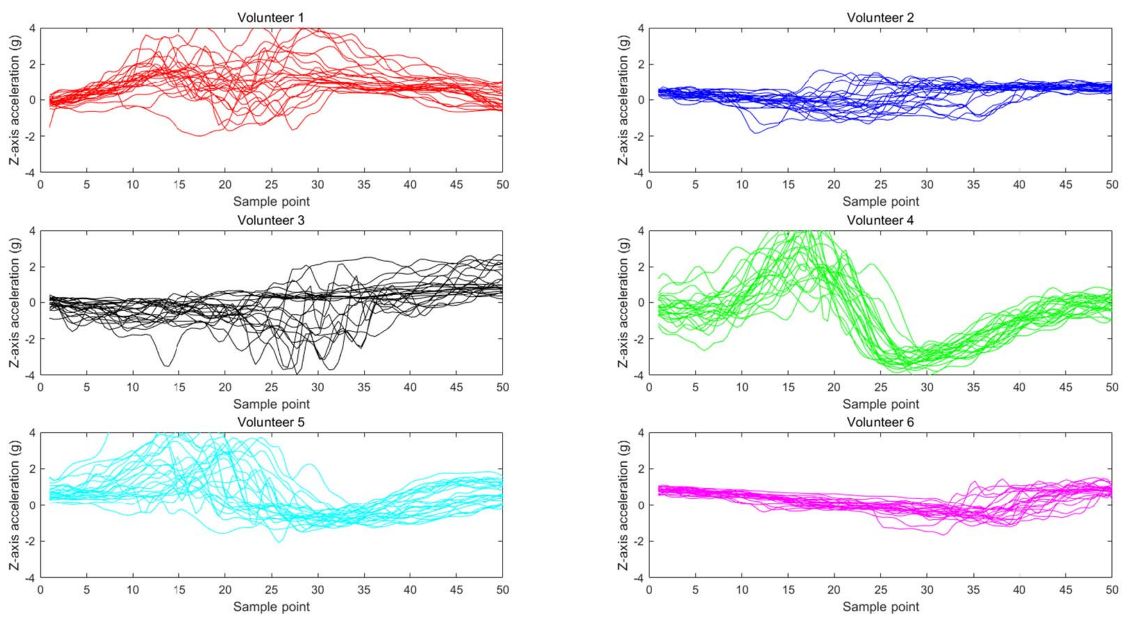


Fig. 4. Z-axis acceleration data waveforms of six volunteers.

After the data segmentation is finished, apply a moving average filter to eliminate the high-frequency noise of the accelerometer data. The filter is as follows:

$$y\left(i\right)=\frac{1}{M}\sum\nolimits_{j=0}^{M-1}x[i-j] \tag{1}$$

where $y(i)$ is the output signal, and M is the size of the moving window of the average filter [21].

The number of hits and misses are shown in Table III. Among them, volunteers who miss more than 10 times are defined as high level, between 10 to 20 times are defined as medium level, and more than 20 times are defined as low level.

Under the observation of the naked eye and the camera, the movements of the six volunteers were roughly the same, and it was difficult to identify the subtle differences in their movements. However, it can be seen from the waveform of the action information collected by the IMU that the actions of the six volunteers are still very different. Through analyzing these differences, we conducted volunteer identification. To ensure the same experimental environment and the same operating habits so as to reduce the impact of other factors for hits and misses, we selected a volunteer with a moderate level to research on hits and misses.

Figure 5 shows the waveforms of hit and miss data after segmentation. There are 24 sets of waveform data, in which red represents 12 sets of data that hit the table tennis ball, and blue represents 12 sets of data that miss the table tennis ball. It can be seen from the figure that when the sampling point is between 10 and 35, there is a big difference between the waveform that hits the table tennis ball and the waveform that misses the table tennis ball, so we analyze the data in detail here.

