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Invisible experience to real-time assessment in elite tennis athlete training: Sport-specific movement classification based on wearable MEMS sensor data

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Abstract

This study examined the reliability of a tennis stroke classification and assessment platform consisting of a single low-cost MEMS sensor in a wrist-worn wearable device, smartphone, and computer. The data that was collected was transmitted via Bluetooth and analyzed by machine learning algorithms. Twelve right-handed male elite tennis athletes participated in the study, and each athlete performed 150 strokes. The results from three machine learning algorithms regarding their recognition and classification of the real-time data stream were compared. Stroke recognition and classification went through pre-processing, segmentation, feature extraction, and classification with Support Vector Machine (SVM), including SVM without normalization, SVM with Min–Max, SVM with Z-score normalization, K-nearest neighbor (K-NN), and Naive Bayes (NB) machine learning algorithms. During the data training process, 10-fold cross-validation was used to avoid overfitting and suitable parameters were found within the SVM classifiers. The best classifier was achieved when $C = 1$ using the RBF kernel function. Different machine learning algorithms' classification of unique stroke types yielded highly reliable clusters within each stroke type with the highest test accuracy of 99% achieved by SVM with Min–Max normalization and 98.4% achieved using SVM with a Z-score normalization classifier.

Keywords

Tennis, wearable sensors, data processing, machine learning, support vector machines

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Introduction

Tennis is a racket sport that relies heavily on strokes such as serve, forehand topspin, forehand volley, backhand topspin, and backhand volley.[1] Real-time analysis and evaluation of tennis strokes can help athletes improve stroke performance and prevent injuries. Therefore, acquiring real-time tennis stroke data during training can be valuable for coaches and athletes. With traditional tennis training, coaches usually evaluate training efficiency based on their observations and experience, which is subjective and may not assess athletes' stroke performance accurately. This process becomes more complex when one coach supervises several athletes at the same time. This study aimed to explore the viability of real-time analysis and evaluation of athletes' tennis stroke performance based on objective data.

Previous studies have used cameras, optical motion capture systems, and other technologies to analyze the motor performance of tennis athletes.[2,3] The video-based analysis method requires a camera system mounted around the tennis court, making the installation and calibration process time-consuming. For

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example, Conaire et al.[2] installed nine time-synchronized IP cameras around an indoor tennis court with a complex calibration process. They then aggregated multiple camera streams to form a single coherent video stream. A composite video was employed to evaluate the motor performance of tennis athletes. The optical motion-capturing systems require researchers to set up several optical cameras around the tennis court and place a set of reflective markers on participants' bodies and the racket.[3] The video-based analysis approach requires a highly controlled environment, expensive equipment, complicated installation, and a complex calibration process. Moreover, the video-based analysis does not satisfy group coaching needs, nor can it provide real-time feedback on athletes' motor performance.

Microelectromechanical systems (MEMS) technology, with its smaller size and low cost, has been developed and applied in different fields.[4] Recent sport-specific technical research in tennis, baseball, badminton, table tennis, basketball, soccer, and volleyball widely used MEMS sensors.[5] For example, Wang et al.[6] used a MEMS sensor to construct a badminton movement recognition system that can automatically capture and categorize badminton strokes and provide real-time feedback to coaches and athletes. Mangiarotti et al.[7] successfully employed wearable devices to detect the movement of a basketball between two basketball players playing against each other.

When it comes to applying MEMS sensors in tennis, most studies used tri-axial accelerometers, tri-axial gyroscopes, and tri-axial magnetometers to collect motion data.[8–23] Notably, these studies usually employed multiple wearable devices with a sampling frequency greater than 100 Hz.[9,17–19,23–25] These wearable devices were placed around major joints of the human body and/or inside the racket's handle connected to a computer or smartphone via Bluetooth technology to transfer the collected data. Recently, many researchers have started to employ machine learning techniques to process MEMS sensor data and classify tennis strokes.[9,14,17–19,21,23,25–28] For example, Whiteside et al.[17] used a 500 Hz sensor combined with discriminant analysis, Support Vector Machine, K-nearest neighbor, Classification Tree, Random Forest, and Neural Network algorithms to recognize and classify four stroke types with the highest accuracy of 93.2%. Liu[23] used four wearable devices (560 Hz) combined with SVM to recognize and classify eight types of tennis strokes with an accuracy of 79%.

However, using multiple wearable devices with a high sampling frequency in some of the studies mentioned above seems to have limited the practical application of MEMS sensors in tennis training.[9,21,23,25] Moreover, the sample sizes of participants and/or sport-specific movements have been relatively small,[9,18,24,26] which makes the establishment of a practical, reliable system for real-time tennis stroke performance problematic. For example, Ó Conaire et al.[9] only recruited five participants, and each participant wore six wearable wireless accelerometers with a sampling frequency of 120 Hz. Büthe et al.[25] recruited only four participants, and each wore three wearable devices with a sampling frequency of 200 Hz. High sampling frequency results in a heavy and complex data flow, which is too slow to facilitate real-time feedback.

In summary, video-based analysis methods are impractical for regular usage. They impose high data-loads that are relatively slow in processing and thus cannot analyze basic motor performance with real-time feedback. Moreover, studies using MEMS sensors and machine learning for tennis stroke performance analysis have limitations such as high sampling frequency and low classification accuracy.

In order to overcome the above limitations, this study used a single wearable MEMS device positioned on the wrist with a sampling frequency of 50 Hz to collect data and classify main tennis strokes, including serve, forehand topspin, forehand volley, backhand topspin, and backhand volley. In addition, this study employed a single wearable device to collect tri-axis acceleration and tri-axis angular velocity data, while using machine learning to process motion data to classify main tennis strokes.

