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Author	徐, 萌艺(Xu, Mengyi) 南澤, 孝太(Minamizawa, Kōta)
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Master's Thesis
Academic Year 2019

Design of a Table Tennis Partner for Self-training Evaluation

Keio University
Graduate School of Media Design

Xu Mengyi

A Master's Thesis
submitted to Keio University Graduate School of Media Design
in partial fulfillment of the requirements for the degree of
Master of Media Design

Xu Mengyi

Master's Thesis Advisory Committee:

Professor Kouta Minamizawa	(Main Research Supervisor)
Project Senior Assistant Professor Roshan Peiris	(Sub Research Supervisor)

Master's Thesis Review Committee:

Professor Kouta Minamizawa	(Chair)
Project Senior Assistant Professor Roshan Peiris	(Co-Reviewer)
Professor Kazunori Sugiura	(Co-Reviewer)

Abstract of Master's Thesis of Academic Year 2019

Design of a Table Tennis Partner for Self-training Evaluation

Category: Design

Summary

People pursuing sports activities due to the charm of sports itself of course, moreover, the identification with great athleticism during skill mastering process. Nevertheless,the learning period before mastery requires regular repetitive training under supervision which is not accessible for all sports enthusiasts.

This research proposed a training partner that takes the responsibility of a coach to provide stroke evaluation in real-time without professional instructions for table tennis novices. The system is realized with a machine learning approach which utilizes haptic data collected from experienced and novice player and Convolutional Neural Network to build the classifier for evaluation.

This research presents effective method for self training without professional coach's supervision and instruction which leads the trainees to thinking actively of performance improvement. The design of the system expands the possibilities of future training scenarios in daily life. Moreover, the attempt explores the possibility of utilizing hapic classification in sports.

Keywords:

sports training, motor skill acquisition, machine learning, classification, cnn, table tennis

Keio University Graduate School of Media Design

Xu Mengyi

Contents

List of Figures

List of Tables

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I'm forever thankful for my parents and my best friends Sihui, Xiaoyu, Yanqing, Yue far away in China but always have faith in me and always being the strongest support during my hard times so that I could go forward without hesitation.

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Chapter 1
Introduction

Professional sports draw people in for many reasons, the excitement of competition, the elegance of performance and the identification with great athleticism. People pursuing sports activities due to the charm of sports itself of course, moreover, the sympathy with top athletes that we experience during skill mastering process.

Sports is far more than a approach to only train your body and build up physical health. Deeper engagement with your teammate and opponents increase the emotional and physical devotion during experience. The satisfactory gained through competitive sports experience is indispensable compared to any other activities.

1.1. Boundaries to Enter Professional

The urge to follow top athletes' footprints, challenge our body limitation, experience accomplishments by exceeding what happens in daily life is the human nature almost everyone possesses. This is the motivation for people who keep trying to improve their expertise in sports even they are not pursuing a professional career. However, superior skill levels of professional players make it hard for amateurs to fully experience the joy of sports like them in many aspects.

A successful sports experience is made up with satisfying sensation and a good performance which in other words a successful sports experience always "feels right".

Professional athletes have almost an intuitive judge towards a certain movement. For example, a professional basketball player would know right after the ball left his hand that if this shoot can make it a buzzer beater for his team to win the game or not. Athletes with intuition are able to process information quickly by recognizing patterns that they have seen before. and make quick decisions, perform accurately to achieve the goal in games.

Top athletes usually have their unique understanding of successful experience about a specific skill which is difficult to pass on to others. When asked about the feeling of accomplishing a successful triple axel jump[1] which is a superior skill that only countable skaters can master, they answered in following totally different expresses. Two times olympic champion Hanyu yuzuru says, "It feels like jump bumping into a wall." The previous king of figure skating Alexei Yagudin describe it as "Jumping and go through a gap between two walls in the air." Asada Mao, as the only female skater who can master this type of triple jump, she says,"It's just ready–jump! (ヨイショって飛びます！)". This differentials

Figure 1.1 Different description from 3 top skaters about triple axel jump

in personal understanding makes it hard in traditional training for transferring subtle feelings in verbal language about a specific technique.