TABLE III
THE NUMBER OF HITS AND MISSES BY THE SIX VOLUNTEERS

Technique level	Volunteer	Number of Hits	Number of misses	Total times
High level	Volunteer 6	96	4	100
	Volunteer 2	98	2	100
Medium level	Volunteer 1	75	15	100
	Volunteer 5	82	18	100
Low level	Volunteer 3	77	23	100
	Volunteer 4	63	37	100

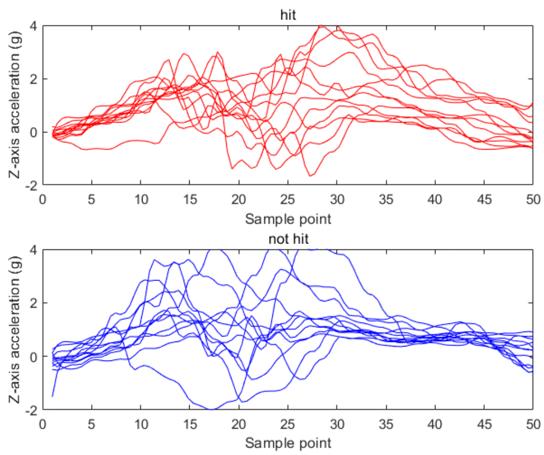


Fig. 5. Red indicates the waveform of hitting the table tennis and blue the waveform of missing the table tennis.

TABLE IV
FOUR FEATURES EXTRACTED FOR VOLUNTEER IDENTIFICATION

Number	Formula	Description
1	Number of peaks	Number of peaks generated during the action
2	Maximum	Maximal data in the whole action.
3	Minimum	Minimal data in the whole action.
4	Number of troughs	Number of troughs generated during the action

C. Feature Selection

After data segmentation, we extracted the features of the volunteer's identity recognition and the features of hit and miss recognition in the hitting action.

1) Feature Extraction for Volunteer Identification: As shown in Figure 4, we can see that the wristband sensor can measure volunteers' motion information. Among them, there are big differences in the maximum value, minimum value, number of crests, and the number of troughs. Based on this, we extracted the four features shown in Table IV in the identification of volunteers.

2) Feature Extraction for Volunteer Identification: Observing Figure 6 we can see that the movements of different volunteers are different. In order to rule out that the hits and misses are caused by the volunteer's exercise habits, we selected the data of a middle-level volunteer for more in-depth identification. By analyzing the waveforms of hits and misses when playing table tennis, the difference in action is identified. We extracted 34 sets of features from the data in the time domain and frequency domain to fully describe the shot process. When selecting features, we are interested in features that have high variance rather than similarity, so next, we filter the extracted features, calculate the correlation between features, and delete highly correlated features. (In Figure 6, MMS (Maximum and minimum slope) represents the slope between the maximum and minimum values, MPPD (Maximum two peak position difference) represents the difference between the two highest peaks, LMT (Location of the minimum trough) represents the position of the minimum valley, SHPP(Slope of the highest peak and lowest peak) represents the slope of the highest and lowest peaks, MMPD (Maximum and minimum position difference) represents the difference in position between the maximum and minimum values, DBMM (Difference between maximum peak and minimum trough) represents the slope between the highest peak and the minimum valley, SMBP (Maximum slope between two peaks) represents the slope between the largest two peaks, MMD (Maximum and minimum difference) represents the difference between the maximum and minimum values, and AAV (The average of absolute values) represents the average of the absolute values.)

In the process of filtering features through correlation, when we define the correlation to be more than 98%, the two features are considered to represent the same meaning. After deleting some features, we finally get 12 sets of features, as shown in Table V.

In Table V, the maximum value (No. 1) represents the maximum acceleration in the Z-axis direction when playing table tennis. The position of the maximum value (No. 2) indicates the moment when the acceleration in the Z-axis direction is the maximum in the course of hitting the table tennis. The minimum value (No. 3) represents the minimum acceleration in the Z-axis direction. The position of the minimum value (No. 4) indicates the moment when the Z-axis acceleration is the smallest in the process of playing table tennis. The number of peaks and valleys (No. 5 and No. 6) represents the change in z-axis acceleration during the exercise. The slope (No. 7) between the maximum and minimum values also represents the change in acceleration on the Z-axis. The three-quarters in the boxplot minus the one-quarter in the boxplot represent the change in power when hitting the ball (No. 8). The position difference between the largest two peaks indicates how fast the ball is hit (No. 9). The slope between the largest peak and the smallest valley represents the rate of acceleration change of the shot (No. 10). The slope between the largest two peaks represents the change in angle during hitting (No. 11). The difference (No. 12) between the position of the maximum value and the position of the minimum value represents the time taken from the minimum acceleration to the maximum acceleration in the Z-axis direction.