This study was designed to construct a more reliable tennis stroke recognition platform to assist coaches in carrying out real-time analysis during training and competition so as to help tennis players review their stroke performance after training sessions.

Methods

Subjects

Trials were conducted at a university tennis court in Beijing, China. Twelve right-handed male tennis athletes certified by the General Administration of Sport of China as High-Level were recruited via convenience sampling. Written records of informed consent were obtained before any experimental procedure. The study protocol was approved by the Ethics Committee of Sports Science Experiment at Beijing Sport University (2020114H). The participants' demographic information is shown in Table 1.

Set-up

Figure 1 illustrates this study's real-time tennis stroke motion data collection and recognition platform. It included the wearable MEMS sensor (with tri-axis

Table 1. Participant characteristics.

Age (year)	Height (cm)	Weight (kg)	Training experience (year)
24.42 ± 2.54	183.42 ± 6.91	79.58 ± 8.80	13.58 ± 3.42

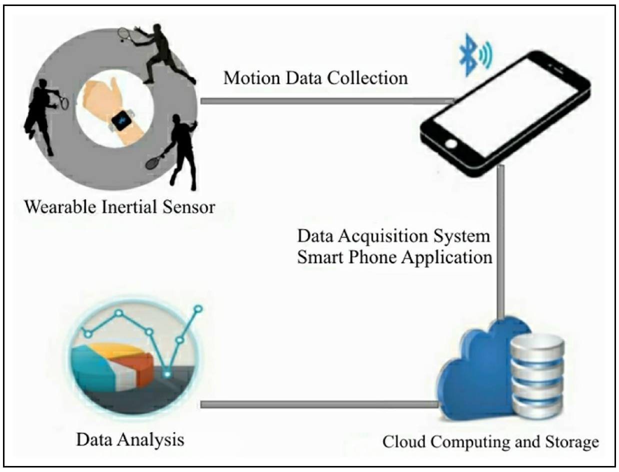

Figure 1. Real-time tennis strokes motion data collection and recognition platform.

Figure 2. Position of the wearable device.

accelerometer and tri-axis gyroscope), a microprocessor, and a Bluetooth module. This module was designed as per specifications described in Wang et al.[6] This platform collected tennis stroke motion data via the wearable device and then sent the data to the mobile application. Features of the raw data could then be extracted in the customized mobile application. After data collection and processing, detection and classification of the tennis strokes were accomplished in the remote server. All motion data were sent to the remote server via cloud technology.

Study participants wore a MEMS sensor on the wrist of the dominant arm to collect the motion data during tennis strokes, as shown in Figure 2. The Inertial Measurement Unit (IMU) BMI160 (3 mm × 2.5 mm × 0.83 mm) manufactured by Bosch Sensortec (Reutlingen, Germany) is an integrated MEMS. Sampling was taken at 50 Hz for the experimental wearable devices. This MEMS sensor provided both orientation (tri-axis gyroscope) and acceleration (tri-axis accelerometer) readings in *x*-*y*-*z* dimensions. The maximum range of the accelerometer was 16 g and the maximum range of the gyroscope was 2000°/s, which are suitable to collect motion data for tennis strokes among elite athletes. An Android-based smartphone application was also developed to collect and visualize the MEMS sensor data.

Data collection

Each participant wore a wearable device on the right wrist during the trials. First, all participants performed a tennis-specific warm-up. They then performed the International Tennis Number (ITN) test (shown in Table 2) under the supervision of a professional tennis expert (www.internationaltennisnumber.com). After completing the ITN test, each participant rested for ten minutes to ensure a comfortable feeling and a rating of perceived exertion no more than six (RPE = 6). Then each participant completed 30 serves, forehand topspins, forehand volleys, backhand topspins, and backhand volleys, totaling 150 strokes per participant. All movements were performed according to ITN standards and only successful tennis strokes were considered valid and recorded.

Data processing

The experimental set-up, data pre-processing, and model development methods were tailored to fit the characteristics of tennis-specific sport movements. Movement recognition went through pre-processing, segmentation, feature extraction, and classification processes programed into the machine learning algorithms.[4] The data processing flow is shown in Figure 3.

Data pre-processing. Because the data collection process is easily affected by noise, missing values, and inconsistent data, the data needed to be pre-processed first. The main steps included cleaning, noise reduction, and filtering. The data cleaning process included missing

Table 2. Participant ITN score information.

Ground-stroke depth assessment	Volley depth assessment	Ground-stroke accuracy assessment	Serve assessment	Mobility assessment	Total score	ITN level
78.00 ± 8.94	61.00 ± 7.01	75.92 ± 6.30	100.08 ± 5.73	69.75 ± 7.72	384.42 ± 17.37	1

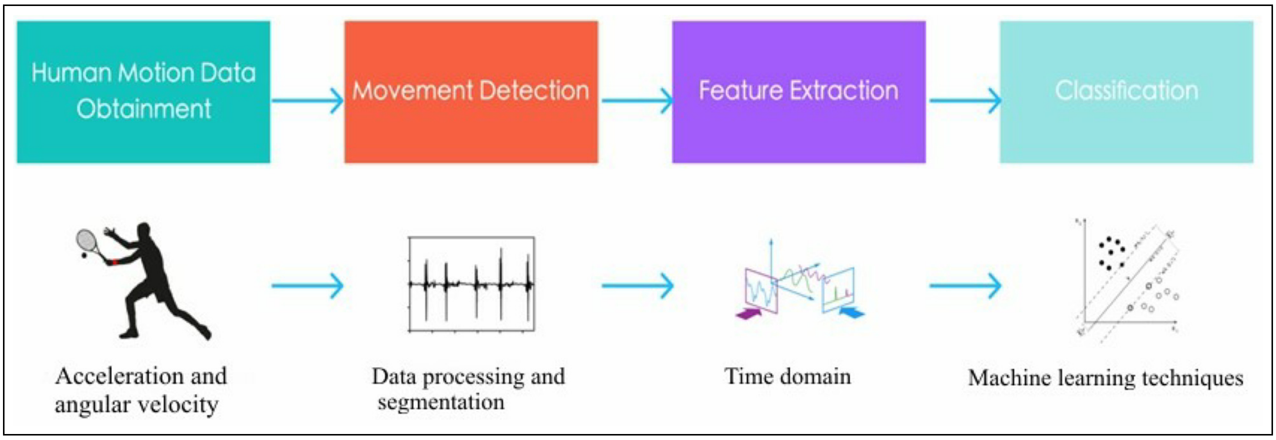

Figure 3. Data processing flow of tennis stroke recognition.

