Tennis Stroke Recognition

Stroke classification using inertial measuring unit and machine learning algorithm in Tennis

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MASTER OF SCIENCE THESIS REPORT

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Xinyu Liu

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Student number: 4519760

Thesis committee:	Prof. dr. H.E.J. Veeger	BMechE, 3ME, Supervisor
	Bart van Trigt, MSc	BMechE, 3ME, daily supervisor
	Jakob Söhl, PhD	Statistics, EWI, external committee member

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Preface

This thesis report contains the entire project process and final results of my Master Thesis Research, with which I hope to complete my degree in Bio-Mechanical Design. In this research, I have investigated human activity recognition (HAR) and machine learning algorithms from a scientific perspective. The research is a tripartite cooperation project in the field of tennis sports, supervised by Delft University of Technology, Vrije Universiteit Amsterdam (VU) and Koninklijke Nederlandse Lawn Tennis Bond (KNLTB). For me, the tennis sports field turned out to be a perfect subject fit with my interests and track specification in Sports Engineering. But human activity recognition, machine learning algorithm, and recognition and classification model were totally unfamiliar topics to me, and I had to study these from scratch. In the project, I proposed an experimental method to collect and record the raw data of tennis strokes of participants by using a special IMU system made by a technician in VU. After that, the pre-processing method, window segmentation and feature extraction were chosen to process the data. Support vector machines was the machine learning algorithm to train the classification model in this project and several "simulated" rally data (between tennis players and ball machine) were used to test the classification model to achieve the results of recognition and classification of eight tennis strokes. After the leave-one-out validation procedure, the classification of the proposed method was detected by comparing results with the Golden Standard (video footage).

This project is new to the field of tennis stroke recognition and classification. Only a few research had been done to comprehensive classification of all eight tennis strokes. A relatively qualified accuracy result of tennis stroke classification was achieved at the end of the research. Through this research, I achieved more professional knowledge and dialectical thinking ability in the scientific research field. Even though this research comprises some weaknesses, both in the experimental process and in the conclusion derivation, I hope they could be improved in future work. And I sincerely hope that this project may have a small step forward in human sports activity recognition and classification field. I sincerely hope that this project may make a small contribution to building real-time tennis stroke strategy guidance and coaching system for both elite players and amateurs.

Xinyu Liu

Delft, November 2019

Acknowledgement

To be honest, the last year of my life in TUD has been a unique experience for me. After just having experienced the pain of losing my loved grandparents, I started this project in a bad mood situation, mild depression, and procrastination. Sometimes during the project, not only the difficulties of research but also my own loss of emotional control both hindered the conduct of this thesis work. But, fortunately, during this hard period, so many people have helped and inspired me not only in my research study but also in my daily life. And since this may be one and only opportunity to thank them all in a formal and public way, then I must say the following words to them.

Foremost, I would like to express my primary and sincere gratitude to my advisor, Prof. Dr. DirkJan Veeger, for not only being my main supervisor who I benefited his expert comments during my thesis, but also showing his kindness, sympathetic, and encouragement to me in my hardest time. And I would like to thank my daily supervisor PHD candidate Bart van Trigt, for giving me the most subtle guidance and help during the entire experimental processing and thesis writing period. Weekly meeting that we had was the most efficient way for me to report the progress of the project and to ask the unfamiliar knowledge and technical problems that are difficult to deal with. Bart always gave me positive feedbacks and inspiration for the research. Besides, I need to say thanks to former PHD candidate Evelien Schat in Applied Mathematics, who is now being PHD candidate at Utrecht University. She gave me the most helpful guidance during my data processing period, even this guidance work is not the compulsory work for her. Also, I would like to thank Ton Leenen from VU Amsterdam, for his revision and guidance in experiments.

During this research, I also got a lot of support from other people. Many thanks are owed to embedded scientist Aldo Hoekstra and other researchers and staffs in KNLTB, who provided convenience and help during the tennis experiment. And I would like to express my sincere gratitude to all the participants in my experiments, for their voluntary participation and contributing themselves to complete the experiments without reservation.

And I would also like to thank my academic counsellor Drs. Lourdes Gallastegui Pujana, who helped me to adjust myself in a good mood and gave me useful guidance in arranging study and life. At last, but not least, thank you, my dear brothers, and friends Mounir El Hassnaoui and Anindito Kusumojati, for your spiritual support and valuable advice pushing me forward, in the times when I lost my way.

I dedicate this thesis to my parents and my grandparents who have always loved, encouraged, and supported me in my life. Thank you for being spiritual support for me.

Abstract

One interesting part of the application of human activity recognition is sports motion recognition and classification. In recent years, many commercial wearable devices have been used for recording and supervising motion data information during sports. However, their claimed high-accuracy results but motion recognition and classification method have not been proven. This thesis project presents work special related to tennis stroke detection and classification. An automated and comprehensive tennis stroke recognition and classification method based on the inertial measuring unit sensor (accelerometer and gyroscope) and machine learning algorithm (Support vector machines) was proposed in this study. Seven tennis players with a different level of tennis skills were tested and recorded using a self-made IMU sensor system with four sensors (forearm, upper arm, trunk, and pelvis). Video footage from Playsight was manually notated as the golden standard for stroke type identification. SVMs was constructed to train the classification model to classify true shots to eight types of tennis strokes from the IMU signals. Across leave-one-out seven-fold cross-validation, the SVMs classification models were trained with data from a single IMU sensor on the forearm and upper arm with the prediction accuracies of 0.69 and 0.70 respectively. And further, both SVMs models were trained by enlarged training data, resulting in improved prediction accuracies of 0.75 and 0.77. Noticeably, the best prediction accuracy was achieved by training the SVMs classification model with fused data from the previous two sensors and with the enlarged training data. The final prediction result was 0.79. Even though there exist deficiencies such as skill level different of subjects, insufficient training dataset which may lead the results of validation and prediction less credible, the IMU sensor and SVMs machine learning algorithm still played well in the tennis stroke classification task. And we expect to have better accuracy results by feeding enough training data and using data-fusion combination of different IMU sensors to the upper extremity to SVMs classification model in future work.

List of abbreviations

Human activity recognition (HAR)

Human-machine interaction (HMI)

Microelectromechanical systems (MEMS)

Accelerated parallel processing (APP)

Koninklijke Nederlandse Lawn Tennis Bond (KNLTB)

Inertial measuring unit (IMU)

Hidden Markov model (HMM)

Naïve Bayes (NB)

Support Vector Machines (SVMs)

Artificial Neural Network (ANN)

Decision Tree (DT)

k-Nearest Neighbour (k-NN)

Degrees of freedoms (DoFs)

Serve (SR)

Forehand topspin (FHT)

Backhand topspin (BHT)

Forehand slice (FHS)

Backhand slice (BHS)

Forehand volley (FHV)

Backhand volley (BHV)

Smash (SM)

File Transfer Protocol (FTP)

Fast Fourier transform (FFT)

One-versus-all (OvA)

One-versus-one (OvO)

Error-correcting output codes (ECOC)

Content

Chapter 1

Introduction

Human activity recognition (HAR) aims to detect and identify the actions and objectives of humans from a series of observations on subjects' movements and the environmental conditions. This active research field shows its advantages in providing personalized support for many different applications and fields of study, such as sports science, healthcare, surveillance, human-machine interaction (HMI) and sociology[1]. Sport-specific movement recognition is one of the most interesting and difficult subfields of HAR. During sports and sportive leisure activities, massive and continuous body gestures, actions and complex movements are generated by human participants. Detection and recognition of human sport-specific motions and gestures could lay the foundation for movement analysis, guidance, and evaluation. Moreover, it also helps the improvement of performance and prevention of injuries. The main process of HAR (same as sport-specific movement) is to interpret human body gestures or motion via sensors and determine the type of activity or action in the next stage.

In the early days, direct observation and annotation for sports activity are quite original and intuitive. The instruction of this method is more based on empirical knowledge. Apparently, activity recognition by observation and annotation costs too many human resources and is time-intensive. Another limitation is that it is prone to human error and bias[1]. Visual information such as video and photography is used to record human movement and achieve activity recognition[2]. But it has the same dilemma as manual notation and needs more specific knowledge of image processing technology. To achieve more precise results, 3D modelling technology is generated by building a 3-

dimensional model of the movement of the human body with a motion capture system[3]. This method could provide activity recognition analysis results accurately, but the exaggerated price of professional devices and the requirement of the specific testing court may be hard for amateurs to afford.

In the recent few decades, thanks to the emergence of micro-mechatronics and microsystems technology, Microelectromechanical systems (MEMS) have changed the way of biometric data acquisition for human movement recognition on medical professionals, business and military forces and so on[4]. For sports applications, small MEMS devices can be embedded in smartphones for more commonly daily use, also in all kinds of wearable accessories, such as a watch, wristband, necklace or even clothes like sports vests or sneakers. Take running, for instance, Nike+ running watch with its accelerated parallel processing (APP) has the ability to distinguish the running type of human to walking, jogging, sprinting and jumping[5]. Moreover, MEMS sensors have more widespread use in some swing-sports, like badminton, tennis, ping-pong, and golf. During these sports activities, human movements and gestures have more significant and representative sports features, which attracted more interest in research in HAR. In the following part of this master thesis, tennis will be the main research object of sport-specific activity.

1.1 Motivation

Tennis is a popular sport for both men and women, youths and elders, amateurs and elites in the world. According to the statistics, there are over 1,700 tennis clubs and more than 570,000 affiliated tennis players registered in the Dutch national tennis association (Koninklijke Nederlandse Lawn Tennis Bond, KNLTB), which is the second-largest sports association in the Netherlands[6]. That indicates that many, no matter professionals, amateurs or novices, engage themselves in tennis sports now. However, as in many other sports, playing and training improve skills and bring better performance. To another extent, practicing also results in sports injury. According to the study of tennis injuries, it shows that tennis has a unique profile of injuries, such as the distal humeral stress reaction which may cause the popular “tennis elbow”. Biomechanics of movement and training strategy can all result in an injury profile that differs from other swing-sports like golf or baseball[7]. For elite players, how to achieve higher and faster performance under high-intensity training without getting any injuries is an urgent problem to be considered most frequently. And for amateurs, how to manage the training intensity and time in a self-dominant way is equally important. For tennis coaches and data analysts, how to analyse movement data, to plan training strategies and to provide suitable guidance are the main emphases of their work.

For solving the problems mentioned above, focusing on tennis activity detection and recognition can be of added value as it reflects every detailed movement of participants during matching or training. To be specific, according to the way of holding the racket, the skills of hitting balls and tennis rules[11]. Tennis activity consists of different types of strokes such as forehand, backhand, topspin, slice, and volley. Macroscopically, the strategy is playing against the opponent with reasonable skills. Therefore, the most important goal of tennis activity recognition is to provide information about a player's behaviour which allows them to improve both stroke skills and preventive strategy.

Like mentioned above in the introduction of HAR, in earlier days, manual notation was the original way in tennis activity recognition, which was time and labour intensive, also in the risk of human error and bias. To overcome these drawbacks, tennis activities detected by computer vision and inertial sensing devices are represented as signal features corresponding to specific strokes in the processing of computers, which can be logged and extracted[8]. Machine learning algorithms with the powerful computational processing of computers can handle a huge amount of signals with less time. Thus, machine learning algorithms take the place of manual notation to achieve the goal of classification and recognition. But it is noteworthy that the camera and inertial sensor are as the carrier for signal input, which reflects different strengths and weaknesses in practical application.

Research in computer vision has been at the forefront of the work of tennis activity recognition. Data from tennis broadcast record information of movements and actions directly. Still, images and videos of tennis matches were used to investigate gestures and activity recognition in many scientific types of research. Relatively accurate results have been achieved successfully through visual approaches even using low-resolution footage[9][10]. Similarly, stroke recognition can be performed by locating the player's racquet arm in the keyframe in which the racquet contacts the ball[11]. But still, several challenges including occlusion, viewpoint variations, and environmental conditions may impact results by using data from video footage. Moreover, most of the video-based recognition systems have to be equipped with high-speed cameras or motion capture systems, which makes the entire recognition protocol costly. And the complicated recording system and a specific court make it hard to meet the requirement of portable use.

With the emerging trend of MEMS sensors, Inertial measuring units (IMU) provide a low-cost, effective alternative for tennis activity recognition. Generally, the most widely used inertial measuring units are accelerometers and gyroscopes measuring along one to three axes, and magnetometers are included in a few specific situations. These sensors measure acceleration, angular velocity and the direction and orientation of movements or actions quantitatively while playing or training tennis. The collected data from IMU reflect detailed information of every tennis stroke in training sessions or competitions. As it is known that human movement activities are considered to be hierarchic construction and are composed of basic movement frames[8]. Therefore, a series of consecutive tennis movements can be detected and recognized to different stroke labels by distinguishing IMU data with a machine learning algorithm. Being wireless, portable and self-contained in operation are the highlights of this method. In daily life, IMUs have been utilized in cellphones, watches, wristbands, and other wearable devices to record tennis activity and provide feedback.

On the commercial market nowadays, Zepp Tennis 2 is a powerful swing analyzer, tracking training sessions and match statistics and gaining insights about stroke performance and classification instantly through mobile app[12]. Sony Smart Tennis Sensor and Babolat POP have similar measurement systems and functions[13][14]. Interestingly, most of the commercial tennis sensors could only detect and record three basic tennis strokes, forehand, backhand and serve. Due to the business confidentiality principle, the processing method and algorithm behind those tiny sensors are unclear. Beyond that, there is no scientific explanation for the reliability of the accuracy of the obtained results.

In terms of scientific research, IMUs play an important role in activity recognition of swing sports like table tennis, baseball, badminton, and tennis as well. Table tennis strokes were detected in time-series and classified into eight-stroke categories by using inertial sensors were attached to table tennis rackets[15]. Similar research did in badminton activity, a more complex classification of 14 types of badminton strokes was recognized based on the IMU sensor network on the body[16]. And it provided a two-layer hidden Markov model (HMM) as a machine learning classification algorithm, which acquired the best accuracy among others such as Naïve Bayes (NB), Support Vector Machines (SVMs)[16]. As for baseball, IMUs have a widely use in identifying the key events and evaluating pitching performance in scientific research[17][18].

When it comes to the IMUs application on tennis stroke recognition, there are several recent pieces of research on developing a new measuring system with IMUs and applying different machine learning algorithms. A single IMU was attached to the forearm of tennis players to detect and recognize their movements and strokes in the work of Connaghan et al[21]. Even a massive data set was detected in their experiment and a high accuracy tennis recognition results were gained, the type of classification is limited to only forehand, backhand and serve. Yang et al. investigated the fusion of two IMU sensors, attached on the racket and right shank of player respectively, is used to achieve an online serve assessment system by distinguishing serve and non-serve strokes in training sessions[22]. To make a step further and broader, Buthe et al. provided a capture coordination system of the dominant arm along with foot reactions of players with three IMUs[23]. By implementing a new machine learning algorithm, tennis strokes are recognized as six types of classification. As the experimental subjects are too limited, meantime, too many variables are involved, the results show highly user-dependent. In terms of machine learning algorithms being used in previous research, there is no statement about why it is chosen to be used and why it brings the most accurate results. In this study, a more detailed tennis stroke classification was considered. A sensor-based machine learning method is proposed to recognize and classify all eight popular tennis stroke types, forehand topspin, forehand slice, forehand volley, backhand topspin, backhand slice, backhand volley, smash and serve.

In a short summary, some research involved with tennis stroke recognition indeed has been done so far. IMU sensors act as an important role in collecting data. But the existing literature is all limited to a simple type of tennis stroke classification. That may be because of some similar gestures and movements of tennis stroke, where the subtle difference of stroke features is hard to detect and recognize.

1.2 Research objective

The main purpose of this project is to develop a practical and accurate experimental setup to measure tennis stroke with IMU sensors and a comprehensive and automated tennis stroke recognition method with the applicable machine learning method. To check the accuracy of results, a manual notation will be used as the golden standard. Thus, the main goal of this thesis can be formulated as:

"Development and validation of comprehensive and automated tennis stroke recognition based on IMU sensors and applicable machine learning algorithms."

To accomplish this objective, we will first review shortly related previous work in both commercial and scientific point of view in chapter 2. After understanding the main structures and limitations of previous work, the main research goal of this thesis will be formulated into several detailed steps at the end of chapter 2.

Chapter 2

Previous work & Challenge

In this chapter, we first make a survey about the specifications and functions of three commercial tennis sensors. Then some previous scientific researches about tennis stroke recognition are briefly reviewed, from where comes the limitations and imperfections of previous methods. In the end, we specify challenges to small steps of this thesis.

2.1 Commercial tennis sensor

There are many applications of wearable tennis sensor on the market, aiming to record and improve players' performance. Three representative products, Zepp[12], Sony Smart[13], Babolat POP[14], are chosen to take the survey. The hardware information and functional components are shown in *Table 2.1* and *Table 2.2* respectively.

Table 2.1 Hardware information of commercial tennis sensor

			
Weight	7.7 gram	8 gram	18 gram
Battery duration	4 hours	3 hours	10 hours

Water resistance	Small rain resistant	Water & dust resistant	Small rain resistant
Internal storage	Up to 2,000 swings	Up to 12,000 swings	More than 10 hours of tennis
Display	Via smartphone	Via smartphone	Via smartphone
Sensor type	Dual accelerometers 3-axis gyroscope	3-axis motion sensor Vibration sensor	9-axis sensor
Sensor measuring range	N/A	N/A	N/A
Attachment	At bottom of racket	At bottom of racket	Around the wrist

Table 2.2 Functional component of commercial tennis sensor

	Zepp	Sony smart	Babolat POP
Effect	Yes	Yes	Yes
Effect type	Topspin Slice Flat	Topspin Slice Flat	Topspin Slice Flat
Impact location	Yes	Yes	No
Number of strokes	Yes	Yes	Yes
Stroke type	Forehand Backhand Serve Smash	Forehand Backhand Serve Smash	Forehand Backhand Serve Smash
Stroke speed	Yes	Yes	Yes
Ball speed	Yes	Yes	No
Video component	No	3D serve simulator	No

As shown in the tables above, all commercial tennis sensors are able to detect effect types (topspin, slice, flat) and stroke types (forehand, backhand, serve, smash). Beyond some insignificant aspects like battery duration or inner memory, the most noteworthy part is the component of inertial sensor units. Babolat POP has a 9-axis motion sensor, which consists of a 3-axis accelerometer, a 3-axis motion sensor, and a 3-axis magnetometer. These three parts are the entire configuration of the IMU. And Sony smart uses a 3-axis accelerometer combined with a vibration sensor while Zepp only uses a dual accelerometer and 3-axis gyroscope. Generally, acceleration and angular velocity measured by accelerometer and gyroscope, are used to calculate angular rates, linear velocity and position of a tennis player, finally, these data are used to achieve the function of different strokes recognition. Playing or training tennis by using the commercial tennis sensors, users could know training time, the number of total swings, type of every stroke, and to some extent, the score of achievement in the session and so on, displaying by smartphone App.