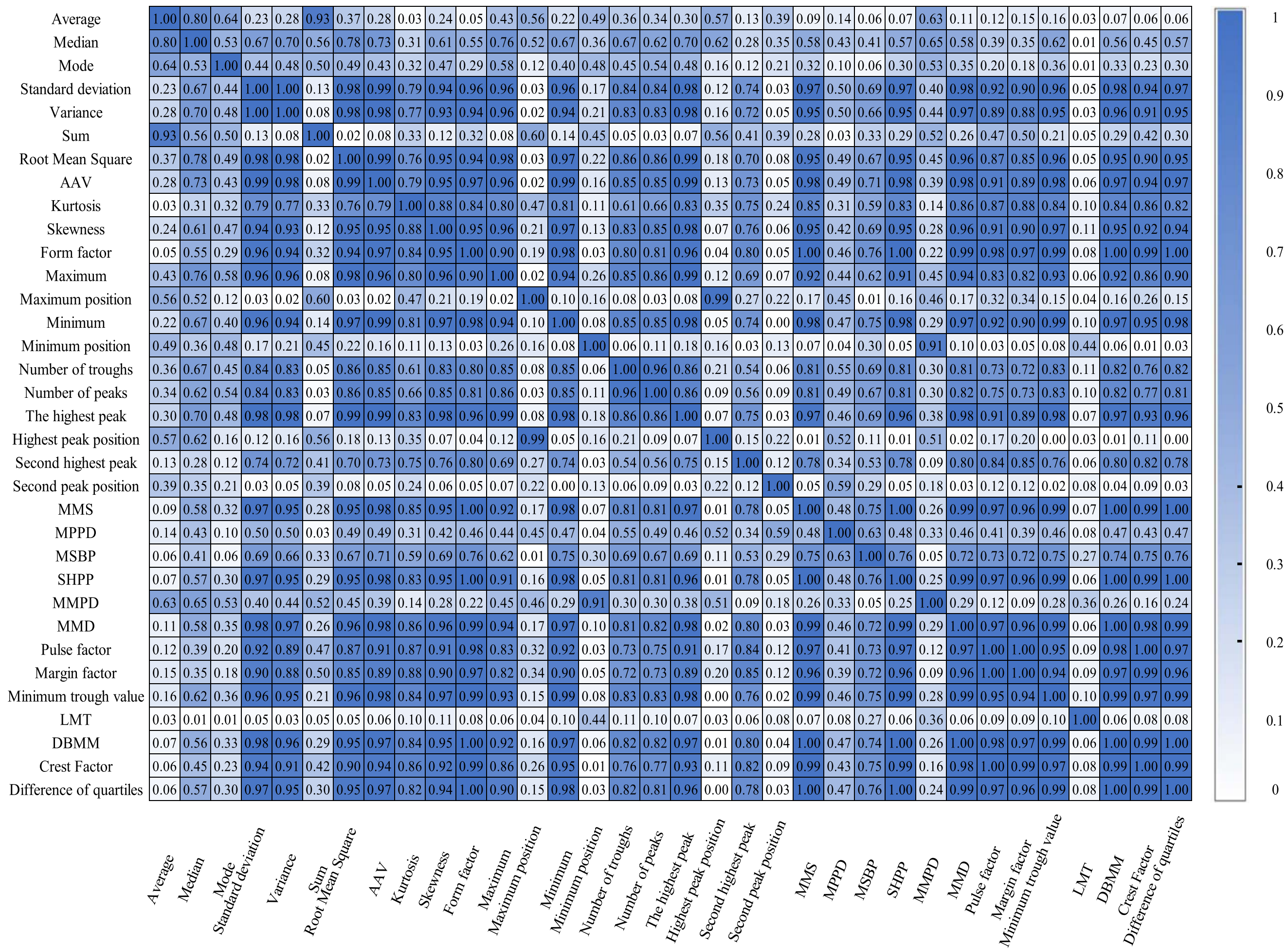


Fig. 6. Correlation of features.

After selecting the features, we extract the selected features by a MATLAB program. Next, we obtain a 24×12 feature matrix, which is used to describe the motion of hit and miss.