data processing and inconsistent data processing. A Gaussian filter removed high frequency noise and a low-pass "smoothing" filter was used on the MEMS sensor raw data to average out rapid changes in signal intensity.

Segmentation. A sliding window-based segmentation, bottom-up, and sequential peak searches were selected to retrieve relevant information from the continuous stream of MEMS sensor data.[4] Under the supervision of tennis experts and video proofreading, the continuous visual graphics were divided into single tennis stroke graphics by sections.

Feature extraction. Extensive input data were reduced in number via feature vector and extraction. The authors extracted 18 features of six-dimensional data: maximum, minimum, mean, variance, standard deviation, root mean square, the difference between maximum and minimum, skewness, etc., for a total of 108 features (Table 3). As performance factors, these features were extracted from raw data of the tri-axis accelerometer and gyroscope according to the time domain analysis for tennis stroke classification.

Raw data from five prototype tennis strokes

Figure 4 shows the six-axis synchronized raw data from five tennis strokes. Figures 5 to 9 display the raw data from the individual strokes. The first row shows the tri-axis acceleration data, and the second row captures the tri-axis angular velocity data for the serve, forehand topspin, forehand volley, backhand topspin, and backhand volley.

Classification

Normalization techniques. Normalization is a systematic process to reduce data redundancy and integrate data better. Several normalization techniques are utilized with different kinds of datasets in statistics, such as Z-score normalization and Min-Max normalization (Min-Max Feature Scaling).

In the following Z-score normalization equation shown in equation (1), x is the raw value, μ is the population mean, and ∂ is the population standard deviation.

$$\frac{x - \mu}{\partial} \tag{1}$$

In the next Min-Max normalization equation shown in equation (2), x is the current value, x_{min} is the minimum value of data set, and x_{max} is the maximum value of the data set.

$$\frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{2}$$

Machine learning. Big data collection is trendy these days, but few realize that data would be worthless without the algorithms to identify and extract useful information. A support vector machine (SVM) was used to recognize and classify the five main tennis strokes. K-Nearest Neighbor and Naive Bayes were used to compare the accuracy of recognizing and classifying with SVMs (https://scikit-learn.org/stable/).

SVMs utilize supervised machine learning to classify two-group data and fit for a limited amount of data with a clear label for each category. This supervised machine learning should give the model labels for each category and then categorize a new dataset.

An optimal hyperplane was defined to separate the data. In equation (3), w is a normal vector of a hyperplane, x is the training set from the peak sample, and b is the bias:

$$w.x + b = 0 \tag{3}$$

The training set was defined as shown in equation (4):

Table 3. Statistical and morphological features.

Feature no.	Description
1–3	Mean value of acceleration from *x, y,* and z axes
4–6	Mean value of angular velocity from *x, y,* and z axes
7–9	Variance of acceleration from *x, y,* and z axes
10–12	Variance of angular velocity from *x, y,* and z axes
13–15	Standard deviation of acceleration from *x, y,* and z axes
16–18	Standard deviation of angular velocity from *x, y,* and z axes
19–21	Maximum of acceleration from *x, y,* and z axes
22–24	Maximum of angular velocity from *x, y,* and z axes
25–27	Minimum of acceleration from *x, y,* and z axes
28–30	Minimum of angular velocity from *x, y,* and z axes
31–33	Root mean square of acceleration from *x, y,* and z axes
34–36	Root mean square of angular velocity from *x, y,* and z axes
37–39	Square root of the amplitude of acceleration from *x, y,* and z axes
40–42	Square root of the amplitude of angular velocity from *x, y,* and z axes
43–45	Kurtosis value of acceleration from *x, y,* and z axes
46–48	Kurtosis value of angular velocity from *x, y,* and z axes
49–51	Skewness value of acceleration from *x, y,* and z axes
52–54	Skewness value of angular velocity from *x, y,* and z axes
55–57	Peak to peak value of acceleration from *x, y,* and z axes
58–60	Peak to peak value of angular velocity from *x, y,* and z axes
61–63	Crest factor of acceleration from *x, y,* and z axes
64–66	Crest factor of angular velocity from *x, y,* and z axes
67–69	Impulse factor of acceleration from *x, y,* and z axes
70–72	Impulse factor of angular velocity from *x, y,* and z axes
73–75	Margin factor of acceleration from *x, y,* and z axes
76–78	Margin factor of angular velocity from *x, y,* and z axes
79–81	Shape factor of acceleration from *x, y,* and z axes
82–84	Shape factor of angular velocity from *x, y,* and z axes
85–87	Kurtosis factor of acceleration from *x, y,* and z axes
88–90	Kurtosis factor of angular velocity from *x, y,* and z axes
91–93	Mean-absolute of acceleration from *x, y,* and z axes
94–96	Mean-absolute of angular velocity from *x, y,* and z axes
97–99	Max-absolute of acceleration from *x, y,* and z axes
100–102	Max-absolute of angular velocity from *x, y,* and z axes
103–105	RMS-absolute of acceleration from *x, y,* and z axes
106–108	RMS-absolute of angular velocity from *x, y,* and z axes

$$T = \{(x_i, y_i | x_i \in R^m, y_i \in \{1, -1\})\}_{i=1}^{n} \tag{4}$$

where x_i is the m-dimensional matrix,
y_i is the binary label (belongs to either 1 or -1),
n is the total number of samples,
i is the current sample number.