Capability on processing sensory feedback to other information is crucial in leading to successful experience as well. For table tennis, experienced players are able to acquire large amount of information from the feeling of different strokes. They can tell the ball spin direction, ball speed, stroke quality and use these information to predict the opponent's movements, make better decisions and control the tempo of the game. For Chinese professional table tennis players with the best sensation ability, he can even compare the weight difference of table tennis ball only by drilling the ball on the table for several times.

Researches has proved that positive emotional change in sports experience varies according to skill levels. By improving motor skill levels, athletes can experience more enjoyment during sports activities.

1 https://en.wikipedia.org/wiki/Axel_jump

1.2. Stride over the Barrier to Mastery

It is a long and repetitive process to pursuing expertise in sports. No matter in which field, significant amount of deliberate practice which is practice aiming at improving performance with appropriate subgoals. [3]However, deliberate practice usually refers to difficult, repetitive, high-intensity activity that was found unpleasant and not motivated to most trainees. [4]

Professional training regularly is the solid foundation to get improved, nevertheless, not accessible to most people. Reasons such as lack of time to commute for regular training, hard to find accompany, have no access to get started were raised by testers in a pre-study questionnaire.

The difficulty of mastering expert skills and high intensity modern life style hold back the mass to pursue easier choices like PC games, eating popcorn and watching movies to gain low cost joy for daily leisure.

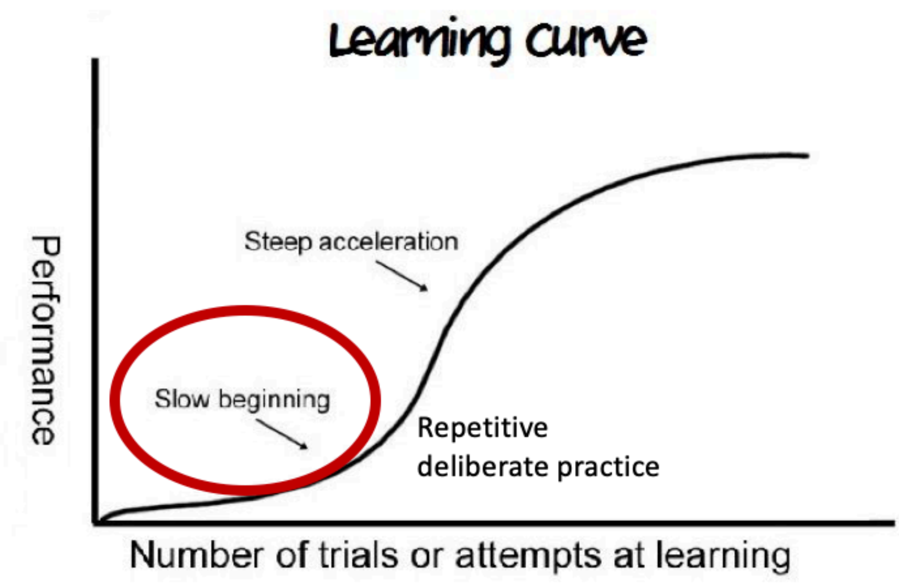


Figure 1.2 Learning Curve for Skill Acquisition

Not only by seeking professional training, regular self training is also significant in strengthen the memory of existing knowledge and build solid foundation for further improvement. However, the self training requires the ability to self evaluation for the operated motor skill format and the outcomes in order to make adjustment during self training which is not an option for most beginners. In consequence, many beginners are facing the dilemma of staying forever in the early phase of the learning curve.

1.3. Research Goal

This design proposes a table tennis partner to support self training by offering real time stroke quality evaluation.

The goal of this research is to enable self training, motivate deliberate practice for novice players to learn table tennis and get improved without supervision and instruction from professional coach.

1.4. Thesis Structure

The thesis is structured into 5 chapters, and the content of each is as follows:

Chapter 1 addresses the differential of successful experience between professional athletes and amateurs and the difficulties that beginners are facing which hold them from getting improvement;

Chapter 2 reviews the existing researches on motor skill acquisition, machine learning, and emerging technologies for supporting sports training;

Chapter 3 presents the concept and the detailed design of the system, and describes the configuration of the hardware and software used;

Chapter 4 describes the user test design and analyzes the results to prove the feasibility of the concept;

Chapter 5 summaries the whole thesis and carries out further discussion.