D. Feature Importance Ranking

To avoid overfitting and reduce the amount of computation, we use Laplacian scores for feature selection and dimensionality reduction. We first use the K- Nearest Neighbor (KNN) algorithm to select a local area to plot a graph, where K needs to be set by ourselves according to the actual situation. In this paper, we have set K $=$ 9 after many attempts. After that, the nine nearest points of each point are connected. The next step is to determine the weight between the points, and convert the distances into the similarity matrix (a matrix representation of the K nearest neighbor points we choose) [22] using the kernel transformation. The formula is as follows:

$$S_{i,j} = \exp(-(\frac{Dist_{i,j}}{\sigma})^2) \tag{2}$$

where σ is the scale factor for the kernel as specified by the 'KernelScale' name-value pair argument, and $Dist_{i,j}$ is the pairwise distance for all points i and j in the neighborhood.

Each feature is then subtracted from the mean to center each feature. The formula is as follows:

$$\bar{x}_r = x_r - \frac{x_r^{\mathrm{T}} D_g 1}{1^{\mathrm{T}} D_g 1} 1 \tag{3}$$

where x_r is the column vector of the r$^{\text{th}}$ feature, D_g is the degree matrix (A degree matrix D_g is an n-by-n diagonal matrix obtained by summing the rows of the similarity matrix S.), and $1^T = [1, 1, 1, \ldots\ldots]^T$.

After the vector $\bar{x}_r$ is solved, the score s_r of each feature is calculated.

$$s_r = \frac{\bar{x}_r^T S \bar{x}_r}{\bar{x}_r^T D_g \bar{x}_r} \tag{4}$$

The Laplacian score is defined [23] as:

$$L_r = \frac{\bar{x}_r^T L \bar{x}_r}{\bar{x}_r^T D_g \bar{x}_r} = 1 - \frac{\bar{x}_r^T S \bar{x}_r}{\bar{x}_r^T D_g \bar{x}_r} \tag{5}$$

where L_r is the Laplacian matrix, defined as the difference between D_g and S.

We use the second term of Formula (4) as the fractional value of the score, so a larger fractional value represents a more important feature. Finally, the feature matrix is

TABLE V
12 GROUPS OF FEATURES OBTAINED AFTER EXCLUDING THE FEATURES WITH HIGH CORRELATION

Number	Feature	Feature description
1	M	Maximum: $M = \max(x_i), i = 1,2,3,\ldots n$
2	MP	Maximum position: $MP = i$, when $M = \max(x_i)$, $i = 1,2,3,\ldots n$
3	S	Minimum: $S = \min(x_i), i = 1,2,3,\ldots.n$
4	SP	Minimum position: $SP = i$, when $S = \min(x_i)$, $i = 1,2,3,\ldots n$
5	T	The number of troughs.
6	P	The number of peaks.
7	SMS	The slope between maximum and minimum: $SMS = \frac{M-S}{MP-SP}$
8	B	Upper quartile minus lower quartile.
9	SB	Positional subtraction between the largest two peaks.
10	SPV	The slope between the largest peak and the smallest valley.
11	SBP	The slope between the two largest peaks.
12	DMS	The position of the maximum value is subtracted from the position of the minimum value: DMS=MP-SP

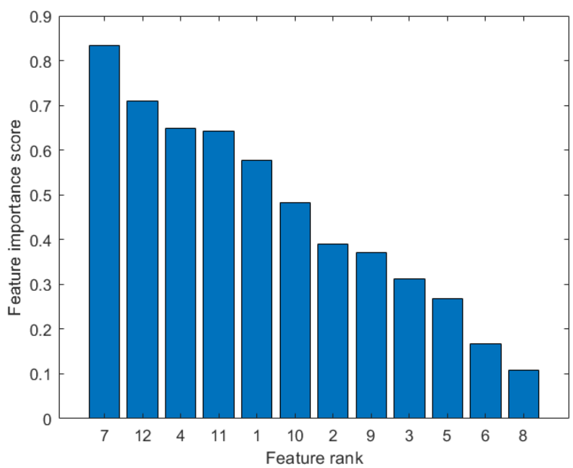


Fig. 7. Feature ranking bar chart.

introduced into the function, and a feature importance map, as shown in Figure 7, is obtained.

Combining Figure 7 and Table IV, it can be seen that the best function is the slope of the maximum and minimum values, which shows that speed and control have a great influence on the hit of the shot. The second is the difference between the maximum position and the minimum position, which also shows that speed is very important during the shot. Next is the position of the minimum value, which represents the acceleration of our hands extending backward during preparation to hit the ball, which also proves the importance of agility when hitting the ball. The fourth-ranked feature is the slope between the two highest peaks. It means the change of the action at the moment of hitting the ball.