SVM is primarily used to map the training dataset into a higher-dimensional feature space and then classify the training dataset with hyperplanes. The optimization process was calculated according to equation (5) as follows:

$$\min_{w,b} \frac{1}{2}||w||^2$$

$$subject\ to\ y_i(w.x_i - b) \geqslant 1, i = 1, \ldots, n \tag{5}$$

Applying Lagrangian multipliers under the Karush-Kuhn-Tucker (KKT) conditions, equation (5) was transformed to equation (6) as follows:

$$L(w, b, \alpha) = \frac{1}{2}||w||^2 - \sum\nolimits_{i=1}^{n} \alpha_i \left\{ \left[y_i \left(w^T.x_i + b \right) - 1 \right] \right\} \tag{6}$$

with α representing the Lagrangian multipliers vector. A derivative transformation of equation (6) with respect to the normal vector of the hyperplane w results in equation (7):

$$w = \sum\nolimits_{i=1}^{n} \alpha_i y_i x_i \tag{7}$$

Transformation of (6) in regards to bias (b) results in equation (8):

$$\sum\nolimits_{i=1}^{n} \alpha_i y_i = 0 \tag{8}$$

Following substitution of (7) and (8) into (6), the simplified Lagrangian dual problem is obtained as shown in equation (9).

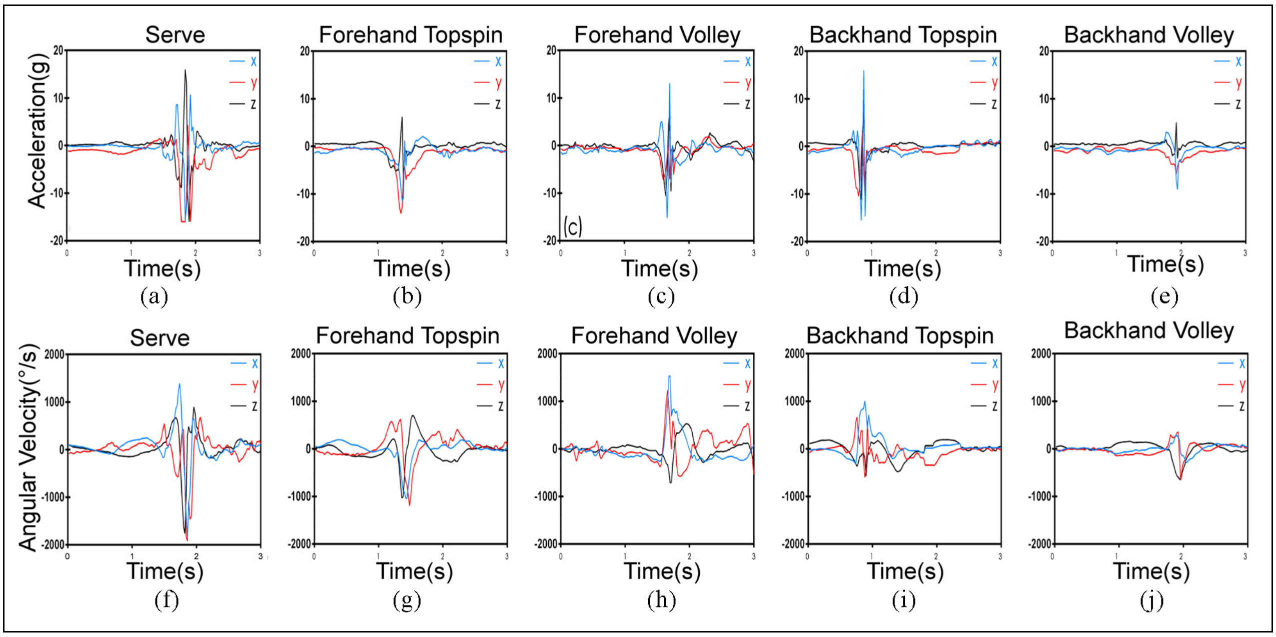

Figure 4. Example MEMS sensor raw data recorded at the wrist from participants among elite athletes. Accelerations of (a) serve, (b) forehand topspin, (c) forehand volley, (d) backhand topspin, (e) backhand volley and angular velocities of the (f) serve, (g) forehand topspin, (h) forehand volley, (i) backhand topspin, and (j) backhand volley are crucial to discriminate the tennis strokes.