Chapter 2
Related Works

2.1. Motor Skill Acquisition Theory

Improvement of sports performance is built on the mastery of multiple motor skills related. To reveal the mechanism of the motor skill acquisition, this section will discuss two mainstream cognitive theory in sports science. Motor skills, distinguished from perceptual skills, cognitive skills, communicative skills, and other skill categories, usually refers to those skills in which both the movement and the outcome of the action are emphasized. [5] Motor skill acquisition is a process in which a performer learns to control and integrate posture, locomotion, and muscle activation that allow the individual to engage in a variety of motor behaviors that are constrained by a range of task requirements. There are three essential features of skilled movement: maximum certainty of goal achievement, minimum energy expenditure, and minimum movement time.

2.1.1 Closed-loop Theory

The open-loop and closed-loop theory explains how different skills are controlled by the brain. There are three levels of control system according to this theory: Level 1 is Open-loop control while Level 2 and Level 3 are both close-loop control.

Level 1 control is open-loop control that includes no feedback which means no conscious thought is involved in the execution of the skill as the decisions have already been made in the brain. All information is sent in one message to the working muscles and the skill cannot be altered during execution. Open-loop control usually used to explain control for fast movements with little time to react and applies to skills that are simple, well-learned and self-paced such as a table tennis serve and a golf swing.

Level 2 control is closed-loop control which involves feedback via muscles which is internal and gathered through proprioception and kinesthesis. This control applies to ongoing movements and skills can be altered by performer during execution as a result of feedback as decisions are made in the brain during performance. Examples of Level 2 control could be balancing in dance, adjusting route through a slalom course for a skier.

Level 3 control is also a closed-loop control involves feedback from the brain which is a longer feedback loop than level 2 as the feedback is external rather than internal. The feedback in level 3 control come from external factors such as the coach, co-actors, opponents and so on. This kind of feedback can cause the skill to be altered during execution as the information sent by the brain can be changed. Level 3 control applies also to ongoing movements such as passing a ball in netball, playing a shot in tennis and is useful for novice performers.