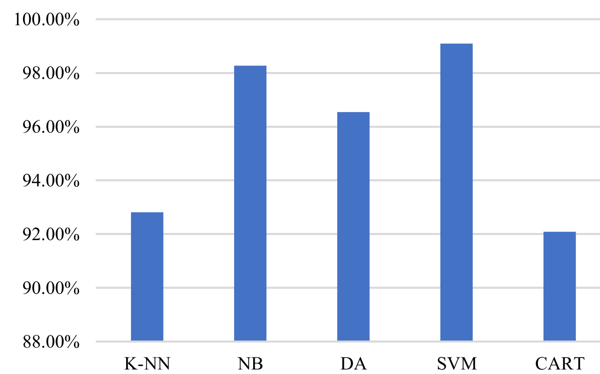


Fig. 8. Histogram of recognition results of different volunteers.

E. Classification Results

In this section, we used five algorithms: support vector machine (SVM) [24]–[27], decision tree (CART) [28], linear discriminant analysis (LDA) [29], K nearest neighbor (KNN) [30], and Naive Bayes (NB) [31], [32] to recognize the identity of six volunteers, and selected a volunteer's hitting to identify the difference between hit and miss.

1) Volunteer Identification Results: Figure 8 shows the result of volunteer recognition. It can be seen from the figure that our highest recognition accuracy rate for volunteers of different levels can reach 99%. This shows that the action differences between volunteers of different levels are obvious. To eliminate the impact of differences in technical level, we selected a middle-level volunteer's action information to recognize the action difference of hit and miss.

2) Motion Identification Results: Subsequently, hits and misses were identified in experiments, and classification results were tested according to the above importance ranking of

TABLE VI
RESULTS OBTAINED WITH DIFFERENT NUMBERS OF FEATURES

Total number of features	KNN-average	NB-average	LDA-average	SVM-average	CART-average
4	77.50%	87.50%	85.00%	82.50%	95.00%
5	87.50%	77.50%	80.00%	82.50%	95.00%
3	87.50%	87.50%	82.50%	70.00%	92.50%
2	80.00%	77.50%	62.50%	57.50%	90.00%
8	70.00%	80.00%	82.50%	80.00%	87.50%
7	77.50%	77.50%	85.00%	87.50%	85.50%
1	80.00%	80.00%	72.50%	67.50%	85.00%
6	75.00%	67.50%	90.00%	82.50%	85.00%
12	67.50%	67.50%	72.50%	80.00%	85.00%
9	55.00%	80.00%	70.00%	85.00%	82.50%
11	72.00%	75.00%	67.50%	85.00%	82.50%
10	65.00%	72.50%	85.00%	85.00%	77.50%

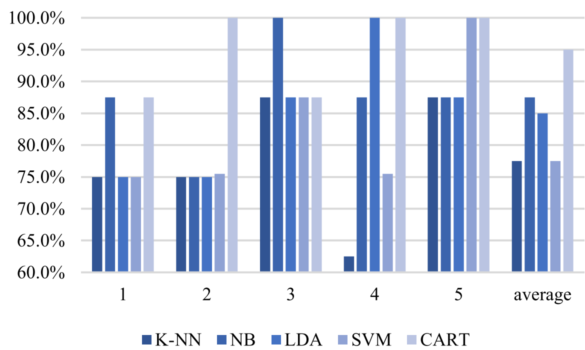


Fig. 9. Classification results were obtained by taking the first four features for classification.

features. Since we do not know the exact number of features to be extracted that contribute to the best classification effect, we tested the classification effect based on the importance of the features from high to low and the number of features from small to large. Classification results are shown in Table VI.

In Table VI, the first column is the total number of features, and the second to sixth columns represent the classification results of the five classifiers. It can be seen from the table that we have the best recognition effect when we take four features, so we choose four features as the basis for action recognition.

Figure 9 shows the recognition accuracy of hits and misses. Here, each of our classifiers has been recognized five times, and the average of the five recognition results is calculated. As shown in Figure 9, the average value of the recognition results can reach up to 95%. This shows that we can accurately recognize the difference between hit and miss actions.