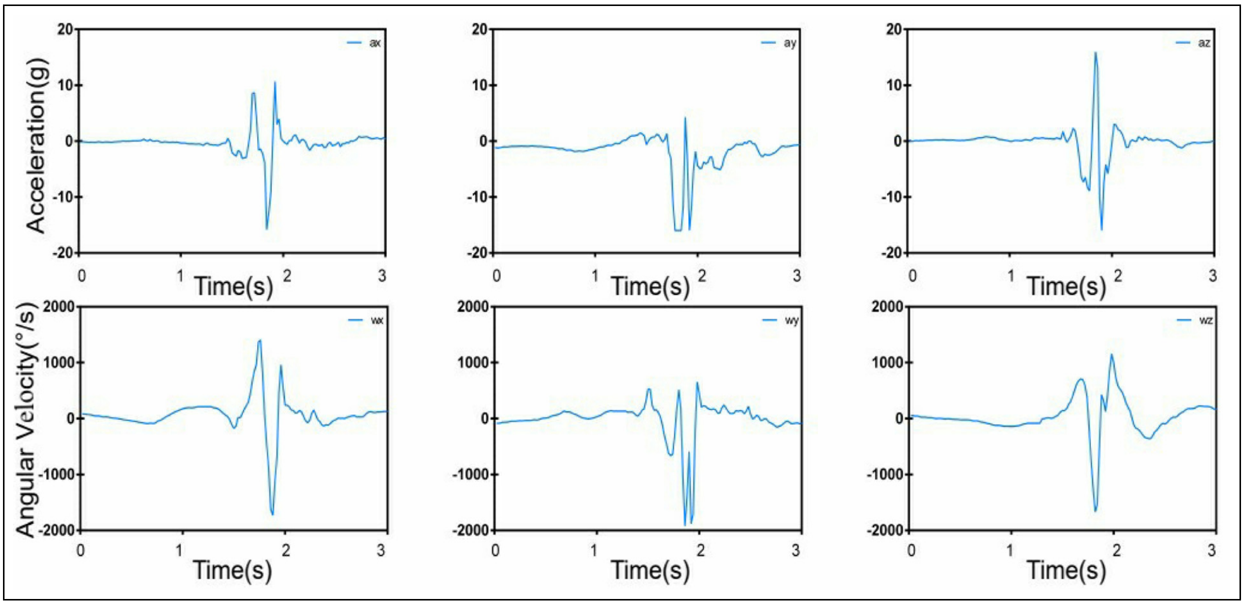

Figure 5. Raw MEMS sensor data plot from serve.

$$\max_{\alpha} \sum\nolimits_{i=1}^{n} \alpha_i - \frac{1}{2} \sum\nolimits_{i=1}^{n} \alpha_i \alpha_j y_i y_j x_i x_j$$

$$subject\ to\ 0 \leqslant \alpha_i, i = 1, \ldots, n$$

$$\sum\nolimits_{i=1}^{n} \alpha_i y_i = 0 \tag{9}$$

Since there were some overlapping data from serve, forehand topspin, forehand volley, backhand topspin, and backhand volley, the data were not linear separable, necessitating the addition of a slack variable ξ_i, as well as the error penalty constant C. Larger values of C result in the optimization choice of smaller-margins, necessitating a trade-off between large margins and error penalties. Subsequent to this, a simplified solution was obtained to the Lagrangian duality for non-linear separable problems as shown in equation (10):

$$\max_{\alpha} \sum\nolimits_{i=1}^{n} \alpha_i \alpha_j y_i y_j \Phi(x_i, x_j)$$

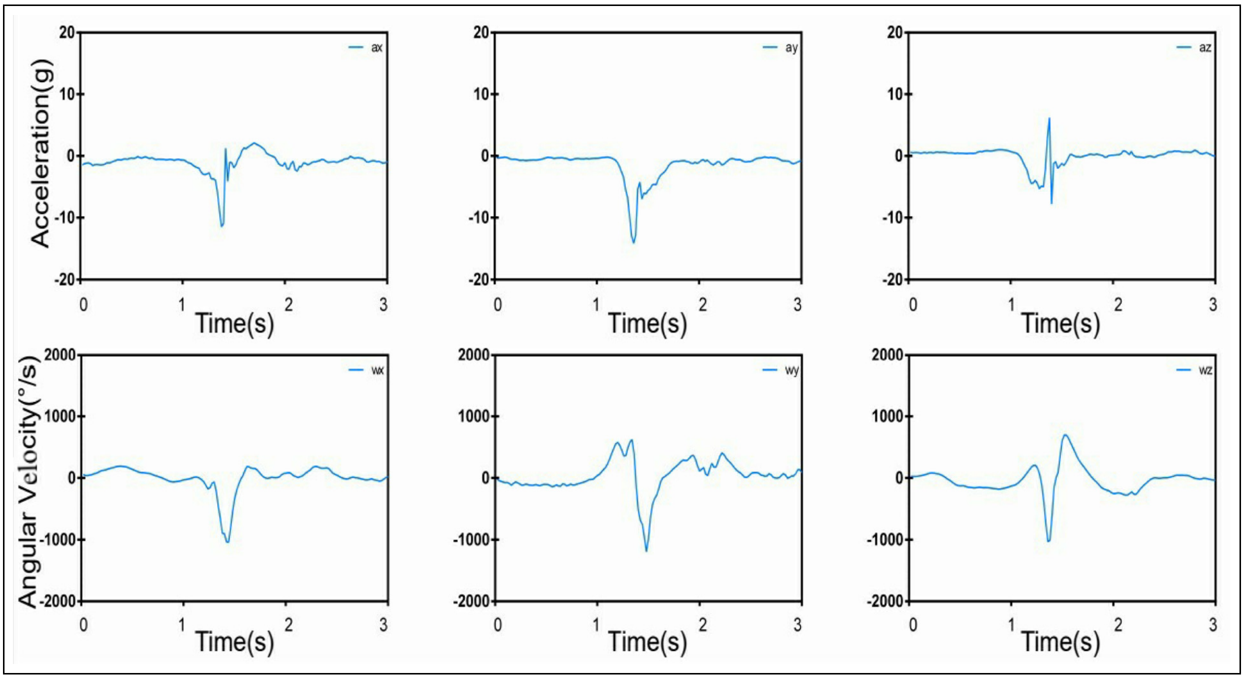

Figure 6. Raw MEMS sensor data plot from forehand topspin.