Noticeably, due to business confidential reason, the measuring specifications of accelerometer and gyroscope, the inner collecting and processing mechanism of commercial sensors are not clear. Beyond that, there exists no information about the validity and reliability of measurement. In a scientific point of view, the accuracy of movement detection and classification from commercial tennis sensor is invalid, even all their instructions claimed a high accuracy rate. Beyond that, as for the performance grading system, there is not much more detailed information about it as well. Therefore, find out how to recognize tennis stroke automatically using IMUs data has considerable practical significance.

2.2 Previous research

Generally, tennis stroke recognition has two main parts, data acquisition, and data processing. As it is mentioned in the last chapter, IMUs help to measure and movement data. While data processing mainly involves signal pre-processing and machine learning procedures. These aspects will be discussed respectively in the following part.

2.2.1 Data acquisition

IMUs & sensor placement

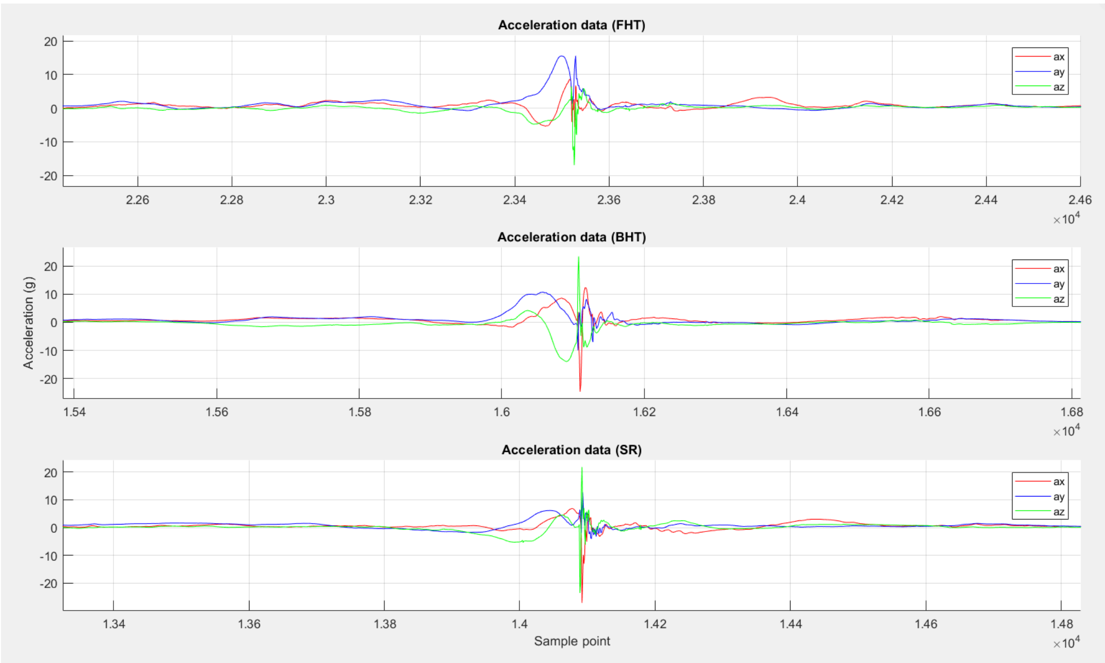
In scientific research, IMUs are widely used as wireless and wearable sensors to collect data of players of swing-sports movement (tennis, badminton, table tennis) and to implement stroke recognition. To some extent, tennis stroke detection and recognition can be defined as a hand gesture problem[24]. Different tennis strokes can be achieved by executing different hand gestures and swing postures. For instance, a smash is a stroke that the hand is travelling all over the head. While a forehand is a stroke that player's palm is facing to the front and a backhand stroke is just exactly the opposite. Therefore, the data from the hand movement give enough information to detect and distinguish different tennis strokes. Connaghan et al. and Kos et al. investigated, similarly, a single standard IMU (a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer) sensor attached to the wrist of tennis player's dominant arm to retrieve hand movement data while playing or training tennis. Due to the limitation and monotony of data only from the wrist, the three most common tennis strokes (forehand, backhand and serve) are able to be recognized in their research [21][24]. A step forward made by Büthe et al. is that a broad view of full-body coordination and timing of the movement was considered. To make it simple, a sensor system with three IMUs is used, two attached to each foot and one on the racket. The fused movement data of racket and footsteps can be used to classify the type of shots of the player[23]. Five different classes of shot strokes can be recognized, including forehand topspin, forehand slice, backhand topspin, backhand slice, and smash. This is the first time that footwork is segmented into tennis stroke recognition. However, due to the lack of experimental subjects, meantime, too many variables are involved (3 amateur males with right-handed, 1 expert female with left-handed), the results show a high user-dependent trend. Similarly, a fusion of two IMUs (3-axis accelerometer and 3-axis gyroscope) system, one mounted on the racket and one on the shank of player, is proposed to achieve online serve assessment in the research of Yang et al.[22]. Only serve and non-serve events were distinguished. Moreover, there exist other attempts like the fusion of IMUs and audio sensor data embedded in a wrist band in Sharma et al. research. 95.6% detection rate was obtained in this research but the classification work is still their look in the future[25].

Summarized, IMUs with six degrees of freedoms (DoFs), 3-axis accelerometer and 3-axis gyroscope are the most commonly used in collecting stroke movement data. And because the swing of the upper limb is the representative action of tennis, the forearm, upper arm, shoulder, and trunk are suitable to attach IMUs for data acquisition. Among the popular attached places, the wrist is the most commonly considered to place the IMU sensor. Due to being the distal part of extremity and connected with the racket, it could reflect the motion of swing to the maximum amplitude with the most discriminative features.

2.2.2 Data processing

Data plotting

Like used in many other sports, acceleration data measured by the accelerometer in an IMU are widely used to solve simple classification problems, for example, the three most often tennis strokes: serve, forehand, and backhand[21][22][24][26].



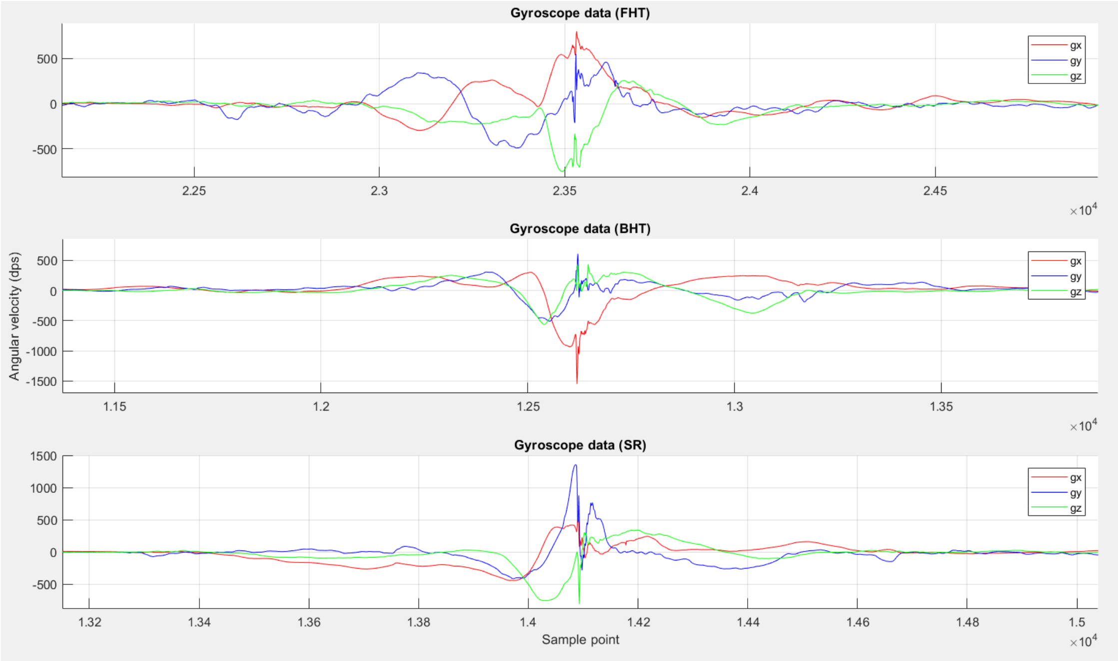


Figure 2.1 Graphical representation of accelerometer and gyro data.

As shown in *Figure 2.1*, spikes in acceleration data signals are recorded due to the impact of the ball on the tennis racket. Detecting such spike-signal provides the temporal location of tennis strokes. Correspondingly, three basic tennis strokes show different configurations and features, which will be adopted in machine learning processing to make the classification. Noticeably, it can be observed that there are some similarities between strokes, for example, there are very similar acceleration curves for both forehand and serve and the feature of peak value is not a discriminative enough[24]. While from observation of *Figure 2.1* of the gyroscope data signal, it could be seen that more discriminative features can be found between strokes. For example, different peak values and acceleration direction of individual gyroscope axes are achieved for those three basic tennis strokes. In Kos et al. new research, gyroscope information for stroke classification is used to supplement the lack of acceleration data in providing enough discriminative features[26]. With a larger tennis stroke database, more accurate classification results were achieved. Connaghan et al. evaluated the best approach for tennis stroke classification using either accelerometer, gyroscope or magnetometer[21]. A conclusion that using a combination of all three types of sensors gives the best performance of stroke classification than using single sensor classification. Therefore, measured data signals with more discriminative features to different tennis strokes should be taken into consideration in tennis strokes classification into more detailed sort.

Beyond that, Wang et. al and Büthe et. al had done with the study that fused more data from different IMUs attached to different parts of players[16][23]. And under the premise of ensuring that computing is not cumbersome, sensor data fusion could give better accuracy results[16]. Sensor data fusion is also an interesting aspect to be considered in this study.

Data screening & filtering

Basically, at the beginning of the tennis stroke classification process, individual tennis strokes in one session first have to be detected accurately. Non-tennis strokes, like fake strokes, twirling rackets and unexpected swing of the arm, should be filtered manually.

The main problem when applying IMU sensors on data acquisition of human activity recognition is the different types of noise mixed in original data due to sensor errors or noisy measuring environments[19]. And Nettleton D.F. et al. managed a study of the effect of different types of noise on the precision of supervised learning techniques. It states that input features with unprocessed noise result in unreliable output class with errors[20]. Therefore, noise in data hampers the human activity recognition and classification process. And noise reduction is one of the most important procedures in data processing of human activity recognition.

Afterward, both accelerometer and gyroscope measured tennis stroke movement could provide corresponding physical parameters (acceleration and angular velocity) as the continuous signal in time series. Correspondingly, enough information can be retrieved from recording signals to distinguish different tennis strokes. Therefore, screening and filtering procedures to the raw data is a quite necessary pre-processing step before machine learning.

Windowing techniques

Signal data stream acquired by IMU sensor for activity recognition contains not only motion data of specific patterns that need to be recognized and classified but also some other unnecessary motions of players. The motion data of specific patterns or shots from recording signals have the main characteristics to stand for corresponding movements. Therefore, windowing techniques are used to divide the sensor signal data into smaller time segments (or windows) in activity classification, also known as window segmentation. After that, feature extraction and classification algorithms are then applied separately to each window. Thus, the data with the most important information is considered comprehensively while the computational amount for machine learning is reduced.

Different procedures have been used in previous activity classification research. Sliding windows is a simple and intuitive method for window segmentation. A signal is divided into the fixed-length window without inter-window gaps. And the range of window sizes was different for different sports activity pattern classification tasks, from 0.1s to 2.5s[15][37]. An over-lapped sliding window including a degree of overlap between adjacent windows was also used in some classification cases to get better results. But sometimes, sliding window segmentation may cause poor results in aperiodic and unregular signals[41]. Therefore, an event-defined window segmentation method is introduced. Specific events are located by pre-processing data signal, then these events are used to define consecutive or inconsecutive windows[16][26]. And there are other window segmentation methods like bottom-up, top-down, and adaptive sliding window which are suitable for specific pattern classification.

In summary, the window segmentation method should divide signals to windows of proper size. For each window, it should include enough data to describe the events or activities. Meanwhile, the unnecessary information needs to be eliminated from the window, which might complicate computation and affect feature extraction.

Feature extraction

To prepare for the next stage of the training classification model, the window segmentation step aims to divide the pre-processed signal data into segments or windows most suitable for recognition and classification. The principle of machine learning is the scientific study of algorithms and statistical models that computing system performs or predict a specific event without using any other explicit instructions, but only relying on default patterns, inferences and features[27]. In practical in tennis stroke classification, machine learning algorithms program a mathematical script based on sample data of tennis strokes, also known as training data, in order to make predictions or decisions without being explicitly programmed to perform the tasks or testing data. Therefore, feature extraction and classification algorithm are two main parts in machine learning processing.

In general, features can be defined as the abstractions of raw data and the purpose of feature extraction is to find out the main characteristics of a data segment that could represent the expected data accurately[2]. To be more specific, feature extraction transforms large input raw data into a reduced representation set of features, which can also be referred to as a feature vector. The feature vectors, with important contents for distinguishing various activities, will be treated as inputs to feed classification algorithms[40].

As mentioned above, in tennis stroke data acquisition and screening, features are the discriminative parts of the different signals to different tennis strokes. For each tennis stroke, features are computed and then used as an instance for the learning or testing phase. In Figo et al. work, a detailed survey shown in *Figure 2.2* of the classification of techniques applied to sensor signals for feature extraction is achieved to guide the feature extraction in human activity recognition[28]. All features from the available sensor signal processing techniques are classified into three broad domains, namely time domain, frequency domain, and discrete representation domain. This survey contributed to identifying the feature extraction process that is better suited for sensor-based signal and human activity recognition. In order to choose the most suitable and representative features in tennis stroke classification, thus, a simple survey is made as follows to show feature extraction in tennis stroke classification literature recently.

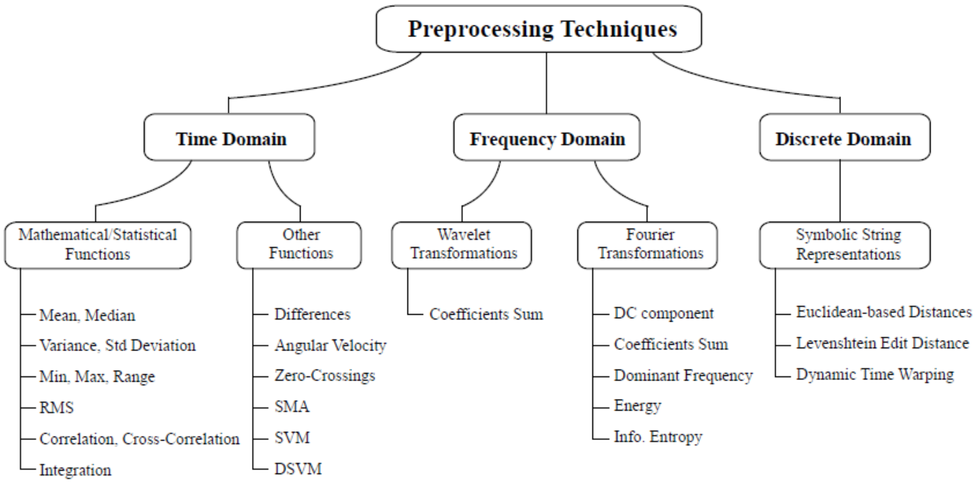


Figure 2.2 Classification of techniques applied to sensor signals for feature extraction[28].

After looking deep into the literature about swing sports activity (especially tennis, table tennis, and badminton) recognition based on IMU sensors, *Table 2.3* shows the survey about the application of a variety of features that were used in sensor-based swing sports activity classification. From the survey, clearly, time-domain features including mathematical and statistical techniques of signal and basic waveform characteristics are the most widely used. That is because simple mathematical and statistical metrics can be used to extract basic signal information from raw sensor data. Additionally, those features are often used as fundamental steps for metrics in other domains as a method to extract key signal features. On the other hand, frequency-domain features, focusing on the periodic nature of the signal, have been extensively used to capture the repetitive structure of a sensor-based signal[28]. More specific, Avci et al. explained that energy and entropy features can be used to capture data periodicity of the accelerometer and it can be used to distinguish sedentary and vigorous activities, and help to discriminate the activities with similar energy values[41]. And time-frequency domain features are often used to investigate complex signal data. The wavelet techniques from time-frequency domain features are mainly used to detect the transition between different activities, usually the classification based on videos or images[9]. In terms of heuristic features, inter-axis correlation is the one, especially useful for discriminating between activities that involve translation in just one dimension. As can be seen from the survey, several studies use the correlation between axes of accelerometer and gyroscope signal data and achieve accurate results for distinguishing swing sports like table tennis strokes[30][31]. To the existing literature, heuristic features have not been studied in feature extraction, especially for tennis stroke classification.

Table 2.3 The most frequently used features and their applications in sensor-based swing sports activity classification

Type	Features	References
Time-Domain	Mean	[16][21][23][25][29][30][31][32][33][34][35][36][37][38][39]
	Variance, Covariance	[16][21][23][25][29][33]
	Standard Deviation	[29][31][32][33][34][35][36][38][39]
	Skewness, Kurtosis	[16][21][30][31][33]
	Root mean square	[33]
	Minimum, Maximum, median	[30][31][32][33][34][35][36][37]
	Zero or Mean Crossing Rate	[37]
Frequency-Domain	Spectral Energy	[23][25][29][31][33][36][37][38][39]
	Spectral Entropy	[25][29][31][33][36][37][38][39]
	Discrete Fast Fourier Transform	[16][37][39]
Time-Frequency Domain	Wavelet Coefficient	[9]
Heuristic Features	Inter-axis Correlation	[29][30][31][33][39]

In a short summary, due to the restriction of computation time and requirement of memory, statistical features and signal characteristics from time-domain are most widely to be studied in sports activity classification. There is a trade-off balance in feature extraction. Simple feature vectors with common features are not able to distinguish different activities, while the complex ones will be subject dependent and have more requirements in computational processing and data storage in running machine learning algorithms. That indicates feature extraction is one critical step in data processing of tennis stroke classification. The application and selection of features are depending on the type of raw data, subject of analysis, expected goal and also the hardware of computational processing and storage. For tennis stroke classification in this thesis, detailed feature extraction will be discussed in the next chapter.

Classification algorithms

After feeding the extracted feature vectors, there starts the step of training classifiers using proper classification algorithms in machine learning processing. In the following part, a short investigation is made to show several state-of-the-art classification algorithms applying in swing-sports activity classification:

1. Naïve Bayes (NB). A simple probabilistic classifier based on Bayes' theorem, also known as Bayesian network, simple Bayes or independence Bayes. Without any complicated iterative parameter estimation schemes, it is simple to construct only requiring a small amount of training data[43].