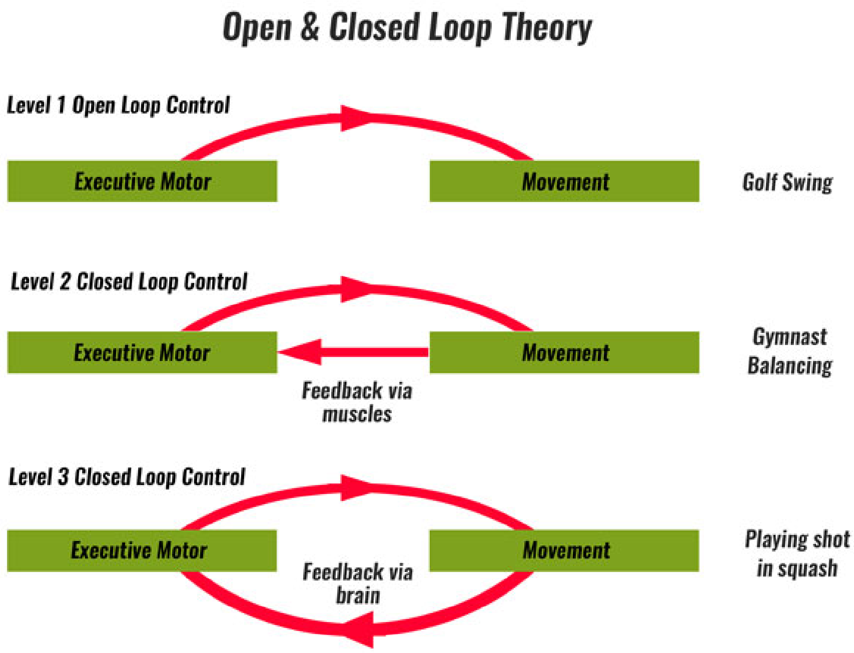


Figure 2.1 Open-loop and Closed-loop Control

2.1.2 Schema Theory

Schmidt proposed a schema theory of discrete motor skill learning which claims that all of the information needed to make a movement decision. [6] It is stored in the brain as long-term memory. Discrete motor skill refers to movements that has a observable start and finish such as shooting a basketball and returning a tennis stroke. Through these experience, the subject builds up a recall schema which pairs the response specifications of a movement with the actual outcome. Later, this recall schema can be consulted to infer, from a desired outcome, the response specification which will produce it. The recall schema is what is now known in the literature of motor control as an ”inverse model” which goes from a desired response to a pattern of commands that achieves it, rather than the “direct” causal path from commands to action

Similarly, a recognition schema pairs the desired outcome with the expected sensory consequences of each movement.

Recall Schema occurs before a movement is initiated and includes the information of initial conditions and response specification which the performer must know to form a schema.

Initial Conditions includes information about the goal of the movement, the environment of the space like temperature, indoor or outdoor and the condition of the player himself. Response Specification includes information of the parameters of a motor programme restored in the performer's brain which typically includes information like the speed, directions, point of action and selection of the best techniques to use. Recognition Schema occurs either during or after the performance of a skill in order to correct or alter a response. The performer need to be aware of the response outcomes(KR) and the sensory consequences(KP) about the experience.

KR stands for the knowledge of results which is the determination of success or failure of the movement.

The end result and a comparison being made with the intended outcome. This updates the memory store for future reference when confronted with a similar situation in the future.

KP stands for knowledge of performance which includes extrinsic feedback like visual and sound feedback of the movement, and the intrinsic feedback which is the kinetic feedback accepted by the performer's body.

The feelings experienced during and after the movement, the sound, the kinesthetic feeling and any other information received via the sensory system then allows suitable adjustments to be made.

The schema theory challenges the open and closed loop theories. He suggested that motor programmes can be clustered and are changeable to respond to the situation. He also stated that the larger the motor programme that is achieved through practice, the easier it can be adapted to new situations. For example, during a tennis match, the performer cannot possibly have experienced every type of shot that they have to face, but they adapt the required stroke to suit the specific situation based on previous experience.

Similar statement that if the trainee is developing simple sensorimotor skill, the feedback should be "learning feedback" which is the feedback of the result instead of a "control feedback" refers to the action. [7]

2.2. Machine Learning Technologies and Classification

2.2.1 Audio Classification

Machine Learning is a trending field in all industry, sport is not an exception. People use machine learning for huge number of data processing to support decision making. [8] In recent years, machine learning has opened up new horizons in a wide range of use cases in audio recognition such as Siri's voice recognition and home surveillance. There are many fantastic machine learning APIs such as IBM Watson, Google Prediction, Microsoft Azure which enables designers and developers build their own projects more easily. Machine learning technologies is applied in audio classification for various scenarios such as sound scene recognition [9]. Sound scene recognition could be implemented to detect a scenarios form human activities like people walking, bird singing, and scenario classification like bus, office, home.

Music is another main field that classification technology were highly developed based on various notation methods such as instruments recognition, music genre

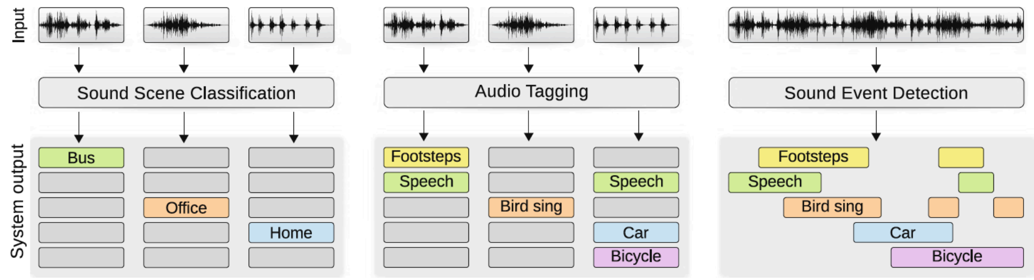


Figure 2.2 sound scene classification, audio tagging, and sound event detection

recognition which are widely used in music applications [10]