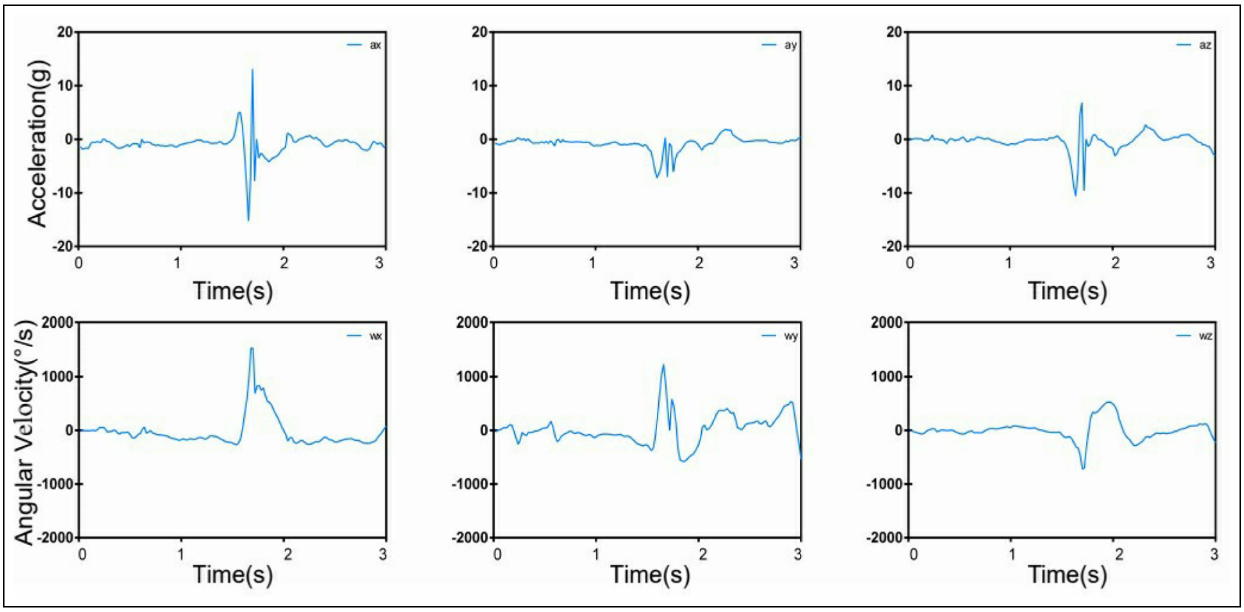

Figure 7. Raw MEMS sensor data plot from forehand volley.

$$subject\ to\ C \geqslant \alpha_i \geqslant 0, i = 1, \ldots n$$

$$\sum\nolimits_{i=1}^{n} \alpha_i y_i = 0 \tag{10}$$

Lagrange multipliers α_i were extracted using a Sequential Minimal Optimization (SMO) algorithm. Equation (6) was then used to calculate the final w and obtain an optimization hyperplane. The classification decision function chosen is shown in equation (11):

$$d = \left(X^T\right) = sgn\left[\sum\nolimits_{i=1}^{n} \alpha_i y_i \Phi(x_i, y_i) - b\right] \tag{11}$$

where y_i refers to the support vector class label, α_i and b refer to two constants, and X refers to the tennis strokes sample testing sets whose labels are y_i.

Five tennis strokes were labeled (serve, forehand topspin, forehand volley, backhand topspin, and backhand volley). One thousand eight hundred datasets were collected from 12 participants, each of whom performed 30 trials for five different strokes. Nine

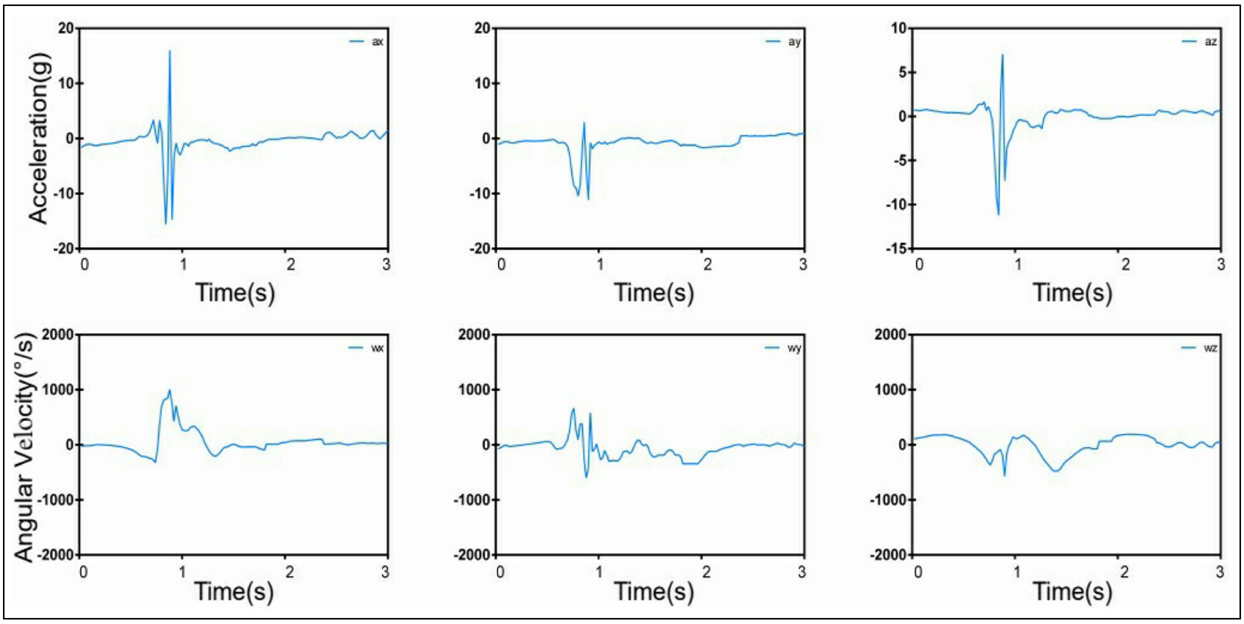

Figure 8. Raw MEMS sensor data plot from backhand topspin.