2. Hidden Markov Model (HMM), represented as the simplest dynamic Bayesian network, is a statistical Markov model in which the system being modelled is assumed to be a Markov process with hidden states[44]. The computational complexity of the HMM classifier is low, additionally, it can do well when dealing with a large dataset.

3. Artificial Neural Network (ANN). A mathematical or computational classifier model has been inspired by biological neural networks. ANN is an adaptive system for which its structure can be changed using external and internal information flowing through the network during the learning phase[45].

4. Decision Tree (DT). This model able to recursively separates the input space into class regions in a hierarchic way. And it is greedy where it locally finds the best attribute to split the data and keep repeating until it cannot separate anymore[29].

5. k-Nearest Neighbour (k-NN). This algorithm is used for the classification of activities based on the closest training examples in the feature space. K-NN is a type of instance-based learning, so-called lazy learning, where the function is only approximately locally and all computation is deferred until classification[46].

6. Support Vector Machines (SVMs). SVMs can be defined as systems that use hypothesis space of linear functions in a high dimensional feature space, which are trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory[47]. It has secure theoretical foundations, strong regularization properties and excellent empirical successes[43]. It is originally to solve binary classification problems, but with some analysis strategies, it can be applied to multi-class classification tasks.

7. Other classification algorithms: Decision Tables, Threshold-based method, Gaussian Mixture Models (GMMs). And some innovative methods by fusion of various classifiers.

The classification algorithms mentioned above all have wide applications in sports activity recognition and classification. The following *Table 2.4* shows the survey about various classification algorithms in the machine learning process of swing sports activity classification, especially tennis, table tennis, and badminton. As can be seen from the table, in every study, not just only one simple classification algorithm was studied in the data processing procedure. Several state-of-the-art classification algorithms in the field of machine learning were compared to deal with the same dataset to show their characteristics or drawbacks when applying on sports activity classification. Among the reviewed literature, Wang et al. did the most detailed stroke classification study on badminton to recognize all 14 badminton strokes with 5 different classification algorithms[16]. To the existing literature, there is no similar work having been done on detailed tennis stroke classification. Most of the tennis stroke classification studies were restricted to three or five basic strokes[21][23][24]. It is shown that the most widely used classification algorithms are HMM, kNNs, NB, and SVMs. According to the accuracy results of classification, regardless of the magnitude of the dataset, a considerable average accuracy can be achieved in all classification algorithms. Noticeably, those innovation methods have the same level of performance. SVMs has become one of the most popular classification methods in the machine learning field in recent years. It will be the main classification algorithm to be studied in this thesis, and a more detailed discussion about SVMs can be found in the next chapter.

Table 2.4 The application of various classification algorithms in the machine learning process of swing sports activity classification

<table>
<tr><th>References</th><th colspan="2">Classification Algorithm</th><th>Type of sports and number of strokes</th><th>Average Accuracy of Classification (%)</th><th>Processing Time (s) or Processing effort</th></tr>
<tr><td rowspan="5">[16]</td><td colspan="2">2-layer HMM</td><td rowspan="5">Badminton
14 strokes</td><td>97.96</td><td>19.5</td></tr>
<tr><td colspan="2">NB</td><td>72.44</td><td>2.5</td></tr>
<tr><td colspan="2">C4.5 DT</td><td>78.44</td><td>16.1</td></tr>
<tr><td colspan="2">Linear discriminant function</td><td>82.09</td><td>6.1</td></tr>
<tr><td colspan="2">SVMs</td><td>96.98</td><td>7452.6</td></tr>
<tr><td>[21]</td><td colspan="2">NB</td><td>Tennis
3 strokes</td><td>90</td><td>NA</td></tr>
<tr><td rowspan="2">[22]</td><td colspan="2">SVMs</td><td rowspan="2">Tennis
Non-strokes & strokes</td><td>98.76</td><td rowspan="2">NA</td></tr>
<tr><td colspan="2">HMM</td><td>97.02</td></tr>
<tr><td>[23]</td><td colspan="2">Longest common subsequence (LCSS)</td><td>Tennis
5 strokes</td><td>94</td><td>NA</td></tr>
<tr><td>[24]</td><td colspan="2">Frame-based prescription and multi-class SVM (FDSVM)</td><td>Tennis
3 strokes</td><td>98.1</td><td>NA</td></tr>
<tr><td rowspan="2">[30]</td><td rowspan="2">ANN</td><td>Convolutional neural networks</td><td rowspan="2">Badminton</td><td>77.2</td><td rowspan="2">NA</td></tr>
<tr><td>Long short-term memory networks</td><td>78.9</td></tr>
<tr><td rowspan="5">[31]</td><td colspan="2">NB</td><td rowspan="5">Table Tennis
8 strokes</td><td>87.1</td><td>mid</td></tr>
<tr><td colspan="2">Random Forest (RF)</td><td>95.7</td><td>low</td></tr>
<tr><td rowspan="2">SVMs</td><td>Linear kernel</td><td>95.6</td><td>mid</td></tr>
<tr><td>Radial based function</td><td>96.7</td><td>high</td></tr>
<tr><td colspan="2">kNNs</td><td>94.7</td><td>high</td></tr>
<tr><td rowspan="4">[32]</td><td colspan="2">SVMs</td><td rowspan="4">Tennis
9 strokes</td><td>93.21</td><td rowspan="4">NA</td></tr>
<tr><td colspan="2">kNNs</td><td>92.52</td></tr>
<tr><td colspan="2">RF</td><td>90.78</td></tr>
<tr><td colspan="2">Neural network</td><td>90.36</td></tr>
<tr><td rowspan="2">[35]</td><td colspan="2">SVMs</td><td rowspan="2">Tennis</td><td>88.36</td><td rowspan="2">NA</td></tr>
<tr><td colspan="2">kNNs</td><td>89.41</td></tr>
</table>

2.3 Project overview

2.3.1 Thesis overview

In this thesis project, an automated and comprehensive tennis stroke recognition and classification method is developed based on IMU sensors and machine learning algorithms. According to the processes of human activity recognition and classification, combining with specific topic on all tennis strokes, the entire project process can be divided into the following subsections: experimental equipment and subjects, method and arrangement, raw data acquisition, data pre-processing, window segmentation, feature extraction, machine learning algorithm, classifier training, model validation, database testing, classification results, and accuracy detection. The contents of this thesis process are organized as follows:

Chapter 3 describes the experimental method about equipment and subjects, data recording and storage step by step. The detailed place of attachment of IMUs and tennis sessions of executing tennis stroke detection and collection are discussed in this chapter.

Chapter 4 presents data processing methods, including raw data pre-processing, window segmentation, feature extraction, machine learning algorithm training, model validation, database testing. Window segmentation method to the pre-processed data is introduced in detailed. And features from both accelerometer and gyroscope signal data in time domain and frequency domain are all considered to come up with a proper feature vector used to feed the machine learning algorithm. After that, Support Vector Machines (SVMs) as the main classifier is used in the training classification model through MATLAB programming.

Chapter 5 includes the classification model validation and final classification results about all 8 tennis strokes. Data from different IMU sensor was fed to train classification model and tested respectively. The accuracy of automated classification is shown by comparing our classification results with the golden standard from video annotation and silver standard from commercial tennis sensors. And a data fusion was chosen to train the classification model again, aiming to check if the classification accuracy can increase by sensor fusion.

Chapter 6 discusses the classification results and precision. In this chapter, the important achievements of this project are presented which can be used as a practical guideline for real-time, automated and sensor-based tennis stroke recognition and classification system in the future. Beyond that, some drawbacks from this study are summarized to avoid recurrence in future work.

2.3.2 Expected contribution

The main goal of this thesis is specified and refined to "*Automated and comprehensive tennis stroke recognition and classification based on IMU sensors and Support Vector Machines*". With this automated tennis stroke recognition and classification method, a real-time, portable and automatic recognition and classification system for swing sports may be studied and developed. It could act as a data analyst or strategy coach for sports athletes by collecting their training or competing data. Consequently, after the project of this thesis, the following support questions should be answered:

- What features could be used to distinguish similar tennis strokes in machine learning algorithms, for example, forehand topspin and forehand slice?
- Do data from different IMUs attached to different parts of players achieve similar classification accuracy by training machine learning model?
- What do data fusion show when data from different sensors is combined? Does it provide the best data for classification? What is the accuracy then?
- How do SVMs perform while training the data? What are the advantages and disadvantages compared to other advanced classification algorithms?
- Does the magnitude of training dataset have influences on the accuracy result of prediction?
- What is the accuracy of tennis stroke classification in this study, and how does it compare with previous studies?

Chapter 3

Method

In this chapter, the experimental set-up and measurement method are explained respectively. The experimental set-up includes subjects, experimental apparatus, tennis court, while measurement method consists of IMU sensor attachment, type of tennis strokes, tennis session arrangement, data recording, and storage.

3.1 Experimental set-up

3.1.1 Subjects

Seven healthy adolescent tennis players (five males, two females) from Koninklijke Nederlandse Lawn Tennis Bond (KNLTB) participated in this study, shown in *Table 3.1*. Detailed information of subjects is shown in Appendix 1. All precautions of the experiment were explained and written informed consent was provided and signed by every participant before the experiment. And the approval of the ethical committee of Vrije Universiteit Amsterdam has been granted. All rights of all subjects are protected through the entire process. In an effort to generate a comprehensive functional classification method across all levels of elite or amateur tennis players, this sample was deliberately heterogeneous.

Seven participants are certainly in good competitive sports states without the following circumstances.

The exclusion criteria were:

- History of wrist, forearm, elbow, upper arm or shoulder surgery
- Incidence of upper extremity pathology in the last six months which restricted the normal performance of tennis play for more than two days
- Recent pain happened on the upper extremity, especially at wrist, elbow or shoulder
- Any circumstance may affect the normal movement of making tennis strokes

Table 3.1 Information for seven participants in the study.

Age (year)	**Weight (kg)**	**Height (cm)**	**Preferred Hand**	**Rank level (Dynamic Playing Strength System (DSS))**	**Years of playing tennis**
19.3±2.7	75.4±15.8	180.7±11.1	right	4.3±1.1	11.3±4.1

3.1.2 Experimental equipment and court

IMU sensor

The special IMU sensor system was made by Sander van Leeuwen (the technician from the technical support team of the VU section Neuro-mechanics), especially used for data collection for the human upper extremity. As it is shown in *Figure 3.1*, it consists of 4 IMU sensors, each IMU sensor contains an integrated tri-axis accelerometer, a tri-axis gyroscope (icm20649), and a tri-axis magnetometer (ak20649).

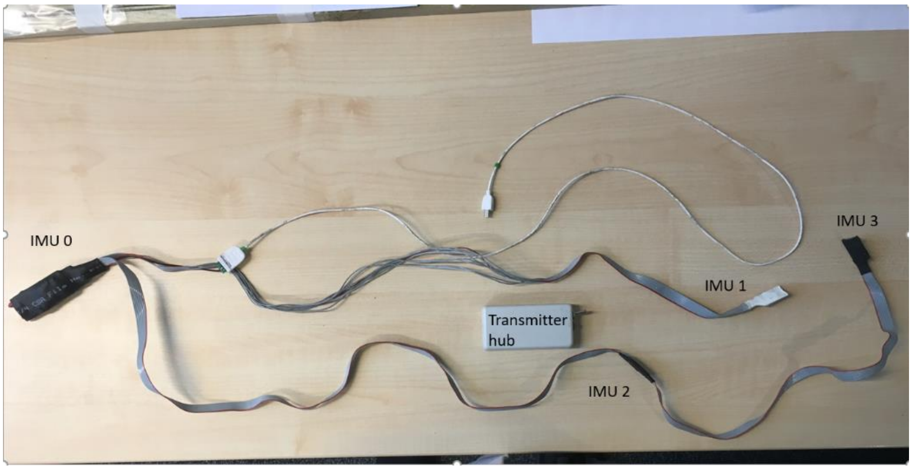


Figure 3.1 IMU sensor system

The icm20649 is a combined tri-axis accelerometer with a range of ±30 g and a tri-axis gyroscope with a range of ±4000 dps. During data recording in the experiment, the frequency of accelerometer and gyroscope are both sampled at 560 Hz. Moreover, the size of the sensor board is 16*24mm and the weight of a sensor board is around 1 gram. The low weight of the sensor does not influence the normal movement of tennis strokes of subjects. The direction of IMU sensors attaching to the forearm and upper arm are shown in *Figure 3.2* below. The detailed specification of sensors is attached in Appendix 2.

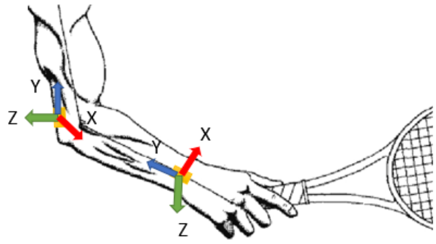


Figure 3.2 The direction of IMU sensor on forearm and upper arm

Attachment of IMU

Before the experiment, the IMU sensor system has to be attached to the subject on the forearm (wrist), upper arm, torso, and pelvis, as shown on the dark spots in *Figure 3.3*. The detailed places of attachment of 4 IMU sensors are shown in *Table 3.2*.

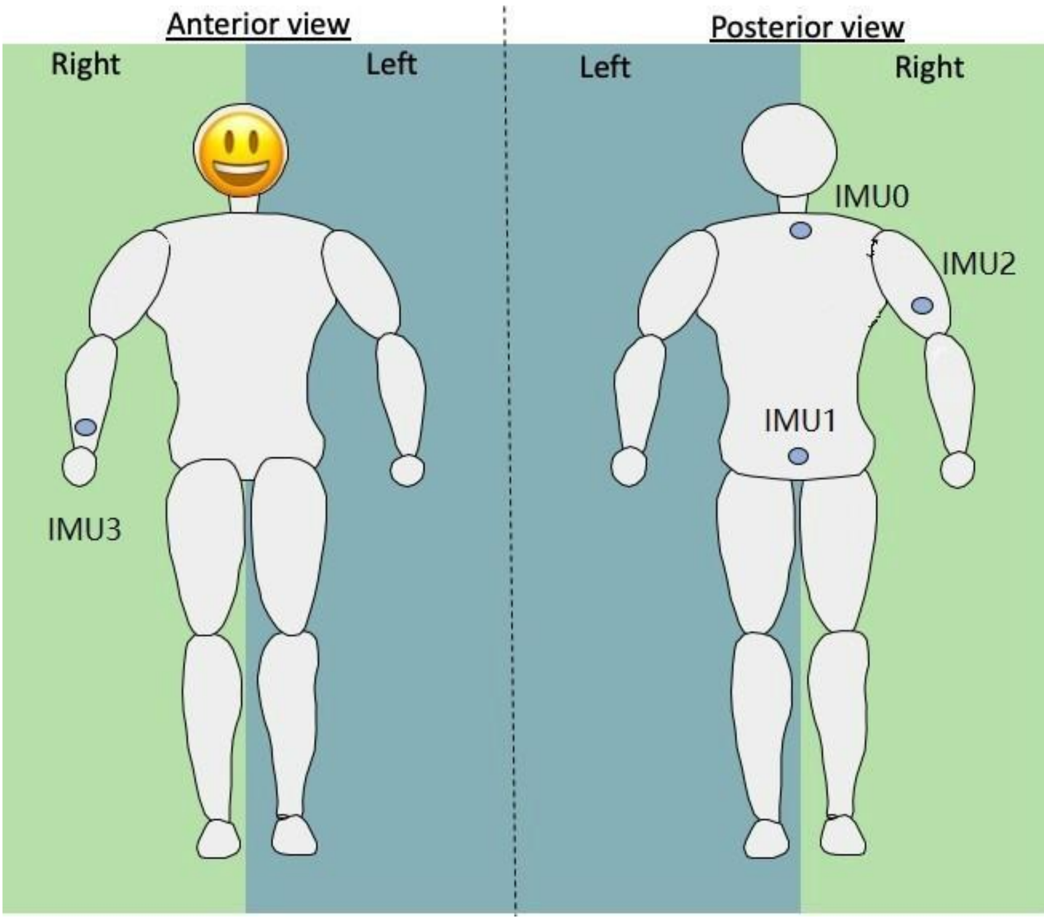


Figure 3.3 The attachment of the IMU system on the upper extremity of participant

Table 3.2 The detailed places of attachment of the IMU system

IMU sensor	Segment	Location
IMU 0	Torso	Attach to the surface of the back, at the point of fifth thoracic vertebra
IMU 1	Pelvis	Attach to the surface right above sacrum on spine in medial level, at the middle point in the line of spina iliaca posterior superior
IMU 2	Upper arm	Attach to the distal of humerus, on the middle point between the lateral and medial epicondyle
IMU 3	Forearm (wrist)	Attach to the distal of ulna and radius, in the middle point between the styloid process of radius and head of the ulna

Commercial sensor

One interesting question in this thesis is to verify tennis stroke classification accuracy of commercial tennis sensors currently on the market. In this study, the Zepp tennis sensor, mentioned in the introduction was used to collect movement data of tennis players during the experiment. Tennis stroke classification results of Zepp were shown through a specific APP on cellphone called ZEPP TENNIS. And all experimental results from Zepp tennis sensor were recorded through this APP.

Attachment of Zepp

As every player has his/her own tennis racket, thus, Zepp tennis performance sensor is attached to the bottom part of the racket handle by using a flex-mount. It will not affect the use of a tennis racket. Moreover, all attached sensors should be stable and cannot block the general swing movement of a tennis player.

Tennis court & ball machine

All experimental procedures were executed in the indoor tennis hardcourt at the KNLTB. The six-camera video recording system, Playsight (see https://playsight.com), was helped to record all movements of players in the entire experiment. It provides detailed information for manual annotation of tennis strokes.

All tennis balls in this experiment were shot automatically by a ball machine. The speed, height, frequency, and direction of the ball were set up in advance to feed subjects the corresponding tennis strokes.