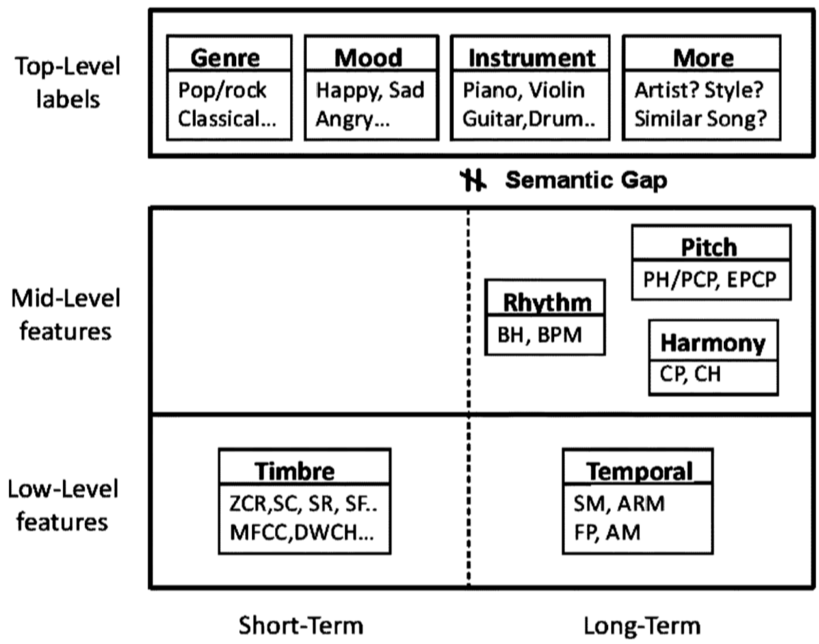


Figure 2.3 Charaterization of Audio Features

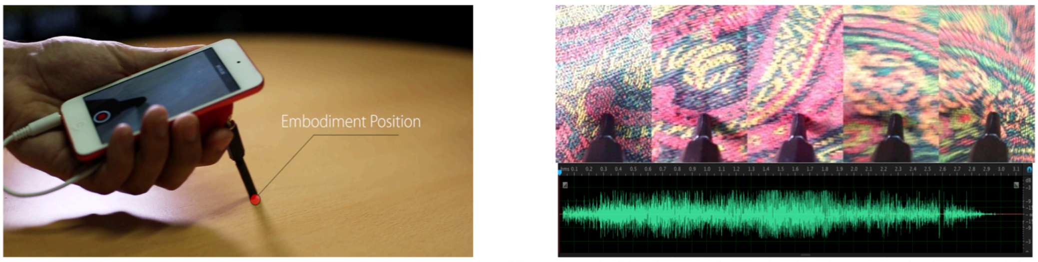
2.2.2 Haptic Classification

Haptic generated while an object contact another surface which is an information can be detected and recorded easily by sensors implemented a lot in daily life such as microphone and accelerometer. Sound wave collected from tool-surface interaction applied to material recognition were developed in multiple researches. Kato and Charith [11] developed a classification method of tactile feeling using a stacked autoencoder-based neural network with two hidden layers on haptic primary colors. They testified tactile feeling for three different surface materials with this method and reached the accuracy of 82.0%.

Combine visual data with haptic data together to complete the classification was proposed by researchers in Technical University of Munich [12],

The most usage of network for haptic classification is convolutional neural network. Haitian [13] presented a novel deep learning method dealing with the surface material classification problem based on a fully convolutional network, which takes the aforementioned acceleration signal and a corresponding image of the surface texture as inputs. introduced a novel method for hardness estimation, based on the GelSight tactile sensor, and the method does not require accurate control of contact conditions or the shape of objects. Experiments show that the neural net model can estimate the hardness of objects with different shapes and hardness ranging from 8 to 87 in Shore 00 scale.

Twech [14] developed a search system based on haptics and a Convolutional Neural Network for 10 different materials which could be applied to future life scenario as online shopping and more. [15] [16]Using accelerometer data and CNN



(a) Recording contacted textures using an embodied probe (b) Captured video image: the probe data is seen at the bottom of the image

Figure 2.4 The application of twech

to classify 18 different materials which reaches a 93.2% for training accuracy and a 67.7% for real-time rendering of data collected byrubbing the material.