IV. DISCUSSION

In the previous researches on table tennis, the main methods are based on images and sensors. The recognition rate is low when using image processing methods to recognize similar movements because of the occlusion of sight. In order to obtain more accurate data when using sensors to recognize actions, it is necessary to wear multiple sensors to collect action information, which results in complicated operations and high costs. In the study of table tennis based on the above methods, most of them are carried out between different large range of movements such as forehand, backhand, etc., but it is difficult to directly correct an athlete's behavior in a small deviation from the correct posture. This article delves into the nuances of the same actions in table tennis with wristband sensors, and we collected the volunteers' hits and misses on the table tennis ball to identify the slight differences between the actions. It is found that the slight differences in the same movements can not only help athlete trains with the right posture, but can also improve his batting average during training. Meanwhile, the identification of the athletes can judge the performance and level of the athletes. It is worth noting that the amount of data studied in this article is relatively small, although there are some limitations, it does not affect the results of the analysis. In the future work, in order to improve the wide range of applicability, we will increase the amount of data, and simultaneously study the difference in the hitting action of multiple people under the same holding racket position, and further divide the action standards such as the actions difference between hitting the edge of the racket and the center of the racket, and the difference of the actions between whether the ball falls on the opponent's table.

V. CONCLUSION

In this paper, the wristband sensor is implemented by using micro-motion sensors, which have the benefits of portability, ease of implementation, and low-cost. MPU9250 is used to collect motion acceleration and angular velocity data, and transmit the data to our computer via Bluetooth. By analyzing the acceleration and angular velocity data of the three axes, we finally select the acceleration data of the Z-axis as the basis of classification. The experiments have been identified the identities of volunteers and the hit or miss of the ball. In volunteer recognition, the wristband sensor can achieve 99% recognition accuracy for volunteers of different levels. At the same time, the analysis of the action difference between the hit and the miss was carried out. The results showed that the recognition rate of the action difference between hit and miss is as high as 95%, which is of great help to the improvement of the later technical level. From the result of feature selection, it can be seen that the speed of the hitting action, the agility of the action, and the angle of the hitting have an important influence on the hitting of the table tennis ball. In this paper, the subtle differences of the same motion are studied and identified in-depth, which is of great significance for broadening the application range of sensors and facilitating the deeper application of the nuance differences of sensors in the same motion. In table tennis, finding out the slight difference of the same movement can not only help us to carry out simple training but also correct the irregular movements in the training. This research can also be extended to badminton, billiards, volleyball, and other sports fields, which has a very important significance in sports science.

REFERENCES

[1] H. Ripoll and I. Latiri, "Effect of expertise on coincident-timing accuracy in a fast ball game," *J. Sports Sci.*, vol. 15, no. 6, pp. 573–580, Jan. 1997.

[2] P. Zhang, P. Ward, W. Li, S. Sutherland, and J. Goodway, "Effects of play practice on teaching table tennis skills," *J. Teaching Phys. Educ.*, vol. 31, no. 1, pp. 71–85, Jan. 2012.

[3] A. Lees, "Science and the major racket sports: A review," *J. Sports Sci.*, vol. 21, no. 9, pp. 707–732, Sep. 2003.

[4] M. Raab, R. S. W. Masters, and J. P. Maxwell, “Improving the ‘how’ and ’what’decisions of elite table tennis players,” *Hum. Movement Sci.*, vol. 24, no. 3, pp. 326–344, 2005.

[5] B. Hou and J. Luo, “Research on application of multi-media technology in colleges table tennis course teaching,” in *Proc. IEEE Int. Symp. Knowl. Acquis. Modeling Work*, Dec. 2008, pp. 1136–1137.

[6] H. Q. Zhao, S. Liu, H. C. Luo, Q. Y. Huang, and W. Ye, “Design and implementation of table tennis technical and tactical analysis software based on streaming media technology,” in *Proc. ACM Int. Conf.*, 2018, pp. 1–5.

[7] P.-E. Martin, J. Benois-Pineau, R. Peteri, and J. Morlier, “Sport action recognition with siamese spatio-temporal CNNs: Application to table tennis,” in *Proc. Int. Conf. Content-Based Multimedia Indexing (CBMI)*, Sep. 2018, pp. 1–6.