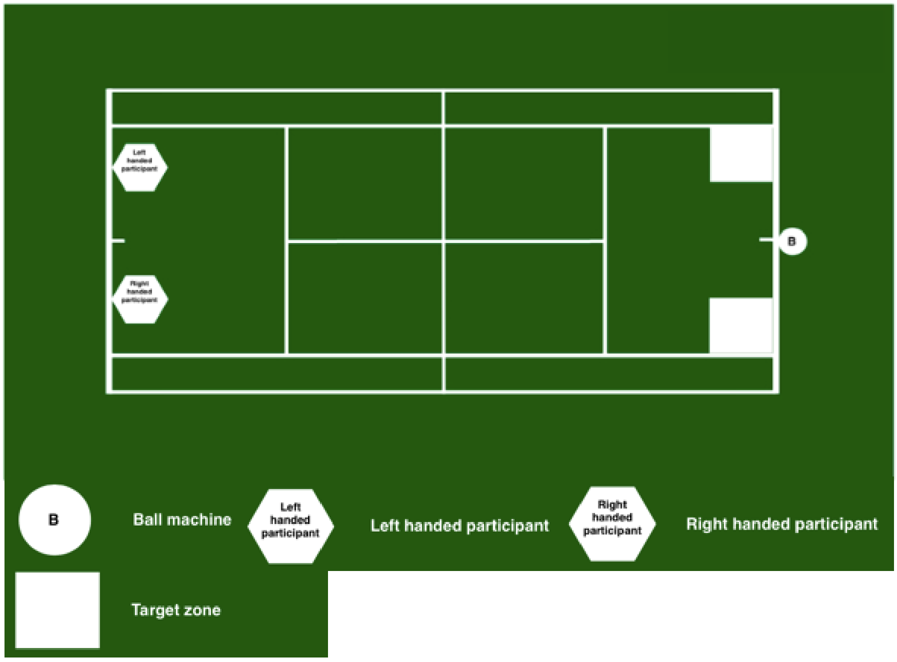


Figure 3.4 Tennis court set-up

The set-up of the tennis court is shown in *Figure 3.4*. During the experiment, the participants stood at the opposite side to the ball machine and were instructed to hit tennis balls back to 2m*2m target areas on the testing court. In this way, the motion data can be collected when there is only one subject in each time. We simulate a "rally" environment for the subject in this study.

3.2 Experimental procedures

3.2.1 Tennis stroke classes

In this study, all eight common types of tennis strokes were recorded.

- Serve (SR) – Tossing the ball into the air and hitting it (usually near the highest point of toss) so that the ball falls into opposite service box without being stopped by the net
- Forehand topspin (FHT) – Hitting over the ball with the racket and giving it forward rotation from the player's dominant hand side
- Backhand topspin (BHT) – Hitting over the ball with the racket and giving it forward rotation from the player's non-dominant hand side
- Forehand slice (FHS) – Hitting the ball with the racket and giving it backward rotation from the player's dominant hand side
- Backhand slice (BHS) – Hitting the ball with the racket and giving it backward rotation from the player's non-dominant hand side
- Forehand volley (FHV) – Hitting the ball before it bounces on the ground with a short punching stroke at the player's dominant hand side

- Backhand volley (BHV) - Hitting the ball before it bounces on the ground with a short punching stroke at the player's non-dominant hand side
- Smash (SM) – Hitting the ball above the head with a serve-like motion from the player's dominant hand side

Other tennis stroke subtypes like half-volleys, flat shots which are less common and used stroke techniques[32] were not included in this study.

3.2.2 Data collection

To collect enough tennis stroke data for both training and testing datasets of the machine learning process, tennis sessions for all eight tennis strokes were performed to collect basic data of all types of tennis strokes used to extract the features of different strokes and feed the classification algorithms. Moreover, a tennis stroke database in a competitive tennis session was collected, mainly used as a testing dataset to input into the classification model. Thus, for each subject, there were two main parts of the data collecting procedure.

First, basic data of all eight tennis strokes were collected separately by testing subjects with tennis session with a fixed number of identical strokes. A ball machine was set up in a repeating model to launch balls for subjects to perform different strokes respectively. And in total, every type of tennis stroke was performed 5 times in each trial except the serve shot. Tennis serve was performed 10 times.

The participants were instructed to hit tennis balls back to the target area on the opposite side of the testing court by performing different tennis strokes on the list. And clear and powerful movement and swing strike were asked to perform when hitting the ball. The data collected in this part were mainly used to extract the features and train the classifier in the data processing.

Second, the tennis stroke database in tennis rally was collected to use as testing data to check the performance of the classification method in the final stage. Due to the inconvenience of arranging the timetable of participants and the unbalanced rank level of players, it was hard to arrange the real competitive tennis rallies for collecting testing data in this study. In an alternative way of thinking, several programs in ball machine were set to simulate as an "opponent". In each program, ball launching direction, speed, height and time interval were set randomly but reasonably in one rally. For each rally, players started with a serve and perform nine tennis shots according to the nine coming balls from the ball machine. They were instructed to perform any tennis strokes according to their judgement, willingness, reaction and technique skills. In this way, the simulated tennis rally between subjects and ball machine was much more similar to the real competitive tennis rally between players. In order to make sure there are eight types of tennis stroke for testing data, the participants were also asked to try to perform as many as types that he or she could. For each subject, there were 3 rallies contains 10 strokes. In total, the testing dataset was around 300 tennis strokes.

3.2.3 Data recording method

IMU data

In a highly efficient and convenient way of IMU data recording and storage, the raw data of four IMU sensors are collected in real-time by a transmitter and sent to a laptop via File Transfer Protocol (FTP) wirelessly. With a MATLAB script for plotting, the raw data can be checked immediately after the experiment. In this study, the program of FTP used on the laptop is called FileZilla[50].

Commercial sensor

All movement data of tennis strokes by participants were recorded and stored automatically when the Zepp tennis sensor was on and connected to the cell phone by APP. Though the APP of Zepp, all tennis training session history could be retrieved. And the results of tennis stroke classification were shown at the same time as shown in *Figure 3.5*. The total number of shots and types of stroke classification were recorded in detailed, which will be used to compare with classification results of the proposed method in this study to verify the classification accuracy of the commercial products. Meantime, the classification results from the commercial sensor were treated as a silver standard.

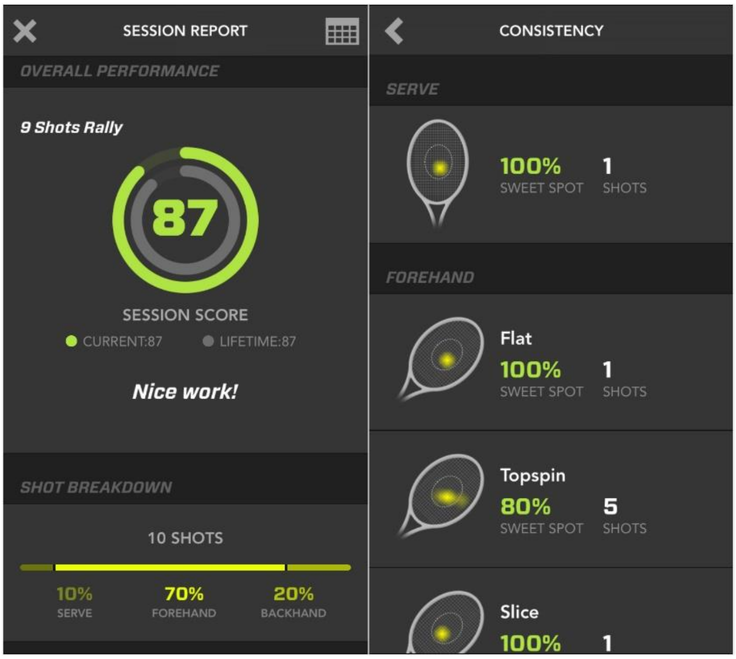


Figure 3.5 The results of tennis stroke classification of the commercial sensor in its APP

Video footage

Experiment video footage was saved through the internet automatically. In order to build the ground truth, the video footage was manually annotated by author and tennis coaches from KNLTB empirically. All tennis strokes in this study from video footage were labelled as “Serve Stroke”, “Forehand Topspin Stroke”, “Backhand Topspin Stroke”, “Forehand Slice Stroke”, “Backhand Slice Stroke”, “Forehand Volley Stroke”, “Backhand Volley Stroke”, “Overhead

Smash". Then, the labelled tennis strokes from video footage were treated as the golden standard, also known as ground truth, to compare with classification results by the proposed classification method in this study in the final stage to achieve validation of accuracy.

Chapter 4

Data processing

Chapter 4 presents data processing after the data collection procedure from the experiment. The detailed information of raw data pre-processing, window segmentation, feature extraction, machine learning algorithms, classification model training and database testing is explained comprehensively in this chapter.

In the last chapter, raw data of all tennis strokes of every subject has been collected. According to human activity recognition based on inertial sensors, raw data cannot be used to training the classifier and testing machine learning model directly. Before the final stage of recognition and classification, for example, raw data should be filtered and smoothed. And, furthermore, not the entire signal will be used to training the classification model and testing. Features should be selected and extracted, as mentioned in the last chapter. Generally, the main steps of data processing in activity recognition can be categorized as pre-processing, segmentation, feature extraction, dimensionality reduction and classification[2]. In this study, data processing was refined in the following steps: raw data pre-processing, shot detection and window segmentation, feature extraction, dimensionality reduction, training classifier, dataset testing(*Figure 4.1*.)

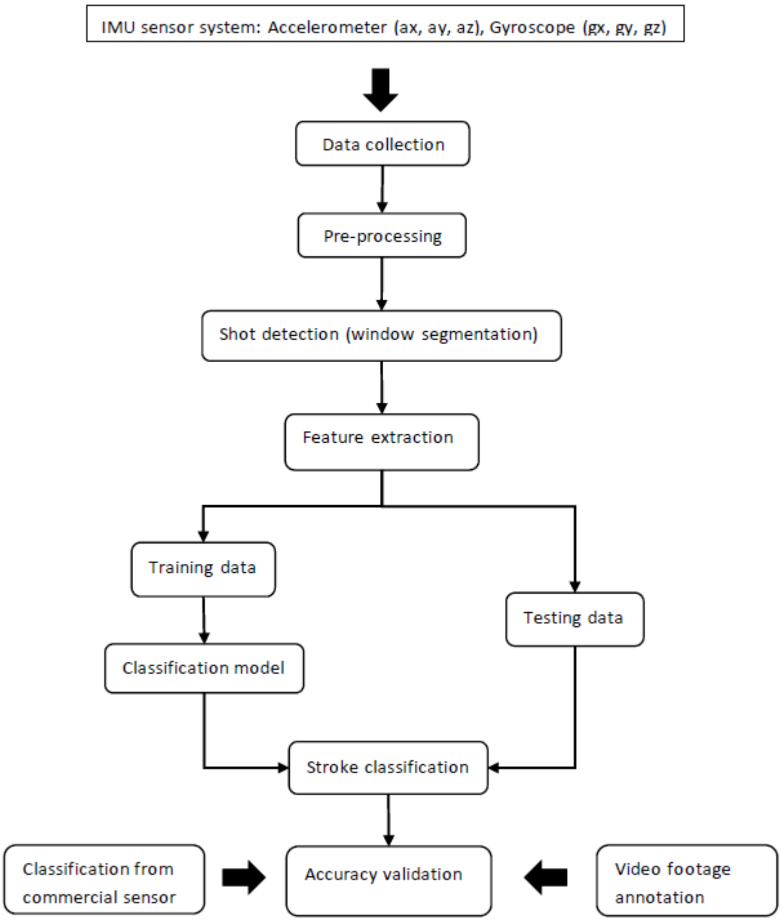


Figure 4.1 Data processing flowchart for tennis stroke recognition

After raw data collection, the preliminary screening of raw data is necessary before it goes to the pre-processing step. Since the IMU sensor system was newly developed just for data collection of the upper extremity of players in swing-sports, it works not as stable as a commercial IMU sensor. Moreover, due to the unstable attachment of IMU sensor system and the effect of sweating during the experiment, parts of IMU sensor had the problems of unstable attachment or falling off sometimes. These could result in incomplete data records and missing data in some trials. MATLAB scripts were programmed to plot acceleration and angular of velocity data in time series to check whether there exists reasonable and pre-set number of spikes generated by ball impact and whether the measured data is reasonable without exaggerated or empty data.

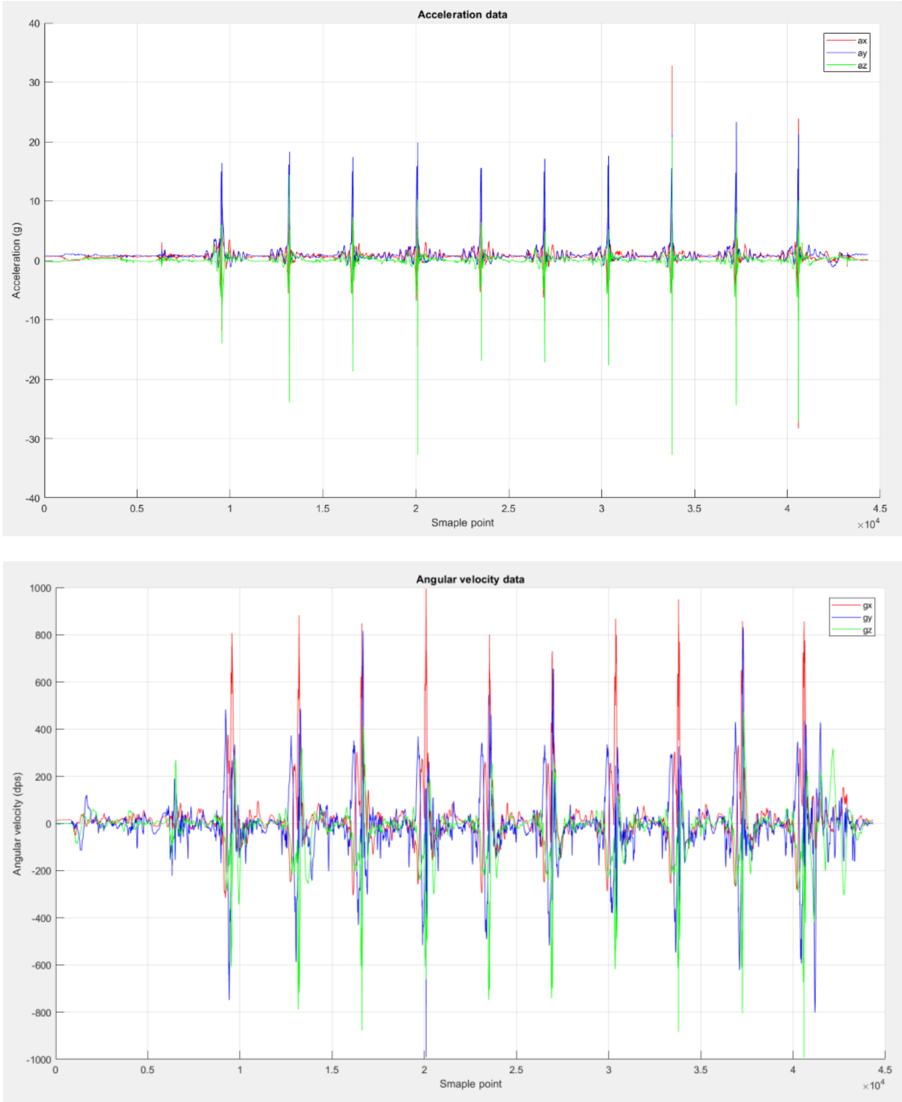


Figure 4.2 Sample signal from preliminary screening

As can be seen from *Figure 4.2* above, it shows clearly that there are ten prominent spikes in both acceleration and angular velocity signals, which represent ten tennis strokes or shots generated by ball compact with the racket. Raw data signals (both acceleration and angular velocity signal) with abnormal fluctuations, dramatic changes, and missing data were rejected in this period. It is clear that the signals have large fluctuations and exaggerated peaks, caused by noise. Denoising and smoothing signal procedures were executed in the next step to make signals refined.

4.1 Data pre-processing

Noise filtering

Raw data acquired by wireless inertial sensor units were subject to noise in the form of system noise, environmental noise, and soft-tissue artefact. In this study, three noise reduction methods were adopted to remove noise from acceleration and angular velocity signals.

1. *Low-pass filter*

   From literature, human activity frequencies are between 0 and 20 Hz, and the frequency range of human body motion is within 10Hz[51]. While the noise generated by IMU sensor system or in the measuring environment is high frequency. A 4-order butter-worth lowpass filter was used in this study. A cut-off frequency of the low-pass filter is selected to 20Hz to attenuate noise with higher frequency than the cut-off threshold. In this way, acceleration and angular velocity signals contain the main characteristics of tennis stroke motion are retained.

2. *Zero-phase digital filter*

   Zero-phase filtering helps preserve signal features in a filtered time waveform exactly where they occur in the unfiltered signal. And it could reduce noise in the signal and generate a clear and smooth waveform of the signal.

3. *Wavelet analysis*

   Wavelet analysis or wavelet transform is a critical analytical method in the field of signal processing. It has found engineering applications in computer vision, pattern recognition, signal filtering. Wavelet denoising technique is popular for processing biomechanical and biomedical signals like acceleration signal and EMG/ECG signal nowadays. The conclusion of Wachowiak et al. is that wavelet-based noise removal techniques are very effective in removing noise from differentiated signals with sharp transients[52]. And Wavelet filter has the added advantage that it is fast and easy to implement through MATLAB Wavelet Toolbox.

By programming script in MATLAB, three noise filter methods above were implemented to all data signals by using *lowpass*, *filtfilt* and *wdenoise* function. In order to show the changes in the signal before and after the noise reduction, a comparison plot of the x-axis acceleration data of one trial is generated in *Figure 4.3*. From the figure, by comparison, raw signal with denoising signal, exaggerated peak value and vibration are eliminated through denoising procedure. And in a zoom-in perspective, the signal waveform after noise reduction is quite smooth than the raw data signal.