Among haptic classification, most of the research are developed for material recognition and Convolutional Neural Network is the most used classifier.

2.3. Technologies in Sports Training

2.3.1 Training in Virtual Reality

In spite of extensive research on skill acquisition, the fundamentals of effective coaching have still not been fully revealed especially with the participation of emerging technologies. The researches in Virtual Environment for sports is increasing among which the most used hardware technologies are optical motion capture, data projector and haptics. [17] Virtual Reality is widely used because of its interactive and immersive condition that can simulate real life scenario but more operable than in actual physical world which can be utilized in sports performance assessing [18], gaming and training and so on. [19]

Virtual reality training sports are widely developed such as virtual table tennis [20] enable two participants to play table tennis with opponent's avatar in a shared virtual environment is presented. There are works with similar concept such as virtual rugby, virtual handball showed in following figures developed as well. However, to what extent the gaming experience in virtual environment can

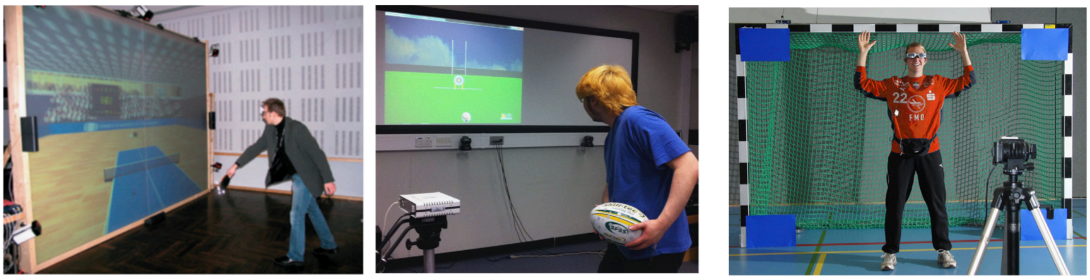


Figure 2.5 Virtual Training VPong(left), Virtual Rugby(mid) and Virtual Handball(right)

transfer into real life motor skills is still debatable. Thus, not only for experiencing, the idea of detecting and analyzing trainees movement in virtual reality in order to give instructive real-time feedback were developed among last decades.

Error detecting and motor skill quality assessment with machine learning is another approach for sports skill improvement. [21] Similar system in augmented reality draw support from a mirror to project visual feedback was also proposed in the project YouMove. [22] Virtual coaching was not stoping at only visual demonstration, a multimodal system with real-time visual and voice feedback was developed to support motor skill learning as presented in figure2.6.

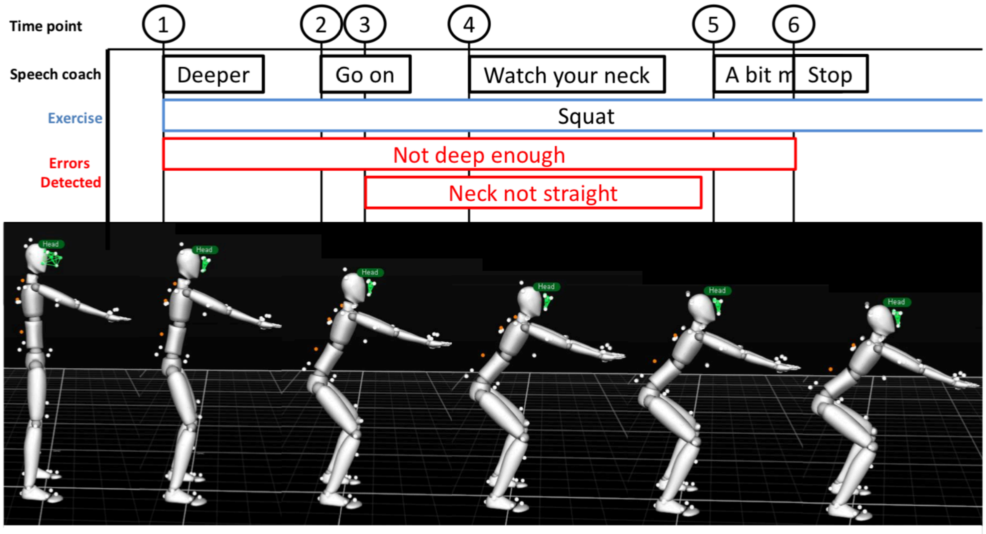


Figure 2.6 Incremental instructions generated by the virtual coach in response to a user ’ s squat