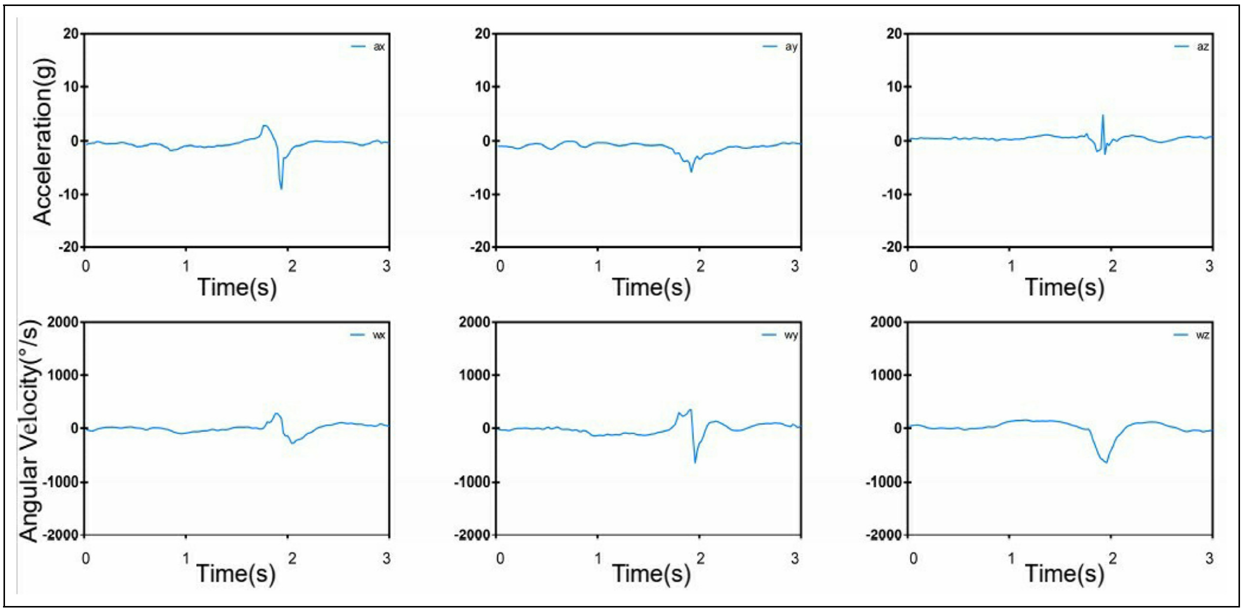

Figure 9. Raw MEMS sensor data plot from backhand volley.

participants' datasets (1350 datasets) were used for the data training and the rest of the datasets (450 datasets) from three separate participants were used for the testing classifier. During the data training process, 10-fold cross-validation was used to avoid overfitting and suitable parameters were found within the SVM classifiers.

In Table 4, the degree 3 polynomial kernel was chosen. Data were compared for Penalty Parameter C values ranging from 1 to 50,000, Gamma g values ranging from 0.0001 to 0.1, and several different kernels, such as Linear, Polynomial, RBF, and Sigmoid. RBF was chosen as the default kernel function. The best classifier was achieved when $C = 1$ when using the RBF kernel function.

Table 4. Randomly chosen parameters of SVM.

Penalty parameter (C)	Gamma (g)	Kernel
1	0.0001	Linear
100	0.0005	Polynomial
1000	0.001	RBF
5000	0.005	Sigmoid
10,000	0.01	
50,000	0.1	

Table 5. SVM without normalization classification results of recognizing different strokes.

Stroke type	Precision	Recall	f1-Score
Serve	0.38	1	0.56
Forehand topspin	0	0	0
Forehand volley	0	0	0
Backhand topspin	0	0	0
Backhand volley	0	0	0
Average	0.076	0.2	0.112

Table 6. SVM with normalization (min–max) classification results of recognizing different strokes.

Stroke type	Precision	Recall	f1-Score
Serve	0.99	1	0.99
Forehand topspin	0.99	1	0.99
Forehand volley	1	0.98	0.99
Backhand topspin	1	0.98	0.99
Backhand volley	1	1	1
Average	0.996	0.992	0.992

Table 7. SVM with normalization (Z-score) classification results of recognizing different strokes.

Stroke type	Precision	Recall	f1-Score
Serve	0.99	0.99	0.99
Forehand topspin	0.99	1	1
Forehand volley	0.99	0.98	0.99
Backhand topspin	0.97	0.98	0.98
Backhand volley	1	1	1
Average	0.988	0.99	0.992

Table 8. K-NN ($k = 6$) classification results of recognizing different strokes.

Stroke type	Precision	Recall	f1-Score
Serve	0.86	0.93	0.89
Forehand topspin	0.79	0.72	0.75
Forehand volley	0.92	0.89	0.9
Backhand topspin	0.81	0.76	0.78
Backhand volley	0.99	0.97	0.98
Average	0.874	0.854	0.86

Results

Tennis stroke classification and assessment

Tables 5 to 9 show the results of sport-specific movement from each of the five prototype tennis strokes studied. As shown in Table 5, the classification accuracies using SVM without normalization for the five different strokes were almost zero. These results demonstrate that SVM without normalization classification could not distinguish between different strokes performed by elite tennis players.

Table 9. Naive Bayes classification results of recognizing different strokes.

Stroke type	Precision	Recall	f1-Score
Serve	0.98	0.89	0.94
Forehand topspin	0.77	0.97	0.86
Forehand volley	0.99	0.95	0.97
Backhand topspin	0.96	0.97	0.97
Backhand volley	0.98	1	0.99
Average	0.936	0.956	0.946

As shown in Table 6 for SVM with normalization (Min–Max), the classification accuracies for the five different strokes were 99%, 100%, 100%, 100%, and 99%. These results suggest that SVM with normalization (Min–Max) classification provides significantly improved classification and distinction parameters within and between each of the five different stroke movement clusters tested. The average precision for classifying the different strokes reached 99.6%.