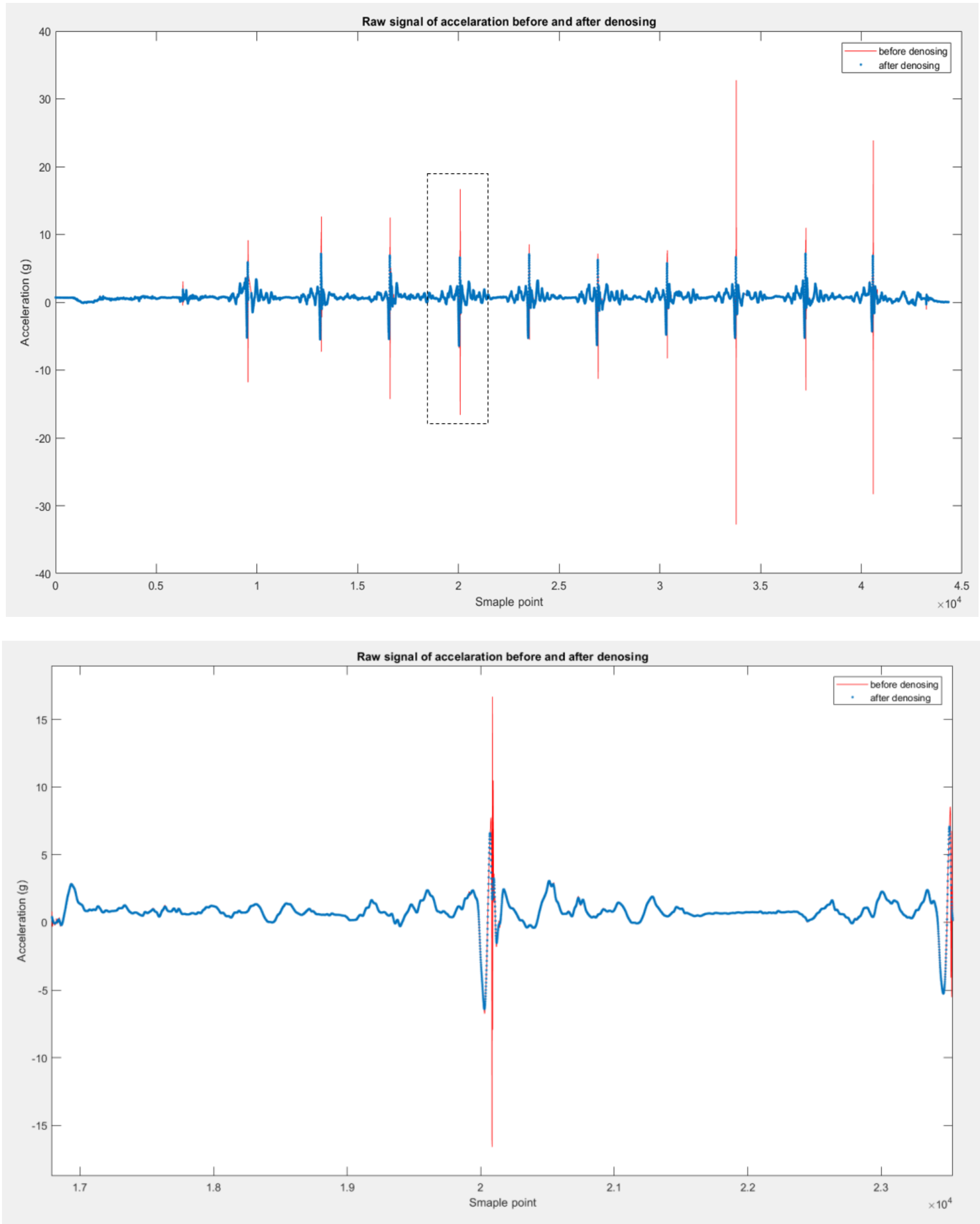


Figure 4.3 Comparison of sample signal before and after denoising

4.2 Stroke detection & Window segmentation

All data signals of movement of players were recording in real-time continuously, which means not only motion data of tennis strokes but also other motion data like waiting, preparation, and step move were fully contained in one signal data stream. To perform tennis stroke motion detection and classification, the signals must be adequately partitioned so that the main representative data only for tennis strokes can be distinguished from other motion data. In this study, window segmentation is implemented and benefited by combing with tennis stroke detection method. It is also called event-defined window segmentation.

4.2.1 Stroke detection

The IMU sensor attached to the dominant arm of players registered a peak acceleration. In recording data, the number of peak accelerations also indicated the number of tennis strokes. By detecting such data-spikes in acceleration signals provided the temporal location of tennis strokes. To get the resultant acceleration magnitude of every sampling point, the length of the 3D acceleration vector is calculated simply.

$$A_m = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

By programming in MATLAB, we could plot resultant acceleration magnitude in time-serious, for example, one of the resultant acceleration magnitude signals of one trial is shown in *Figure 4.4.* We may find out that there are five tennis strokes in this acceleration signal. By implementing *findpeaks* function in MATLAB[53], local peaks of the input signal were returned and additionally, the indices (time in our case) at which the peaks occur were obtained at the same time. For example, the peak values and time indices that were found out in *Figure 4.4* represent the stroke points in this acceleration signal. Additionally, to avoid find redundant peaks and irrelevant peaks, the minimum threshold of acceleration magnitude and the time interval between peaks were pre-set to find the real peak for tennis strokes respectively. In this case, the exact orientation of IMU is irrelevant, which makes the system more robust.

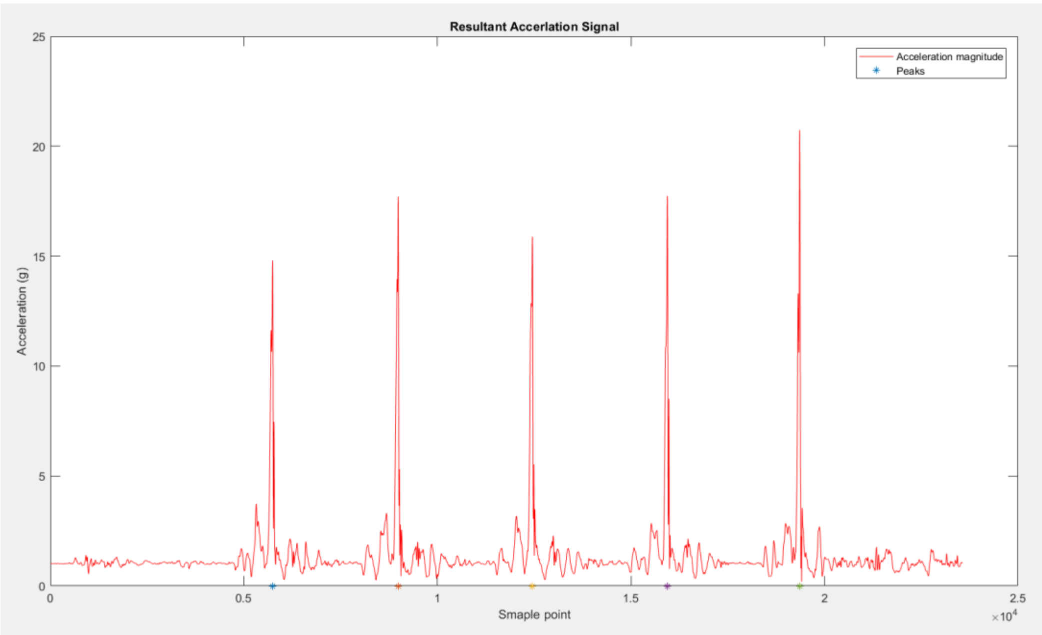


Figure 4.4 Sample resultant magnitude of acceleration and the found peaks

4.2.2 Window segmentation

From stroke detection to acceleration data signals, the positions of tennis strokes were located. Empirically, the window size of 1s has information to describe tennis strokes sufficiently, avoiding additional movement motions before and after tennis strokes. To fill the window with useful data and remove any irrelevant information, the stroke points were put at the centre of window. For each stroke point, a time extending 0.5s to either side of the stroke was considered to form one observing window. Taking a signal for example, as shown in *Figure 4.5*.

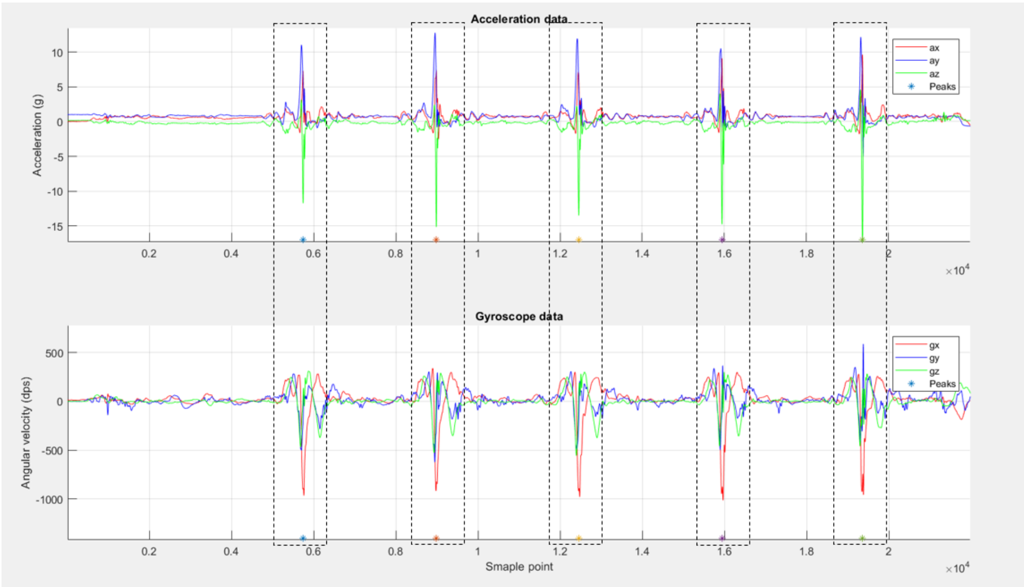


Figure 4.5 Window segmentation to sample signal

This sample signal contains both 3-axis acceleration data and 3-axis angular velocity data. The detailed window segmentation procedure is described as follows:

1. By finding peak points of resultant acceleration magnitude, tennis strokes of this signal were located. Peak values and location time were obtained;
2. For one tennis stroke point t, a time interval [t-0.5s, t+0.5s] was chosen to form the corresponding observation window. The sampling frequency of IMU sensor was around 560 Hz, which means there were 561 sample points for one single signal;
3. For each window, it contained 3-axis acceleration data and 3-axis angular velocity data. Totally, there were approximately 3366 sample data points for every window.

4.3 Feature selection & extraction

During data processing period of human activity recognition and classification, feature selection and extraction are affected greatly by subjective factors of the researcher. As mentioned in Chapter 2, there are many features that could represent the characteristics of signal data distributing in the time domain, frequency domain, and discrete representation domain. In order to better describe the representative characteristics of tennis stroke signals, features in both time domain and frequency domain were selected in this study.

4.3.1 Feature selection

In this study, both time domain and frequency domain features were selected to extract and form the feature vector to feed the classification algorithm. The selected features are shown in *Table 4.1*.

Table 4.1 All selected features in this study.

	Time-domain	Frequency-domain
Feature name	Mean, Covariance, Skewness, Kurtosis, Maximum, Minimum	Magnitudes of fast Fourier transform coefficients; Spectral energy

Mean, with a small computational cost, can describe the speed of players' tennis strokes. And covariance stands for the stability of the players' stroke motion. As for maximum and minimum, they often used to combine with covariance to discriminate distinctly different tennis strokes. And skewness of acceleration and angular velocity signal represents the instantaneous explosive force of performing tennis strokes of players. While kurtosis describes the situation of stroke force of motion signal. In terms of frequency-domain features, the magnitudes of fast Fourier transform (FFT) coefficients and spectral energy indicate the situation of tennis stroke energy of players. They can distinguish different strokes with similar acceleration and angular velocity from the internal relation of energy level.

4.3.2 Feature extraction

To time-domain features, mean, covariance, skewness, and kurtosis were statistical functional metrics while maximum and minimum were envelope metrics. All of them were mathematical metrics that were calculated by the corresponding function in MATLAB. As for frequency domain features like FFT coefficients and spectral energy, in order to drive those features, firstly, the windows of all signal data of IMU sensors which were all in time domain must be transformed into the frequency domain, using the fast Fourier transform method. After that, the results of fast Fourier transform typically performed a set of basis coefficients which represented the amplitudes of the frequency components of signals. And the spectral energy of the windows in signal data was computed as the squared sum of its spectral coefficients normalized by the length of the sample window. These FFT spectral features were named energy metrics.

All seven features were extracted for both acceleration data and angular velocity data from each sensor of IMU sensor system. Acceleration and angular velocity data both consisted of 3 component signals in three directions. Beyond these six signals, two synthetic signals of resultant acceleration and angular velocity were considered in this study. By fusing all features together, the dimensionality of the feature vectors was 56 (7 features × 8 signal waveforms). It means that for each window, there were 56 features that could describe the characteristics of the window. For all training data and testing data, a training data matrix of features and a testing data matrix were formed to feed the machine learning algorithm. Before feature extraction, all features needed to be normalized to a specific range [0, 1]. This is because, for instance, many classifiers calculate the distance between two points by the Euclidean distance[54]. And if the selected features have a broad range of values, the distance will be governed by some particular features, which will result in bias. Therefore, all selected features in this study were normalized to [0,1], so that each feature contributes approximately proportionately to the classification.

With tennis strokes in all training data and associated signal features identified, the last stage of data processing required that detected strokes from training data signals be assigned with the true tennis stroke labels. The label matrix for training data was an important input for the training classification model. In this study, the label for tennis strokes is listed in the following *Table 4.2*.

Table 4.2 Numbering and labels for tennis strokes.

Numbering	Name of tennis stroke	Label
1	Backhand slice	BHS
2	Backhand topspin	BHT
3	Backhand volley	BHV
4	Forehand slice	FHS
5	Forehand topspin	FHT
6	Forehand volley	FHV
7	Smash	SM
8	Serve	SR

Due to the training dataset is designed especially for this study, the false tennis stroke is eliminated in data screening procedure and tennis stroke detection. In the classification process, there is no need to consider false strokes.

4.4 Machine learning algorithm

An extremely powerful machine learning technique known as the Support Vector Machines is introduced. It is one of the best "out of the box" supervised classification algorithms[55]. In this study, SVMs are used to train supervised learning models with associated learning algorithms that analyse testing data for tennis stroke classification. In the following part, a short demonstration was made to introduce the principle of support vector machines and how to apply it in this study.

From literature, the SVMs algorithm is an extension of the support vector classifier, combing with the theory of the kernel method[58]. The support vector classifier can solve the problem of linear boundaries classification with two classes. In this case, the support vector classifier is also regarded as a non-probabilistic binary linear classifier. However, in the input feature space, the data points will not always be split by linear boundaries. In addition to performing linear classification, SVMs has the ability to perform a non-linear classification using kernel method or kernel trick, implicitly mapping the input feature points into high-dimensional feature spaces. We will look into support vector classifier, kernel trick and SVMs in multi-class classification respectively.

4.4.1 Support vector classifier

The support vector classifier is originally applied to solve dichotomous classification problems. If we consider a classification problem with 2-class and linear boundaries, as shown in *Figure 4.6.* In the left panel, the training data are linearly separable while the case that the training data are not distributed linearly in the right panel. In general, many possible decision boundaries, as called hyperplane in SVMs, can classify data regardless of the classification results. As can be seen in the left part from the figure below, H_1 cannot separate the classes, H_2 separates the classes but with a small margin, but H_3 achieves the classification task with the maximal margin. This maximum-margin hyperplane, also called hard-margin, is the one we could obtain from the support vector classifier. In principle, one that represents the largest margin between the two classes makes the best hyperplane reasonable. The found the best option of hyperplane is called the maximum-margin hyperplane or optimal hyperplane while this support vector classifier is known as a maximum-margin classifier.

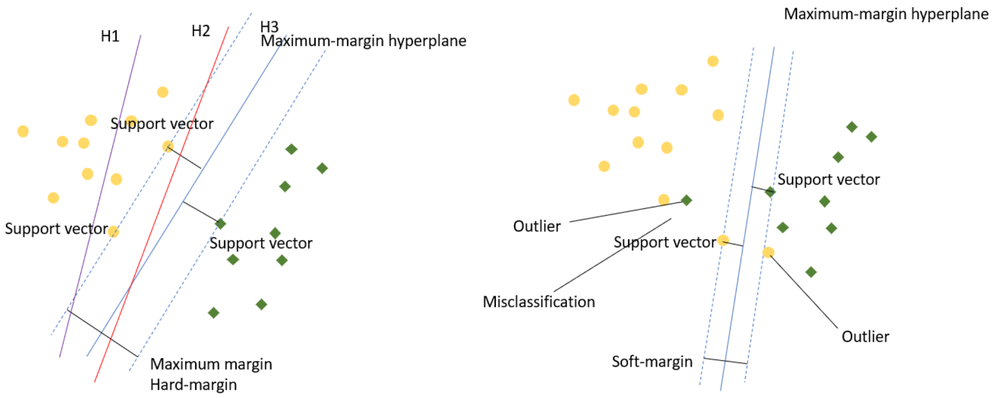


Figure 4.6 A linear boundaries classification with 2-class (left-data linearly separable; right-data linearly inseparable)

Besides, in a linearly inseparable data situation, there exist outliers in training data. Maximum margin classifiers are super sensitive to outliers and that makes them incapacitated in classify linearly inseparable data. To have a hyperplane that is not so sensitive to outliers, the support vector classifier allows misclassifications, which is shown in the figure above on the right. As it allows misclassifications, the distance between the hyperplane and the observation data is called soft margin. Cross-validation method is used to determine how many misclassifications and observations to allow inside of the soft margin to get the best classification. The name support vector classifier comes from the fact that the observations on the edge and within the margin are called support vectors. The mathematical computational details of support vector classifiers are provided in Appendix 3.

4.4.2 Kernel trick

In the above, linear boundary classification problems are already discussed by applying support vector classifier. However, the data points in the input space will not always be located by linear boundaries in the same space. For example, the data points are split non-linearly in *Figure 4.7.*

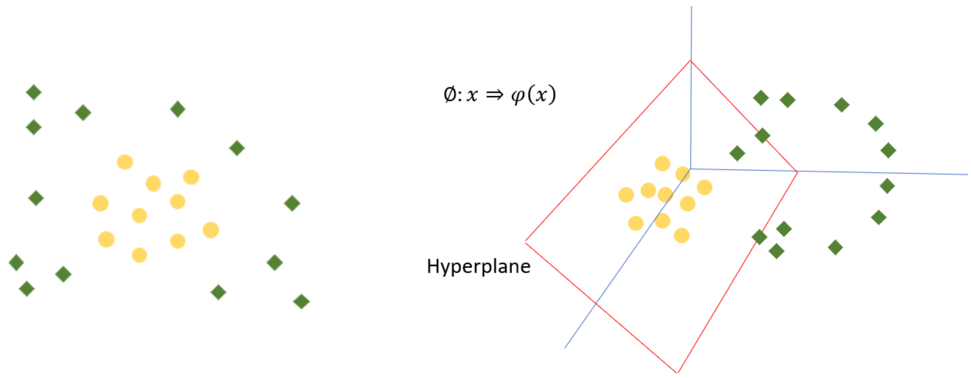


Figure 4.7 Non-linear boundary classification problem

The idea to solve non-linear boundary classification situations is to transform the data from the input space (the original attributes of the upper example, left part) to a higher dimensional space using a function $\phi(x)$. In this way, linear decision boundaries are sought in the high-dimensional feature space, which is shown in the figure above the right side. And the advantage of the transformation is the linear operations in the feature space are equivalent to non-linear operations in the input space. Besides, during the transformation, only the inner product of the original input data is needed.

Kernel functions enable them to operate in a high-dimensional, implicit feature space with simply computing the inner products[59]. In the field of SVMs, this approach by using kernel functions is the kernel trick. There are many popular kernel functions such as linear kernel, fisher kernel, polynomial kernel, and radial basis function kernel. Here in this study, the Neural Network (sigmoid) kernel function was constructed in SVMs for tennis stroke classification.