2.3.2 Haptics and motor skill learning

The usage of concurrent haptic feedback in motor skill learning [23] assisting movement with visual and haptic(handwriting) Haptic guidance is the most used approach to accelerate learning of motor skills in various contents such as surgery rehabilitation and sports. One of the sports that can benefit from the use of technology in sport is soccer. An important part of training in soccer -as well as other sports- is sprinting, as it is a high intensity exercise that increases athletes ’ performance in ways that soccer specific training routine does not address. This system presents a haptic automated sprint training system for soccer players. can be personalized by a coach as recommended for each athlete, and the athletes can then use it independently to perform the training. The coach can use the system to monitor and analyze the athletes ' performance.

Another perspective in haptic training scenario is to let user experience errors by utilizing haptic feedback. The accumulation of failure experience is also signicant in motor skill acquisition. The ultimate goal of skill acquisition is to perform a task with minimal errors. There are several previous studies that support the idea of the effectiveness of avoiding error during the training process. Camille [24] did a comparison study about how error minimizing, error augmenting and no haptic feedback while learning a self-paced curve-tracing task impact performance on delayed (1 day) retention and transfer tests, which indicate learning. They assessed performance using movement time and tracing error to calculate a measure of overall performance – the speed accuracy cost function. They reached the conclusion that haptic error augmentation is more beneficial than error minimization for learning spatial accuracy, even when learners have full control of the speed of performance. On simple motor task like following the trejectory, two perspective that haptic feedback as error augmentation [25]

In overall, haptic feedback was proved to be effective [26] in relatively simpler motor tasks such as trajectory drawing, but not so much in complex motor skill acquisition such as in sports.

2.3.3 Future Sports with AI

Sports live technologies are increasingly developed for various purposes such as creating brand new sports viewing experience, providing better real-time data analysis based on tracking technologies. [27]The effectiveness of robotic training depends on motor task characteristics IBM developed AI Vision project[1] which is an AI system that could recognize both audio and visual data in basketball games. This system was firstly applied in editing Durant' s highlight movie right when the game ends and he was named as FMVP. This system processes audio and visual data which enables it to track and recognize players' faces and facial expressions, identify objects like basketball, baskets, jersey numbers and categorize actions such as slam dunks and shoots in order to edit the highlight video properly.