[8] Z. M. Wu and W. W. Y. Ng, “Human action recognition using action bank and RBFNN trained by L-GEM,” in *Proc. Int. Conf. Wavelet Anal. Pattern Recognit.*, Jan. 2014, pp. 30–35.

[9] Z. Tu, H. Li, D. Zhang, J. Dauwels, B. Li, and J. Yuan, “Action-stage emphasized spatiotemporal VLAD for video action recognition,” *IEEE Trans. Image Process.*, vol. 28, no. 6, pp. 2799–2812, Jun. 2019.

[10] S. Ali and M. Shah, “Human action recognition in videos using kinematic features and multiple instance learning,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 2, pp. 288–303, Feb. 2010.

[11] Z. Wang, B. Guo, Z. Yu, and X. Zhou, “Wi-Fi CSI-based behavior recognition: From signals and actions to activities,” *IEEE Commun. Mag.*, vol. 56, no. 5, pp. 109–115, May 2018.

[12] Z. Chen, L. Zhang, C. Jiang, Z. Cao, and W. Cui, “WiFi CSI based passive human activity recognition using attention based BLSTM,” *IEEE Trans. Mobile Comput.*, vol. 18, no. 11, pp. 2714–2724, Nov. 2019.

[13] Z. Wang *et al.*, “A survey on CSI-based human behavior recognition in through-the-wall scenario,” *IEEE Access*, vol. 7, pp. 78772–78793, 2019.

[14] Y. Shu, C. Chen, K. I. Shu, and H. Zhang, “Research on human motion recognition based on Wi-Fi and inertial sensor signal fusion,” in *Proc. IEEE SmartWorld, Ubiquitous Intell. Comput., Adv. Trusted Comput.*, Oct. 2018, pp. 496–504.

[15] C. Chen, Y. Shu, K. I. Shu, and H. Zhang, “WiTT: Modeling and the evaluation of table tennis actions based on WIFI signals,” in *Proc. Int. Conf. Pattern Recognit.*, Aug. 2018, pp. 3100–3107.

[16] L. Ruichen and Z. Wang, “Table tennis stroke recognition based on body sensor network,” in *Proc. Int. Conf. Internet Distrib. Comput. Syst.*, 2018, pp. 1–10.

[17] Z. Wang, M. Guo, and C. Zhao, “Badminton stroke recognition based on body sensor networks,” *IEEE Trans. Human-Mach. Syst.*, vol. 46, no. 5, pp. 769–775, Oct. 2016.

[18] Y. Wang, Y. Zhao, R. H. M. Chan, and W. J. Li, “Volleyball skill assessment using a single wearable micro inertial measurement unit at wrist,” *IEEE Access*, vol. 6, pp. 13758–13765, 2018.

[19] H. Huang, X. Li, and Y. Sun, “A triboelectric motion sensor in wearable body sensor network for human activity recognition,” in *Proc. 38th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2016, pp. 4889–4892.

[20] K. Roth, *Taktik im Sportspiel*. Schorndorf, Germany: Hofmann.1989.

[21] S. W. Smith, “Oving average filters,” in *Proc. Sci. Eng. Guide Digit. Signal Process.*, 2003, pp. 277–284.

[22] X. He and D. P. Cai Niyogi, “Laplacian score for feature selection,” in *Proc. NIPS*, 2005, pp. 507–514.

[23] U. Von Luxburg, “A tutorial on spectral clustering,” *Statist. Comput. J.*, vol. 17, no. 4, pp. 395–416, 2007.

[24] Y. Fei, “Simultaneous support vector selection and parameter optimization using support vector machines for sentiment classification,” in *Proc. 7th IEEE Int. Conf. Softw. Eng. Service Sci. (ICSESS)*, Aug. 2016, pp. 59–62.

[25] X. Wu and Y. Zhou, “Prediction of data classification based on support vector machine,” in *Proc. 4th Int. Conf. Electr. Electron. Eng. Comput. Sci. (ICEEECS)*, Dec. 2016, pp. 694–699.

[26] H. Elaidi, Y. Elhaddar, Z. Benabbou, and H. Abbar, “An idea of a clustering algorithm using support vector machines based on binary decision tree,” in *Proc. Int. Conf. Intell. Syst. Comput. Vis. (ISCV)*, May 2018, pp. 1–5.