Additionally, the details of mathematical computations of kernel tricks and the functions of popular kernel methods are shown in Appendix 4.

4.4.3 Multi-class SVMs

In this study, all eight types of tennis strokes need to be classified by applying SVMs. This involves the classification problems of multiclass SVMs. It aims to assign labels to instances by using support vector classifiers, where the labels are drawn from a finite set of training data. While SVMs are fundamentally designed as two-class classifiers as mentioned in the previous subsection. The dominant method for multi-class SVMs is to reduce one single multiclass classification problem into multiple binary classification problems[60]. Here three most commonly used methods for multiclass reduction are introduced as follows. And the detailed information for the principle of multi-class SVMs is in Appendix 5.

1. One-versus-all (OvA)[61].
   OvA builds binary classifiers that distinguish one of the classes and the rest. When N is the number of classes or labels, N classifiers are constructed in OvA strategy, and each of them separates one class from the rest of the N-1 labels. The results of the new testing data classification for OvA are decided by a winner-takes-all strategy. A new instance will be tested on all of the N classifiers and it will be assigned to the one with the highest-output function (or largest decision value).

2. One-versus-one (OvO)[61].
   OvO is to design a binary classifier between every pair of classes, to N classes classification, $\frac{N(N-1)}{2}$ classifiers are built. To the results of new instance classification, it follows the max-wins voting strategy, in which every classifier assigns the new instance to one of the two classes, also known as voting. In the end, the new instance will be classified to the most frequently predicted class. Compared with OvA, OvO is quite computationally intense, but it has been shown to provide robust classification results with SVMs classifiers[56][57][58].

3. Error-correcting output codes (ECOC)[62].
   ECOC is used as an output representation for multi-class classification tasks. The main idea is to define a series of code words with M bits for each of the N class categories in advance. When classifying, it is only needed to compare the distance measure between the sample to be classified and each string of codes. And ECCO has a significant advantage of being able to correct errors by using some redundant "error-correcting" bits[62]. In this case, some errors are introduced by finite training samples, poor choice of input features, and flaws in the training algorithm can be tolerant. In this study, ECOC was implemented in multi-class SVMs.

4.5 Algorithm evaluation

For the evaluation procedure, a leave-one-out cross-validation strategy is used in this study. First, the feature samples of 7 subjects are divided into 7 parts according to different players. Then, for each time, we leave the feature samples of one subject to be the testing data and the other parts of the data of the rest subjects as the training data. After the classification, the true labels of the leave-out subject compared with the predicted labels from the SVMs model trained by 7 subjects. This evaluation method iterates for every part. Essentially, the leave-one-out validation method is equal to a special seven-fold cross-validation. The final result can be obtained by calculating the average classification rate of every fold. The below will show the process of leave-one-out cross-validation more intuitively.

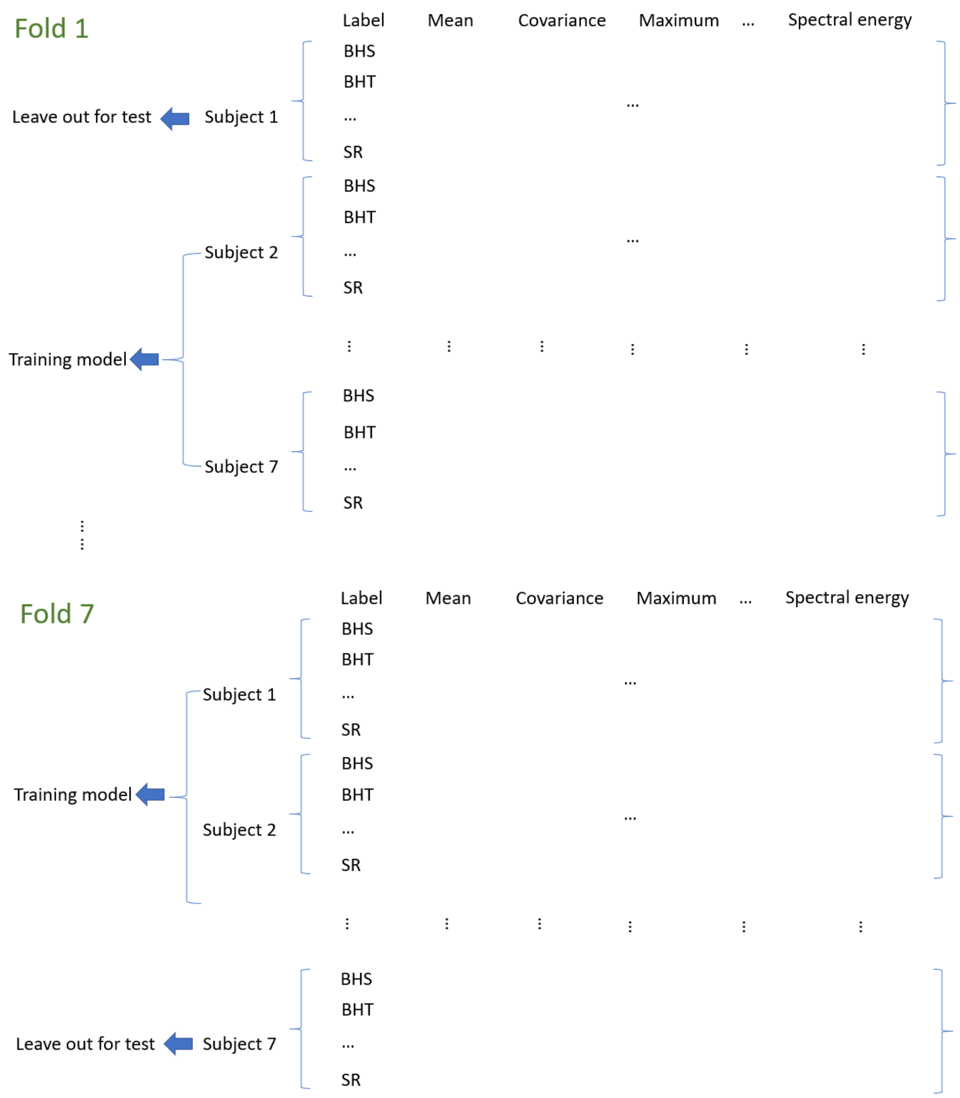


Figure 4.8 Seven-fold cross-validation method

4.6 Model training & Prediction assessment

4.6.1 Train multi-class SVMs model

After evaluating the SVMs algorithm of our case, there came to the final classification step. We trained the SVMs classification model with the training data matrix of feature vectors and true labels. After obtaining the SVMs classification model, we predicted the labels of testing data by feeding the testing data matrix of feature vectors to the classification model. All training and testing procedures were implemented by programming MATLAB script with SVMs Toolbox. To achieve reliable prediction results and deep discussion about our tennis stroke classification method based on IMU sensor and SVMs. There are three main parts of the model training period.

To obtain a dialectical comparison of the classification results with SVMs, we trained the SVMs classification model and validated the model with data from IMU sensors on forearm and upper arm respectively.

In the next stage, by statistics from window segmentation, there were around 300 tennis strokes as training data and 200 as testing data. To some extent, the training data was at an insufficient level compared with testing data. To validate SVMs algorithm with proper training data, half of the testing data with true labels were put into training data to train SVMs model. In this way, we could find out whether the magnitude of the training data affects the results of SVMs classification. And the training efficiency of SVMs model was verified in this part.

In the last part, both datasets from IMU sensors on forearm and upper arm were used to train the SVMs classification model. We introduced the data fusion method by combing feature vectors of training data, testing data to validate SVMs algorithm and to check if the accuracy of prediction was affected by data fusion from different IMU sensors.

4.6.2 Classification results and assessment

We trained and validated SVMs model through three main stages with different training data from IMU sensors. Both validation and final classification results were analysed by the confusion matrix. It allows visualization of the performance of SVMs algorithm in the field of machine learning with the multi-class classification task. To make a prediction assessment, all final classification results were compared with the golden standard and silver standard. The detailed results, prediction assessment, and discussion are in the next chapter.

Chapter 5

Results

In this chapter, there are three main parts of SVMs model training. First, we train SVMs model with data from IMU sensor on the forearm and upper arm respectively. Both validation and classification prediction were executed to two training models. Next, for the same SVMs model from one sensor, we enlarged the training data by adding half of the testing data with true labels. In the last stage, combing forearm sensor and upper arm sensor by data fusion, a combined feature vector of training data and testing data were used to train and test a new SVMs model. Confusion matrixes for all validation and prediction results were provided.

To check the validation results and final prediction accuracy in an intuitive way, confusion matrixes were constructed in the following results display process. And precision (positive predictive value) and recall (sensitivity) were computed for each tennis stroke type. Precision presented the proportion of tennis stroke predictions that were correct, while recall denoted the proportion of actual stroke labels that were classified correctly. The calculation of accuracies reflected the reliability and precision of the validation of SVMs classification model and were the indicators of accuracy assessment of the prediction of final trained SVMs model.

5.1 Train SVMs with single sensor data

5.1.1 SVMs classification model with forearm sensor data

IMU sensor attached to the wrist is the most popular one for human sports activity recognition[16][21][32]. As for tennis strokes in this study, swing-motions of tennis strokes are nearly dominant by the upper extremity of players. The wrist, as the distal end of the upper extremity kinetic chain connected with the racket, reflects the motion of tennis strokes to the maximum amplitude with the most discriminative features. Thus, the training data from IMU sensor on the wrist was taken to train SVMs. And the testing data were used to feed the trained SVMs model to do classification.

Validation

Table 5.1 below shows an example of confusion matrix of results of SVMs validation with data from the forearm sensor. The full validation results are shown in Appendix 6.

Table 5.1 Confusion matrix subject1 was left out (forearm sensor)

Training data: 251 strokes					Testing data: 40 strokes					
Training time: 3326s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	4	1							0.8
	BHT		3							1.0
	BHV	1		4						0.8
	FHS		1		5					0.83
	FHT					6				1.0
	FHV		0	1			4			0.8
	SM							4		1.0
	SR					4	1	1	NaN	NaN
Recall		0.8	0.6	0.8	1.0	0.6	0.8	0.8	NaN	
Accuracy = 0.75										

The average accuracy of SVMs validation with the forearm sensor is 0.69$\pm$0.1. “NaN” indicates that there is no input training data for this type of tennis stroke of the subject.

Classification

Table 5.2 Confusion matrix of SVMs model Prediction (forearm sensor)

Training data: 291 strokes					Testing data: 218 strokes					
Training time: 3747s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	10	2	2						0.71
	BHT		14							1.0
	BHV	1	5	5						0.46
	FHS		1		14	15		2	2	0.41
	FHT					74			6	0.94
	FHV				6	1	19			0.73
	SM					3		3	1	0.43

	SR					18		1	13	0.42
Recall		0.9	0.64	0.71	0.7	0.67	1.0	0.5	0.63	
Accuracy = 0.69										

5.1.2 SVMs classification model with upper arm sensor data

The training data from the IMU sensor on the upper arm was taken to train SVMs. And the testing data was used to feed the trained SVMs model to do classification. Processed from consideration of controlled variable method for scientific research, feature vectors of training and testing data were extracted from the same windows of tennis strokes by using data from upper arm sensor. And the numbers and labels of training and testing strokes were exactly equal to the SVMs model with forearm sensor data.

Validation

Below *Table 5.3* shows an example of confusion matrix of results of SVMs validation with data from upper arm sensor. The full validation results are attached in Appendix 7.

Table 5.3 Confusion matrix subject1 was left out (upper arm sensor)

Training data: 251 strokes					Testing data: 40 strokes					
Training time: 3217s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	4		1						0.8
	BHT		3							1.0
	BHV	1	2	4						0.57
	FHS				4	1	1			0.67
	FHT					5				1.0
	FHV				1	3	4			0.5
	SM							3		1.0
	SR					1		2	NaN	NaN
Recall		0.8	0.6	0.8	0.8	0.5	0.8	0.6	NaN	
Accuracy = 0.675										

The average accuracy of SVMs validation with forearm sensor is 0.67±0.04.

Classification

Table 5.4 Confusion matrix of SVMs model Prediction (upper arm sensor)

Training data: 291 strokes					Testing data: 218 strokes					
Training time: 3772s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	9	1							0.9
	BHT		13							1.0
	BHV	2	8	7						0.41
	FHS				17	5	5			0.63
	FHT					79			2	0.97
	FHV				3	1	14			0.78
	SM					3		3	9	0.2
	SR					23		3	11	0.3
Recall		0.81	0.59	1.0	0.85	0.71	0.74	0.5	0.5	
Accuracy = 0.70										

5.2 Train SVMs model with enlarged training data

In this part, we enlarged former training data by using half of the testing data and their true labels in previous model. The testing data were chosen randomly and their feature vector was put into feature vectors of original training data. And the label of new training data was revised according to the appropriate order. At last, we trained the SVMs model with enlarged training data for both forearm and upper arm sensors. The confusion matrixes of their classification results are shown as follows.

Table 5.5 Confusion matrix of SVMs model Prediction with enlarged training data (forearm sensor)

Training data: 390 strokes					Testing data: 119 strokes					
Training time: 3945s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	7								1.0
	BHT		7							1.0
	BHV		2	5						0.71
	FHS				7					1.0
	FHT				1	44	1		4	0.88
	FHV				2	4	12			0.67
	SM					1	1	NaN		NaN
	SR					11	2		8	0.38
Recall		1.0	0.78	1.0	0.7	0.73	0.75	NaN	0.67	
Accuracy = 0.75										

Table 5.6 Confusion matrix of SVMs model Prediction with enlarged training data (upper arm sensor)

Training data: 390 strokes						Testing data: 119 strokes				
Training time: 3912s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	5								1.0
	BHT		9							1.0
	BHV	2		5						0.71
	FHS				8					1.0
	FHT				2	46	1			0.94
	FHV					4	13		1	0.72
	SM							NaN	4	NaN
	SR					10	2		7	0.36
Recall		0.71	1.0	1.0	0.8	0.76	0.81	NaN	0.58	
Accuracy = 0.77										

5.3 Train SVMs model with data fusion of two IMU sensors

In this part, the idea of data fusion was verified by combing data from IMU sensors on the forearm and upper arm. The new feature vectors of training data and testing data were built by matrix fusion of original feature vectors of training and testing data from each sensor. Here we also trained the SVMs model with enlarged training data. The confusion matrixes of the prediction results are shown below.

Table 5.7 Confusion matrix of SVMs model Prediction (data fusion)

Training data: 291 strokes						Testing data: 218 strokes				
Training time: 3967		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	9	5	1						0.6
	BHT		17							1.0
	BHV	2		6						0.75
	FHS				16	1	1			0.89
	FHT				4	85			11	0.85
	FHV					4	14			0.78
	SM					2	4	4		0.4
	SR					19		2	11	0.34
Recall		0.81	0.77	0.86	0.8	0.76	0.74	0.67	0.5	
Accuracy = 0.74										

Table 5.8 Confusion matrix of SVMs model Prediction with enlarged training data (data fusion)

Training data: 390 strokes						Testing data: 119 strokes				
Training time: 4012		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	5								1.0
	BHT		9							1.0
	BHV	2		5						0.71
	FHS				7					1.0
	FHT				1	48	1		4	0.89
	FHV				2	3	12			0.71
	SM						1	NaN		NaN
	SR					9	2		8	0.42
Recall		0.71	1.0	1.0	0.7	0.8	0.75	NaN	0.67	
Accuracy = 0.79										

Chapter 6

Discussion

This chapter presents in-depth discussion and findings by exploring and analysing the results from the last chapter. By comparing our results with literature, we can conduct the advantages and deficiencies of this study in field of human sports activity recognition.

The aim of this study was to develop an automated and comprehensive tennis stroke recognition method based on IMU sensors and SVMs machine learning algorithms. Both acceleration and angular velocity signals of four parts (forearm, upper arm, trunk, and pelvis) of the player's upper extremity were recorded by a self-made IMU sensor system consists of a 3-axis accelerometer and a 3-axis gyroscope. Detailed data processing procedures were implemented to refine the data to representative feature vectors which could describe the characteristics of different tennis strokes and be used to distinguish eight types of tennis shots. And we trained the classification models through the SVMs algorithm and validated the models by leave-one-out strategy. Finally, confusion matrixes were used to visualize the prediction results and accuracy assessment, which were shown in detailed in the last chapter.

When the SVMs models were trained with data from a single IMU sensor on the forearm and upper arm respectively, the classification accuracies of SVMs algorithm across seven-fold leave-one-out validation of forearm and upper arm sensor are 0.69 ± 0.1 and 0.67 ± 0.04. In general, the results indicate the SVMs algorithm does not work exceptionally well when trained on data from a single sensor. Compared with Whiteside et al. results, they had indeed extreme good classification accuracy results of SVMs across 10-fold cross-validation, 97.43 ± 0.24 for 4 basic shot classes and 90.36 ± 1.08 for 9 shot classes[32]. The good classification accuracy of their work is due to a large group of subjects which are all 20 elite tennis players and sufficient training data around 30.000 shots. Noticeably, when the classification requirement comes to 9 shot classes, the validation results also has a large decrease. For our study, on one hand, not only elites but also amateurs, 7 subjects in total, were involved in this study, different level of tennis skills of players increased the uncertainty in data samples, which can be seen from the manifest differences of accuracy between every subject during leave-one-out validation. It makes the SVMs model trained by data from signal IMU sensor a bit extent of user-dependent. Büthe et al. faced the same problems as in the current study. In their study, the data of 4 subjects were recorded and validated, resulted in a classification accuracy 0.47±0.3[23]. Compared with their study, the classification method that we proposed is relatively reasonable and accurate. To the rest, less literature about tennis classification claimed the results of algorithm validation but only the results of final prediction accuracy.

As for the final prediction assessment, the accuracies of SVMs classification model with forearm and upper arm sensor data are 0.69 and 0.70 for 8 types of tennis strokes respectively. The results are predictable according to the previous validation accuracy. To our knowledge, White et al. is the only previous study that has attempted to discriminate such detailed stroke classification, achieved the best results 0.97 for 4 shots classification and 0.93 for 9 shots classification. While Büthe et al. obtained a general accuracy of prediction 5 types tennis strokes around 0.79 and Kos et al. made three basic shots classification with 0.96 accuracy. Because it is a more difficult multi-classification problem with a small training dataset, it is acceptable to have a final prediction accuracy around 0.7 in stage one. According to the precision and recall values, the greatest likelihood of misclassification happened within a subtype of tennis strokes (slices and volleys). As can be seen that, even if the subtype of strokes was predicted incorrect, the side of swing was recognized right. It may explain why prediction accuracy was superior high for basic tennis strokes classification (forehand, backhand and serve) in the previous study. And this is confirmed by the results of Zepp sensor we used in study. It had a high precise classification of 92.7% to five types of tennis stroke except for volley. Moreover, from the confusion matrix, among 218 testing strokes, forehand topspin (111 shots) accounts for the majority of all types of tennis strokes, backhand slice, backhand topspin, forehand slice, and forehand volley are around 20 shots. Backhand volley and smash are the least two shots groups with 7 and 6 shots. All these numbers mean when encountering the real or simulated rally games, players have the trend to perform the type of tennis stroke that they are familiar with, forehand topspin in this study. And subtypes like slice, volley and difficult skills like smash were not performed so much. Thus, with the insufficient training data, the precision and recall value of strokes with a small number is not very persuasive. As for forehand topspin, the average recall of 0.75 and precision of 0.95 for a single IMU sensor could be able to show the prediction accuracy of the SVMs algorithm.