As shown in Table 7, SVM with Z-score normalization yielded classification accuracies for the five different strokes of 99%, 100%, 97%, 99%, and 99%. These results suggest that SVM with normalization (Z-score) also provides highly significant classification and distinction within and between each of the five prototype stroke cluster groups tested. On average, the precision of classifying the five tennis strokes tested reached 98.8%.

As shown in Table 8 for data analysis using K-NN ($k = 6$), the classification accuracies for five different strokes among athletes' performance were 86%, 99%, 81%, 92%, and 79%.

As shown in Table 9, NB classification accuracies for the five different strokes were 98%, 98%, 96%, 99%, and 77%. Thus, the average NB classification of the five tennis strokes tested reached 93.6%.

Comparison of different classifiers

Finally, the different algorithm classifiers tested (SVMs, K-NN, and NB) were compared as shown in Table 10. SVM Min–Max yielded the highest accuracy in recognizing and classifying the five tennis strokes tested, averaging 99%. The results from testing two other normalization algorithms demonstrated that the computational efficiency of SVM with normalization was very accurate. However, reasonably wide variations in individual participants' stroke movements made SVM without normalization untenable for this study.

Discussion

This study used a single wearable device positioned on the wrist with a sampling frequency of 50 Hz to collect data and classify five basic tennis strokes. One hundred and eight features extracted from MEMS sensor data were selected to classify different strokes. As a result,

Table 10. Tennis movement classification accuracy of different algorithms.

Classification algorithm	Parameters	Accuracy (mean ± SD)
SVM without normalization	$C = 1000$, $\gamma = 0.0001$	0.385 ± 0.0039
SVM with min–max normalization	$C = 1000$, $\gamma = 0.0005$	0.990 ± 0.0059
SVM with z-score normalization	$C = 1000$, $\gamma = 0.0001$	0.984 ± 0.0094
K-nearest-neighbor	Euclidean score = 0.870 Manhattan score = 0.896 Chebyshev score = 0.856 Minkowski score = 0.870 $K = 6$	0.859 ± 0.0354
Naive Bayes	N/A	0.955 ± 0.0168

SD: standard deviation.

five tennis strokes, including serve, forehand topspin, forehand volley, backhand topspin, and backhand volley, were recognized.

These results indicate that SVM with normalization (Min–Max) was able to recognize and classify five uniquely different tennis strokes with a surprisingly high level of precision (99.6%). Previous studies using similar paradigms provided substantial evidence that MEMS sensor data and machine learning algorithms can reliably classify tennis strokes.[9,17–19,23] However, the high sampling frequency (100–1000 Hz) and/or a large number of features (more than 200) for extraction makes real-time feedback impossible.[22] For instance, Ó Conaire et al.[9] used a sampling frequency of 120 Hz, but the classification precision was only found to be 93.44%. Büthe et al.[25] used a sampling frequency of 200 Hz and its classification accuracy only reached 95%. Also, multiple sensors (3–12 units) were not friendly for training or competition situations.[9,23,25] The recognized tennis stroke types were few in number and/or the recognition accuracies were less than 90%.[14,23] Ó Conaire et al.[9] employed six wearable devices to collect data, but only recognized three types of tennis strokes with an average accuracy of 93.44%. Liu[23] used four wearable devices with a sampling frequency of 560 Hz, classifying different strokes with an average accuracy of 79%. The results from the present study confirm those by Taghavi et al.[22] indicating 50 Hz is the optimal frequency for data processing efficacy. However, whereas Taghavi et al. extracted 1440 features, in the present study a slightly higher accuracy was obtained using only 108 features with results that were not significantly different.

In the present study, the participants wore only one MEMS sensor on the wrist with a sampling frequency of 50 Hz. The lower sampling frequency enabled the system to provide enough computing power to analyze data with machine learning techniques and real-time assessment and feedback. Furthermore, according to the kinetic chain theory,[29] the ground reaction force is transmitted from the lower extremity to the trunk, shoulder, elbow, and wrist during the tennis stroke. Therefore, the wearable device worn on the wrist can collect the maximum acceleration at the end of the kinetic chain during the tennis stroke.

Comparing the classification results of SVMs, K-NN, and NB algorithms, the results of this study further verified the excellent performance of SVM, the most commonly used classification algorithm. For example, the NB algorithm classification precision reached 93.6%, whereas the K-NN algorithm only reached 87.4% when $k = 6$. In summary, SVM was determined to be the most accurate in classifying the five tennis stroke tasks addressed in this study.

In future studies, the authors plan to improve the algorithm by employing feature reduction and increasing the types of tennis strokes classified. Furthermore, algorithms will also be written to distinguish between the stroke performance accuracies of beginner, intermediate, and advanced level tennis players. The platform can also be used to collect data and optimize algorithms. With big data, benchmarks can be built for athletes at different motor skill levels and ages.

This study included the successful design and testing of a real-time tennis stroke recognition and performance evaluation platform for elite athletes and coaches. This platform included a MEMS sensor, microprocessor, and Bluetooth module. Five different machining learning algorithms were employed to analyze the online data stream from the wearable device, and the results were compared. Movement recognition was achieved through pre-processing, segmentation, feature extraction, classification, and trained with machine learning algorithms, such as SVM. The SVM with Min–Max normalization performed best, demonstrating 99.6% accuracy in recognizing and classifying the five prototype tennis strokes tested, followed by SVM with z-score normalization, which yielded recognition and classification results with an accuracy of 98.8%.

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