[27] X. Xie and S. Sun, “PAC-bayes bounds for twin support vector machines,” *Neurocomputing*, vol. 234, pp. 137–143, Apr. 2017.

[28] S. Patil and U. Kulkarni, “Accuracy prediction for distributed decision tree using machine learning approach,” in *Proc. Int. Conf. Trends Electron. Inform. (ICOEI)*, Apr. 2019, pp. 1365–1371.

[29] J. Ghosh and S. B. Shuvo, “Improving classification model’s performance using linear discriminant analysis on linear data,” in *Proc. 10th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Jul. 2019, pp. 1–5.

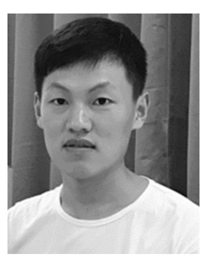
[30] U. Okfalisa, I. Gazalba, Mustakim, and N. G. I. Reza, “Comparative analysis of K-nearest neighbor and modified K-nearest neighbor algorithm for data classification,” in *Proc. 2nd Int. Conf. Inf. Technol., Inf. Syst. Electr. Eng. (ICITISEE)*, Nov. 2017, pp. 294–298.

[31] X. Mao, G. Zhao, and R. Sun, “Naive Bayesican algorithm classification model with local attribute weighted based on KNN,” in *Proc. IEEE 2nd Inf. Technol. Netw., Electron. Autom. Control Conf.*, Jan. 2018, pp. 904–908.

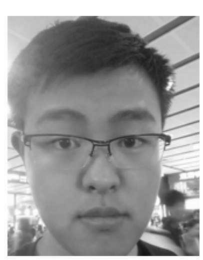
[32] S. Wang, L. Jiang, and C. Li, “Adapting naive Bayes tree for text classification,” *Knowl. Inf. Syst.*, vol. 44, no. 1, pp. 77–89, 2015.

Xiaopeng Sha received the M.S. degree from the Department of Information Engineering, Tangshan College, and the Ph.D. degree from the School of Electrical Engineering, Yanshan University, China. She is currently a Lecturer with Northeastern University at Qinhuangdao. Her research interests include micro visual servoing, microrobotic systems, and intelligent sensors.

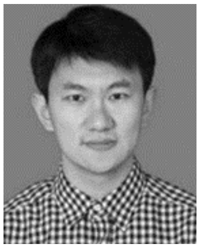
Guanghua Wei received the bachelor’s degree from the Inner Mongolia University of Science and Technology in 2019. He is currently pursuing the M.S. degree with the School of Control Engineering, Northeastern University at Qinhuangdao, China. His current research interests include machine learning, data fusion, wearable device, and pattern recognition.



Xueliang Zhang received the B.S. degree in automation from Qingdao Technological University in 2018. He is currently pursuing the master’s degree in control engineering with Northeastern University at Qinhuangdao, Qinhuangdao, China. His research interests include intelligent wearable devices, inertial measurement units, and cyber physical systems.



Xianshou Ren received the B.E. degree from the University of Jinan in 2019. He is currently pursuing the M.S. degree with the School of Control Engineering, Northeastern University at Qinhuangdao, China. His current research interests include machine learning, data fusion, wearable device, and pattern recognition.



Shuyu Wang received the B.S. degree in mechanical engineering from the Huazhong University of Science and Technology in 2013, and the Ph.D. degree in mechanical engineering from Stony Brook University (SUNY) in 2017. He is currently an Associate Professor with the Control Engineering Department, Northeastern University at Qinhuangdao, China. He has semiconductor industry experience with Global-Foundries. His current research interests include biosensing and machine learning's applications in sensing.

Zhonghai He received the B.S. degree in precision instruments from the Hefei University of Technology, and the M.S. and Ph.D. degrees in testing and metering technique and machinery from Tianjin University. He is currently an Associate Professor with Northeastern University.

Yuliang Zhao (Member, IEEE) received the B.S. degree in mechanical engineering from the Hubei University of Automotive Technology, the M.S. degree in mechanical engineering from Northeastern University, and the Ph.D. degree in mechanical and biomedical engineering from the City University of Hong Kong in 2016. He is currently an Assistant Professor with Northeastern University at Qinhuangdao, Qinhuangdao, China. His research interests include intelligent sensors, machine learning, motion analytics, and big data analyses. His recent work involves applying these technologies to sports and biomechanical analyses.