From the comparison perspective between IMU sensors, results of validation and final prediction from SVMs models trained by data from forearm and upper arm sensors are almost the same. This part has not been done in the previous study to our knowledge. The existing literature about tennis stroke classification using SVMs algorithm only used one single IMU attaching to player's wrist (forearm). Here in this study, we trained SVMs classification model through training data from forearm and upper arm sensor, while the results present there is not much difference when using IMU sensor data on forearm and upper arm. This may be because that forearm and upper arm are both located at the distal part of upper extremity compared with trunk and pelvis. Sensors on these two parts could reflect the motion of swing to the maximum amplitude with the most discriminative features which can be used to distinguish different types of tennis strokes. We have not trained the SVMs model with data from trunk and pelvis sensor in this study. The conclusion of data from different attachment places of IMU sensor on the upper extremity may have an effect on the training effect of SVMs that cannot be drawn. We can only know from this study that IMU sensors on forearm and upper arm both have the ability to provide enough data information to train SVMs classification models respectively. And the training effects and prediction accuracies of SVMs model with data from forearm and upper arm are almost the same.

At last, the training time of SVMs algorithm is another important vector need to be considered in this study. The mean and standard deviation of the training time of SVMs in stage one including validation and prediction process is 3391 ± 195s. It means that one entire training and testing with SVMs algorithm costs around one hour. Most literature about tennis stroke classification has no clear claim about time cost when using different machine learning algorithms. Wang et al. listed the time cost of different classification algorithms when dealing with badminton shots classification study[16]. Among several popular machine learning algorithms, SVMs algorithm costs the longest training time. Similarly, there cost around one hour to training every SVMs model in this study. We could conclude that the time cost of SVMs algorithm is quite large.

When enlarged training data were built to feed the same SVMs classification models from forearm sensor and upper arm sensor respectively, an increased prediction accuracy from 0.69 to 0.75 is achieved for SVMs model trained by forearm sensor, while for the model trained by upper arm sensor, the accuracy of prediction also rises from 0.70 to 0.77. This further illustrates that the magnitude of training dataset has a large effect on the training results of SVMs model and the prediction accuracy. By looking into the confusion matrixes, the precision and recall values of subtype like slice and volley are all slightly improved, which indicates the proportion of predictions and proportion of actual strokes are predicted right is slightly increased. “NaN” of smash means all six smashes were selected to put into training data, there is no smash for the new testing data in the case of enlarged training data. Noticeably, the prediction results of serve are still lower than the average level of recall and precision of other tennis strokes. By statistics, in stage one, 20 serve shots were trained through SVMs model and 22 serve shots were tested, while 30 serve shots were trained and 12 were tested in enlarged training data case. Even the training data was enlarged, but still few serve strokes were feed to train SVMs model. This is why the prediction accuracies of serve before and after the enlarged training data were not improved significantly.

But from a general point of view, the prediction assessment performance has been improved for both SVMs models (trained by forearm and upper arm sensors) with the enlarged training dataset. Therefore, we believe that with a larger dataset of all eight tennis strokes of more subjects, we will be able to train better SVMs classification model, allowing for a user-independent approach to predict all types of tennis strokes. But as mentioned in the last discussion part, the magnitude of the training dataset also affects the time cost of a training prediction model with the SVMs algorithm. Thus, there exists a trade-off between prediction accuracy and time costs.

At last, the idea of sensor fusion for training SVMs model was achieved by fusing data from forearm and upper arm sensors in this study. With the original training data of 291 strokes, the SVMs model trained by fused data achieved a prediction accuracy of 0.74. While with the enlarged training data, it obtained the best accurate prediction 0.79 in this study. In the former condition, six subtypes of tennis strokes both forehand and backhand (except serve and smash) have relatively high recall of 0.80 $\pm$0.04 and precision of 0.82$\pm$0.13. As for the SVMs model with data fusion, trained by enlarged training data, the recall and precision values of six subtypes of tennis strokes are 0.83 ± 0.13 and 0.89 ± 0.14 respectively. There exists no literature applying the idea of data fusion to tennis stroke recognition and classification study. Wang et al. applied data fusion from different IMU sensors (attached on the right and left wrist, waist, and right ankle) to badminton shots classification used several machine learning algorithms[16]. They have drawn the conclusion that the IMU sensor plays the dominant role when providing discriminative data information among those four sensors. And most importantly, data fusion from different body-attached IMU sensors could provide better results for recognizing different badminton strokes. Similarly, we draw the conclusion that data fusion by using both forearm and upper arm sensor can feed better to train SVMs classification model and improve the prediction accuracy to some extent.

Beyond that, we also find that low values of recall and precision of serve and smash shots appear in the confusion matrix of the new SVMs classification model trained with original and enlarged training data. This special situation also happened in the previous SVMs model. Therefore, we can conclude that data fusion with different sensor data cannot compensate for the shortcomings caused by insufficient training data. The insufficient training data for all types of tennis strokes in this study was the lapse in data acquisition.

In summary, we first trained the SVMs classification model by using data from single IMU sensors on the forearm and upper arm respectively. The accuracy results of validation for the trained two SVMS models are 0.69$\pm$0.1 and 0.67$\pm$0.04. And the results have large differences between individuals. The average accuracy results are not as precise as what we expected, which may because we only have few subjects and their skills of performing tennis strokes are not on the same level. It increases the bias of the trained SVMS model, reducing the accuracy results from validation. And due to the unstable performance of the IMU system itself, some of the data files were missing or inferior, as can be seen, the “NaN” in confusion matrixes. Generally, around 40 strokes for eight type tennis strokes for every subject were added to the SVMs model. Compared with some similar studies, the training data is quite small. The insufficient training data for SVMs model makes the classification accuracy results of validation less credible. For the final prediction assessment, these two SVMs classification models provide the final prediction accuracy of 0.69 and 0.70. Compared with similar tennis stroke classification study with a large group of subjects, the prediction accuracy in this study is not as high as their result. But our results have surpassed some peer results when involving fewer subjects and insufficient data.

To make further study, we trained both SVMs model with enlarged training data. Both of them result in improved final prediction accuracy to some extent. So we can conclude that the data of the IMU sensor attached to the forearm and upper arm can provide enough information to train SVMs classification models used for tennis stroke prediction independently. And sufficient training data affect the final prediction results. Moreover, we trained a new SVMs model by fusing data from the previous two SVMs model. It shows the best prediction accuracy of 0.79 in this study. Therefore, we draw another conclusion that SVMs classification model trained by fusing data from the forearm and upper arm IMU sensor helps to improve the prediction accuracy for tennis stroke classification.

Chapter 7

Recap & Future work

The objective of this study was the development and validation of a tennis stroke recognition and classification method based on the IMU sensor and machine learning algorithm. The experimental method and results of validation and classification were discussed in-depth in the previous chapters. This chapter provides an overview of the achievements of this study and the concluded outcomes and drawbacks from the discussed results in chapter 6. At last, some recommendations for further studies and the practical application of tennis stroke recognition and classification are presented.

7.1 Recap

- ***Previous works about tennis stroke recognition were reviewed from both commercial and scientific perspective.***
  Commercial tennis sensors have a wide range of applications, recoding and recognizing basic types of tennis shots. But the inner classification algorithms and the claimed accuracy of prediction are not clear and verified. Most of the scientific literature, similarly, are restricted to simple type of classification without subtype of strokes. Extremely high prediction accuracies (above 95.6%) were achieved by Whiteside et al., using several machine learning algorithms[32].

- ***The experimental method was designed to obtain motion data of tennis strokes with IMU sensors.***
  IMU system contains four sensors attaching to entire upper extremity was used to collect motion data from forearm, upper arm, trunk, and pelvis. Raw signals of motion data were divided into training data and testing data for every sensor. This is the first

time that a continuous sensor system attached to the kinetic chain of upper extremity was applied in tennis stroke classification task.

- ***Discriminative information for distinguishing different types of strokes was extracted through data processing procedures.***
  Screening and filtering procedures were implemented to raw data signals to filter out noise and smooth the waveform. An event-based stroke detection method was used to achieve window segmentation which contains representative and discriminative information used to distinguish tennis strokes. Consequently, eight data signals (3-axis acceleration, 3-axis velocity, resultant acceleration, and resultant gyroscope) and seven features (mean, covariance, maximum, minimum, skewness, kurtosis, spectral energy) formed the feature vectors which were fed the machine learning algorithm.

- ***SVMs algorithm was used to train classification model in machine learning process.***
  SVMs was introduced comprehensively in this study and used to train classification model for tennis strokes. To test and validate SVMs algorithm, there were three stages in training the SVMs model when using training data.

  1. Stage one: The SVMs model was trained by using data from single IMU sensor. The data from forearm and upper arm sensors were fed to train the classification model respectively in this stage. In previous work, IMU sensor on the wrist was the only option when collecting motion data[21][23][26][32]. Across leave-one-out seven-fold cross-validation, the accuracy results of validation and final prediction of those SVMs classification models were quite similar. Therefore, we have drawn the conclusion that IMU sensor on forearm and upper arm can both provide enough information to train SVMs model to classify tennis strokes.

  2. Stage two: Due to insufficient training data, the results in stage one were not as precise as we expected. Two SVMs classification models from stage one were trained with enlarged training data. The prediction accuracies were improved in both cases. Thus, we concluded that the SVMs algorithm is competent to achieve the goal of tennis stroke classification. And the magnitude of training data could affect the validation results and prediction accuracy of the model trained by SVMs. Moreover, we found out that the magnitude of training data and time costs is a trade-off problem.

  3. Stage three: To optimize the prediction accuracy of the SVMs model, the idea of data fusion was tested in this stage. This was also new for tennis stroke classification task, similar study has been done with badminton[16]. Data from forearm sensor and upper arm sensor was combined to form the new feature vector to feed SVMs algorithm. The new SVMs model was tested by original training data and the enlarged one. The best prediction accuracy of tennis stroke

in this study was 0.79, obtained by training data-fused SVMs model with the enlarged training dataset. We concluded that data fusion of different IMU sensors can improve the performance of SVMs classification model.

7.2 Deficiencies

- ***The group of subjects was small.***
  Only seven subjects were involved in this study. And their tennis skills were not at the same level (mixed with elites and amateurs), which brings the uncertainties of user-dependent to the validation results of the SVMs model.

- ***The sampling frequency was high.***
  The high sampling frequency resulted in that a window with 1s time interval of tennis strokes contains 561 sampling points, which increases the computational complexity when training the SVMs model. Consequently, the training time of SVMs model in this study was round one hour, which was quite time-intensive.

- ***Both the training and testing datasets of eight tennis strokes were small***
  Due to the instability of self-made sensor and flaws in arrangements, some of the data recorded were disabled or missing. Through the conclusion of stage two, insufficient training data affected the performance of SVMs classification model. Similarly, insufficient testing data with less magnitude of all types of tennis strokes could not ensure the confidence of prediction accuracy.

- ***Data from trunk and pelvis IMU sensors have not been used in this study.***
  The SVMs classification model has not been trained by using data from trunk and pelvis. We did not know how they performed when providing information for SVMs algorithm to train classification model compared with data from forearm and upper arm sensor. Moreover, data fusion for training new SVMs model only considered the combination of forearm and upper arm sensor. The other combinations were not included.

7.3 Recommendations for future work

From the work has been done in this study and the summary of deficiencies, we list some recommendations for future work to make a comprehensive classification of tennis strokes.

- ***Sufficient subjects and motion data of tennis strokes should be collected and tested.***
  A larger group of subjects with similar tennis skills (for example, all elite players) should be arranged. For each subject, both training and testing datasets need to be collected sufficiently. Moreover, if it is possible, collecting motion data when players deal with a real tennis rally or tennis training session. In this case, the collected motion data will be closer to the real tennis motion of movement. Additionally, a stable and reliable IMU sensor system is needed to record tennis strokes with a relatively low sampling frequency (100Hz may meet the requirements).

- ***Take every IMU sensor from sensor system into consideration.***
  Train SVMs model with data from four single IMU sensor respectively (forearm, upper arm, trunk, and pelvis). From which, we could know if all four IMU sensors on upper extremity have the ability to provide enough information for training SVMs classification model to distinguish different types of strokes. Additionally, train SVMs model through the data fusion method by using all combinations of four IMU sensors. With this study, we can find out the best combination of IMU sensors on upper extremity which could improve and optimize the prediction accuracy of SVMs classification model.

- ***Applying different machine learning algorithms.***
  The final objective of the study is to find the best way to achieve automated and comprehensive tennis stroke classification. Here in this study, SVMs is the only machine learning algorithm to be considered. In future work, more algorithms like kNN, ANN, HMM, and NB should be applied to train classification model by using the same training and testing dataset. The best machine learning algorithm can be decided for tennis stroke recognition and classification. It will benefit to the final goal of its practical application.

7.4 Practical application

The main application of the proposed tennis stroke classification method in this study is to provide guidance to develop a real-time and effective tennis stroke strategy and coaching system for both tennis amateurs and elites. This system will record every stroke and its type for users in training rallies or competition matches. From the results, the batting habit and coping strategy are investigated and analysed comprehensively, which will provide the players and coaches the guidance and advice to improve their performance and adjust different counterattack skills. Beyond that, with this collection and recognition system, a huge database of the user will be established. Through the statistics, the user can manage their training skills and detect the shortcomings when performing specific strokes from a long-term perspective.

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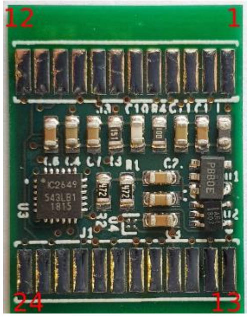
Appendices

Appendix 1: Information of Subjects

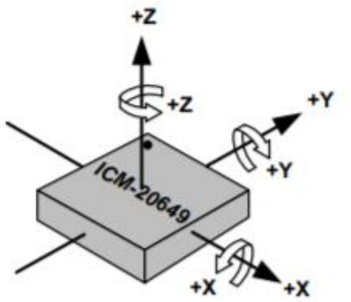
Subjects	Gender	Age	Weight (kg)	Height (cm)	Preferred Hand	Rank level (Dynamic Playing Strength System (DSS))	Years of playing tennis
PP01	Male	15	73	180.5	right	3	10
PP02	Male	22	72.5	190	right	5	14
PP03	Male	16	90	189.5	right	6	5
PP04	Female	20	57	160	right	4	8
PP05	Male	20	92.5	185	right	3	14
PP06	Female	20	54	172	right	4	11
PP07	Male	22	88.7	188	right	5	17

Appendix 2: Specification of IMU sensor system

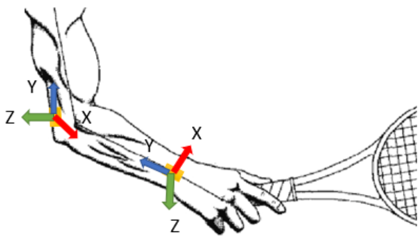
The IMU system consists of four sensor boards, each board has two type of sensors the icm20649 and the ak09918c.
The size of the board is 16x24mm.
The weight is of the sensor board is ~ 1 gram.
The icm20649 is a combined 3d +/- 30G accelerometer and a 3d +/- 4000dps gyroscope.
The ak09918c is a magnetometer.
The icm20649 is sampled around at ~575Hz.
The ak09918c is sampled around at 100Hz.
Here is a picture of one sensor board.



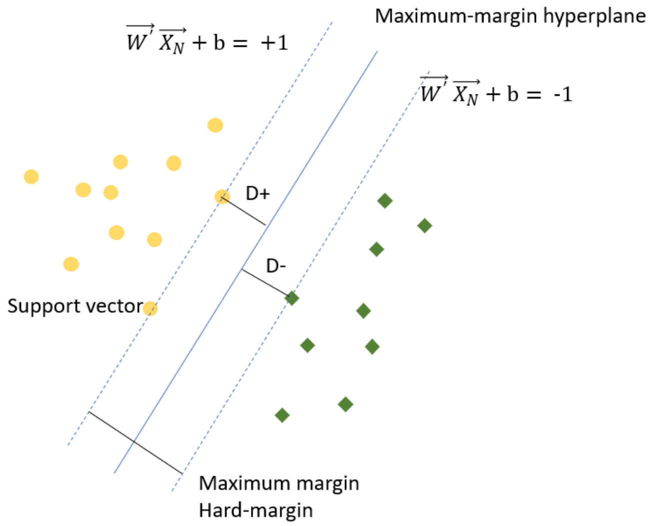
Datasheet of the icm20649 and the ak09918c are listed as follows:
https://www.invensense.com/wp-content/uploads/2016/06/DS-000192-ICM-20649-v1.0.pdf
https://www.akm.com/content/dam/documents/products/electronic compass/ak09918c/ak09918c-en-datasheet.pdf
The direction of IMU sensor is shown below.



The direction of IMU sensor on the forearm and upper arm is shown below.



Appendix 3: The mathematical details of the support vector classifier



Here we consider a two-class classification task. A training set T with N observation data (X_1, y_1), (X_2, y_2), …, (X_N, y_N), where $X_N \in R$, N = 1, …, N are the input features, and y_N = {-1, 1}, N = 1, …, N are the true label of class. If the two classes of points are linearly separable, then we assume there exist at least one hyperplane, defined by

$$\overrightarrow{W'}\overrightarrow{X_N} + \mathrm{b} = y_N \quad (2)$$

If the data to be classified exceeds their boundaries, then a good classification can be made. And we could get the following equations:

$$\begin{cases} \overrightarrow{W'}\overrightarrow{X_N} + b \geq +1, y_N = +1 \\ \overrightarrow{W'}\overrightarrow{X_N} + b \leq +1, y_N = -1 \end{cases} \quad (3)$$

For the convenience of expression, they can be formed to one equation.

$$y_N\left(\overrightarrow{W'}\overrightarrow{X_N} + b\right) \geq +1, N = 1,2, \dots, N \quad (4)$$

According to principle of support vector classifier, since the two classes are linearly separable, the best hyperplane could divide the two classes with large margin between the points on the boundaries. And the classification task is redefined as a problem to find the best hyperplane by calculating the largest margin.

The margin D is calculated as

$$D_N = \frac{\left|\overrightarrow{W'}\,\overrightarrow{X_N} + \mathrm{b}\right|}{\|\overrightarrow{W}\|} \tag{5}$$

As we already know that

$$\left|\overrightarrow{W'}\,\overrightarrow{X_N} + \mathrm{b}\right| == 1 \tag{6}$$

Then, we can deduce that

$$\mathrm{D} = \frac{1}{\|\overrightarrow{W}\|} \tag{7}$$

And

$$D_N = \frac{2}{\|\overrightarrow{W}\|} \tag{8}$$

Finally, we conclude a constraint equation as follows

$$\begin{cases} D_N = \dfrac{2}{\|\overrightarrow{W}\|} \\ y_N\left(\overrightarrow{W'}\,\overrightarrow{X_N} + b\right) \geq\ +1, N\ = 1,2, \dots, N \end{cases} \tag{9}$$

For the convenience of mathematical calculations, the above constraint equation is equal to

$$\begin{cases} D_N = \dfrac{\|\overrightarrow{W}\|^2}{2} \\ y_N\left(\overrightarrow{W'}\,\overrightarrow{X_N} + b\right) \geq\ +1, N\ = 1,2, \dots, N \end{cases} \tag{10}$$

After that, we use Lagrangian solve this constrained optimization task by introducing Lagrange multiplier.

$$\mathrm{L}\left(\overrightarrow{W}, \mathrm{b}, \alpha\right) = \frac{1}{2\|\overrightarrow{W}\|^2} + \sum \alpha_N \left(1 - y_N\left(\overrightarrow{W'}\,\overrightarrow{X_N} + b\right)\right) \tag{11}$$

Then we let $L(\overrightarrow{W}, b, \alpha)$ do partial derivative of $\overrightarrow{W}$ and b

$$\begin{cases} \overrightarrow{W} = \sum \alpha y_N X_N \\ 0 = \sum \alpha y_N \end{cases} \tag{12}$$

In the end, we will get

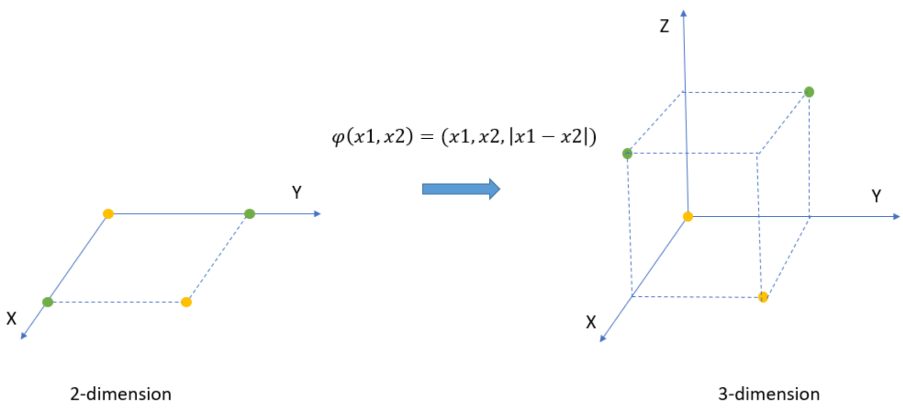
$$F(X) = \sum \alpha y_N X'_N X_N + b \tag{13}$$

After input of all data, the final best hyperplane can be obtained.

Appendix 4: The mathematical details of the Kernel method[58]

The support vector classifier can solve linear boundary 2-class classification task like mentioned in Appendix 3. However, in practical, the training data are located linearly separable in most of classification cases. To solve non-linear separable tasks, support vector classifier still uses linear boundaries, but in the high-dimensional feature space where all the input data in the original input feature space are mapped into by a transformation.

Let take an example for deep study. Set four input data points in R^2: (0,0), (0,1), (1,0), and (1,1), as can be seen in figure below. The 2 classes are indicated by different colour of points.



We cannot separate a 2-class classification task by linear boundary with input data points like this, while curve lane boundary will do. But this is not what we do in SVMs. In SVMs, we use a transforming function $\varphi(x)$ to map the data from the input space to a higher dimensional space. Like the one in example above,

$$\varphi(x_1,x_2) = (x_1,x_2,|x_1 - x_2|) \tag{14}$$

In this way, the four-input data is shifted to 3 dimensions. New data points are (0,0,0), (0,1,1), (1,0,1), and (1,1,0), which are shown in right part in the figure. From a 3-dimension perspective, we can easy to find out any plane which parallel to the x-y plane with z from 0 to 1 can be the hyperplane to classify the data. The advantage of the transformation is the linear operations in the feature space are equivalent to non-linear operations in the input space. Besides, during the transformation, only the inner product of the original input data is needed. It means that if the computational method of the product is defined, then, there is no necessary to explicitly build it.

In SVMs, for some classification cases, the formulas we use to transform input data ($\varphi: R^p \rightarrow R^q$) only through the form of its inner product are like

$$K(x, y) = \varphi(x), \varphi(y) \tag{15}$$

for all x, y $\in R^p$, then we do not have to transform all the data points. We can only work in the original input space through the newly defined kernel function K.

Several kernel functions are popular used in SVMs recently. Here list some of them.

1. Linear

$$K(x, x') = x^T x' \tag{16}$$

2. Radial Basis

$$K(x, x') = e^{-\gamma \|x-x'\|^2} \tag{17}$$

3. Neural Network (Sigmoid)

$$K(x, x') = \tanh(k_1 x^T x' + k_2) \tag{18}$$

4. dth Degree Polynomial

$$K(x, x') = (1 + x^T x')^d \tag{19}$$

Appendix 5: The principle of multi-class SVMs

Disassembly method: disassemble the multi-class classification task into several binary classification. And the classic strategy of disassembling multi-class SVMs are split, train, and integration.

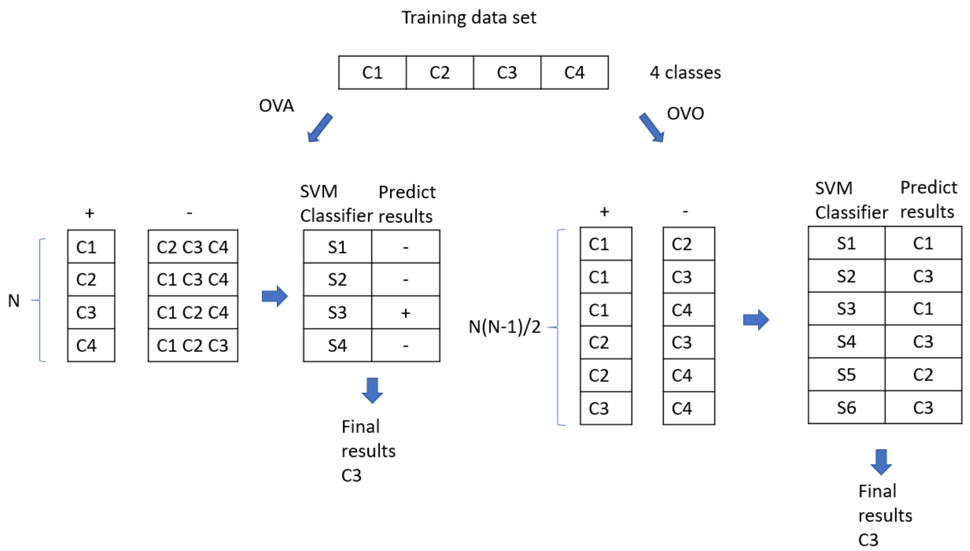
OVA

Take one of the N classifications as a positive label of a binary classifier and set the rest as negative examples. In this way, the multi-class task is divided into N binary classification tasks. The integrated method is to consider the confidence of each classifier that is judged as a positive example, and it selects a class label with a large confidence as the classification result. (If there is only one, choose it directly.)

OVO

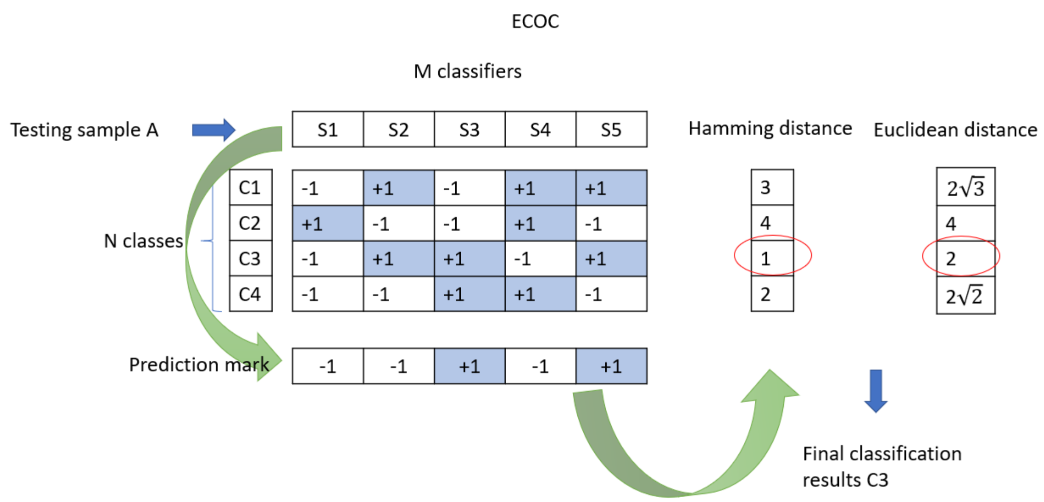
The N classifications task is paired one by one to divided them into N(N-1)/2 binary classification tasks. In order to distinguish the two classes C_p and C_q during training, one of binary classifier treats C_p as positive, and C_q as negative. During testing the new sample, it is submitted to all classifiers at the same time, N(N-1)/2 classification results will be obtained. The integrated method is to vote for the final result among these results.

Here we take a 4-class classification task as an example.



ECOC

There are two main steps for ECOC in SVMs. The first is encoding, which divides the N classes classification task with M times and generates M classifiers. After that, the classification comes to the decoding step. The testing sample will be tested by M classifiers to get M prediction marks. These prediction marks compose to a code. Comparing this code with each of the N categories of codes, the category with the smallest distance is returned as the result of the final prediction. Additionally, the encoding form is further divided into binary code and ternary code. The former designates "positive class" and "negative class", and the latter one has an additional "Null class". Here we take a 4-classes classification with binary code strategy as example.



Appendix 6: Leave-one-out validation results when use forearm sensor

Confusion matrix subject1 was leaved out (forearm sensor)

Training data: 251 strokes						Testing data: 40 strokes				
Training time: 3326s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	4	1						NaN	0.8
	BHT		3						NaN	1.0
	BHV	1		4					NaN	0.8
	FHS		1		5				NaN	0.83
	FHT					6			NaN	1.0
	FHV		0	1			4		NaN	0.8
	SM							4	NaN	1.0
	SR					4	1	1	NaN	NaN
Recall		0.8	0.6	0.8	1.0	0.6	0.8	0.8	NaN	
Accuracy = 0.75										

Confusion matrix of Leave subject2 out validation (forearm sensor)

Training data: 259 strokes						Testing data: 32 strokes				
Training time: 3192s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	6	1	3		NaN			NaN	0.6
	BHT		3			NaN			NaN	1.0
	BHV			2		NaN			NaN	1.0
	FHS				3	NaN			NaN	1.0
	FHT					NaN			NaN	NaN
	FHV				3	NaN	3		NaN	0.5
	SM					NaN	2	5	NaN	0.71
	SR		1			NaN			NaN	NaN
Recall		1.0	0.6	0.4	0.5	NaN	0.6	1.0	NaN	
Accuracy = 0.68										

Confusion matrix of Leave subject3 out validation (forearm sensor)

Training data: 251 strokes						Testing data: 40 strokes				
Training time: 3122s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	5	1					1	NaN	0.71
	BHT		2						NaN	1.0
	BHV		2	5					NaN	0.71
	FHS				2	7	1		NaN	0.2
	FHT					3			NaN	1.0
	FHV				3		4		NaN	0.75

	SM							4	NaN	1.0
	SR								NaN	NaN
Recall		1.0	0.4	1.0	0.4	0.3	0.75	0.75	NaN	
Accuracy = 0.625										

Confusion matrix of Leave subject4 out validation (forearm sensor)

Training data: 242 strokes					Testing data: 49 strokes					
Training time: 3217s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	5						1		0.83
	BHT		1	1						0.5
	BHV		4	4			2			0.4
	FHS				5			1		0.83
	FHT					5				1.0
	FHV						3			1.0
	SM					5		3	7	0.2
	SR								2	1.0
Recall		1.0	0.25	0.75	1.0	0.5	0.6	0.6	0.28	
Accuracy = 0.57										

Confusion matrix of Leave subject5 out validation (forearm sensor)

Training data: 241 strokes					Testing data: 50 strokes					
Training time: 3361s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	5								1.0
	BHT		1							1.0
	BHV		4	5						0.44
	FHS				2	7		3	4	0.12
	FHT					2				1.0
	FHV						5			1.0
	SM				3			1		0.25
	SR					1		1	6	0.75
Recall		1.0	0.25	1.0	0.4	0.2	1.0	0.1	0.6	
Accuracy = 0.55										

Confusion matrix of Leave subject6 out validation (forearm sensor)

Training data: 251 strokes					Testing data: 40 strokes					
Training time: 3548s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	4							NaN	1.0
	BHT		5						NaN	1.0

	BHV	1		5					NaN	0.83
	FHS				2	1			NaN	0.67
	FHT					9			NaN	1.0
	FHV				3		5	3	NaN	0.45
	SM							2	NaN	1.0
	SR								NaN	NaN
Recall		0.8	1.0	1.0	0.4	0.9	1.0	0.4	NaN	
Accuracy = 0.8										

Confusion matrix of Leave subject7 out validation (forearm sensor)

Training data: 251 strokes						Testing data: 40 strokes				
Training time: 3473s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	3							NaN	1.0
	BHT		5						NaN	1.0
	BHV	2		5			1		NaN	0.625
	FHS				5	2		3	NaN	0.5
	FHT					7			NaN	1.0
	FHV						4		NaN	1.0
	SM					1		2	NaN	0.67
	SR								NaN	NaN
Recall		0.6	1.0	1.0	1.0	0.7	0.8	0.4	NaN	
Accuracy = 0.775										

Appendix 7: Leave-one-out validation results when use upper arm sensor

Confusion matrix of Leave subject1 out validation (upper arm sensor)

Training data: 251 strokes		Testing data: 40 strokes								
Training time: 3217s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	4		1					NaN	0.8
	BHT		3						NaN	1.0
	BHV	1	2	4					NaN	0.57
	FHS				4	1	1		NaN	0.67
	FHT					5			NaN	1.0
	FHV				1	3	4		NaN	0.5
	SM							3	NaN	1.0
	SR					1		2	NaN	NaN
Recall		0.8	0.6	0.8	0.8	0.5	0.8	0.6	NaN	
Accuracy = 0.675										

Confusion matrix of Leave subject2 out validation (upper arm sensor)

Training data: 259 strokes		Testing data: 32 strokes								
Training time: 3273s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	4		2		NaN			NaN	0.67
	BHT	2	4			NaN			NaN	0.67
	BHV			3		NaN			NaN	1.0
	FHS				3	NaN	2		NaN	0.6
	FHT				1	NaN			NaN	NaN
	FHV				2	NaN	3		NaN	0.6
	SM					NaN		5	NaN	1.0
	SR		1			NaN			NaN	NaN
Recall		0.67	0.8	0.6	0.5	NaN	0.6	1.0	NaN	
Accuracy = 0.68										

Confusion matrix of Leave subject3 out validation (upper arm sensor)

Training data: 251 strokes		Testing data: 40 strokes								
Training time: 3331s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	5	1						NaN	0.83
	BHT		4						NaN	1.0
	BHV			5					NaN	1.0
	FHS				3	2	2		NaN	0.42
	FHT					5			NaN	1.0
	FHV				2	3	3		NaN	0.375

	SM							2	NaN	1.0
	SR							3	NaN	NaN
Recall		1.0	0.8	1.0	0.6	0.5	0.6	0.4	NaN	
Accuracy = 0.675										

Confusion matrix of Leave subject4 out validation (upper arm sensor)

Training data: 242 strokes					Testing data: 49 strokes					
Training time: 3459s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	3		1						0.75
	BHT		4							1.0
	BHV	2	1	4						0.57
	FHS				3		1			0.75
	FHT					6			3	0.67
	FHV				2	1	3	2		0.375
	SM					3	1	3	4	0.27
	SR								3	1.0
Recall		0.6	0.8	0.8	0.6	0.6	0.6	0.4	0.3	
Accuracy = 0.59										

Confusion matrix of Leave subject5 out validation (upper arm sensor)

Training data: 241 strokes					Testing data: 50 strokes					
Training time: 3482s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	4		1						0.8
	BHT	1	3							0.75
	BHV		2	4						0.67
	FHS				4	2				0.67
	FHT					5				1.0
	FHV				1		3		2	0.6
	SM						2	3	5	0.3
	SR					3		2	3	0.375
Recall		0.8	0.6	0.8	0.8	0.5	0.6	0.6	0.3	
Accuracy = 0.58										

Confusion matrix of Leave subject6 out validation (upper arm sensor)

Training data: 251 strokes					Testing data: 40 strokes					
Training time: 3329s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	3							NaN	1.0
	BHT	1	3	1					NaN	0.6

	BHV	1	2	4					NaN	0.57
	FHS				3	2			NaN	0.6
	FHT					5			NaN	1.0
	FHV				2		5		NaN	0.71
	SM					3		3	NaN	0.5
	SR							2	NaN	NaN
Recall		0.6	0.6	0.8	0.6	0.5	1.0	0.6	NaN	
Accuracy = 0.65										

Confusion matrix of Leave subject7 out validation (upper arm sensor)

Training data: 251 strokes					Testing data: 40 strokes					
Training time: 3413s		Actual Strokes								Precision
		BHS	BHT	BHV	FHS	FHT	FHV	SM	SR	
Predicted Strokes	BHS	3							NaN	1.0
	BHT		3						NaN	1.0
	BHV	2	2	5					NaN	0.56
	FHS				4	3	1		NaN	0.5
	FHT				1	4		1	NaN	0.67
	FHV						4		NaN	1.0
	SM							2	NaN	1.0
	SR					3		2	NaN	NaN
Recall		0.6	0.6	1.0	0.8	0.4	0.8	0.4	NaN	
Accuracy = 0.625										

Appendix 8: List of figures

Appendix 9: List of tables