1 `https://www.ibm.com/blogs/research/2018/06/ai-highlight-reel/`

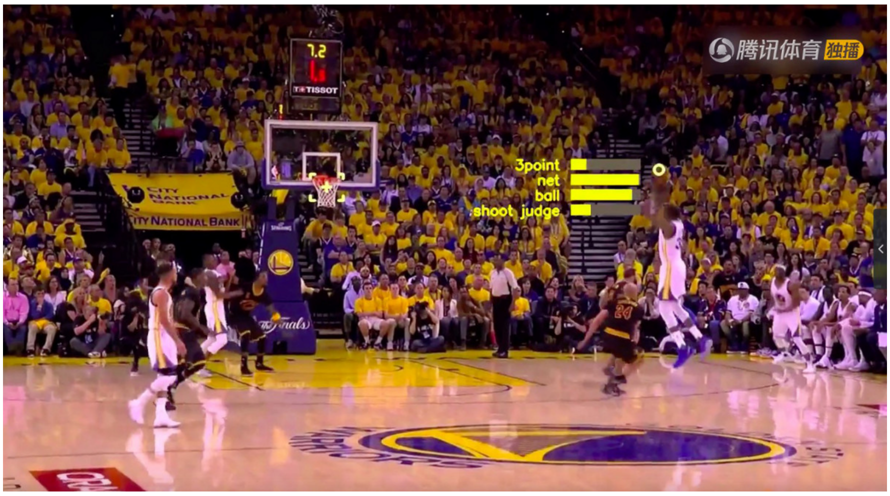


Figure 2.7 IBM AI Vision for NBA

Tracking technology is a topic cannot be ignored when refers to sports. There are many data involved such as human motion and object trajectory which are key factors to analyze sports activity. There are many focused on detect and analysis human motion to interpret motor skills. Peter Blank [28] presented a sensor-based table tennis stroke detection and classification system. They attached inertial sensors to table tennis rackets and collected data of 8 different basic stroke types. This approach reaches a relatively high accuracy with a specific experienced player's data. ComBaT [1] proposed a training system that use wearable device to collect and process EMS data in real time for badminton beginners. The visualize the real time EMS data in comparison with a pre-recorded master data from expertise player as a waveform and generate haptic feedback right after each play. However, it was mentioned by experiment participants that this kind of graph did not scaffold them to translate the differences to shot. A high-speed stereovision system with two smart cameras is presented to recognize and track the table tennis ball in the images. Then, the flying trajectory of the ball is estimated and predicted according to the measured positions and the flying and rebound models. The main motion parameters of the ball such as the landing point and striking point are calculated from its predicted trajectory. The predicted landing point and striking point of the ball reach satisfactory precision. Tracking technologies like mentioned above build the basis of robotics and big

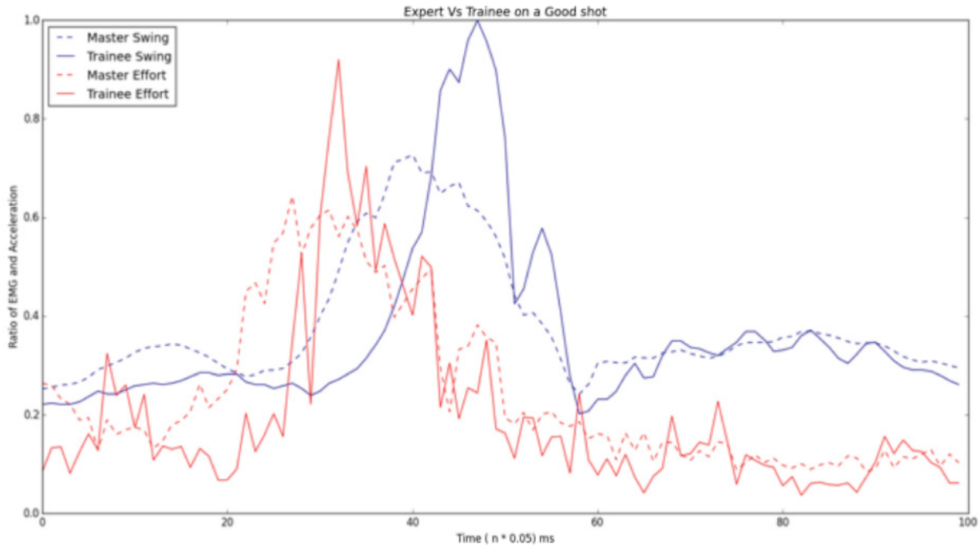


Figure 2.8 Visualization interface of ComBaT [1]

data analysis in sports and possesses huge potential in future application.

”Sports and AI” is an attractive term nowadays. Many researchers in the field of artificial inteligence assambled the knowledge of sports science, desiring to exceed human’s limitation in perspective of sensory data receiving and processing, movement range, react time and the list goes on. OMRON developed a table tennis robot Forpheus[2] claims the concept of state-of-the-art technology that embodies the world of ”harmony” where machines can bring out human ability. This robot is equipped with high speed camera for human motion and object detection algorithm which works for the robot control system and human player analysis system.

Researchers at the Japanese Volleyball Association and the University Tsukuba University developed a ”volleyball block machine” [29] that is programable in terms of different training goals which aims to support for professional training. The robot can reproduce the moment by positioning the arms to stand in for opposition team members. They can also mimic the tactical styles of future opponents.

2 https://www.omron.com/innovation/forpheus.html

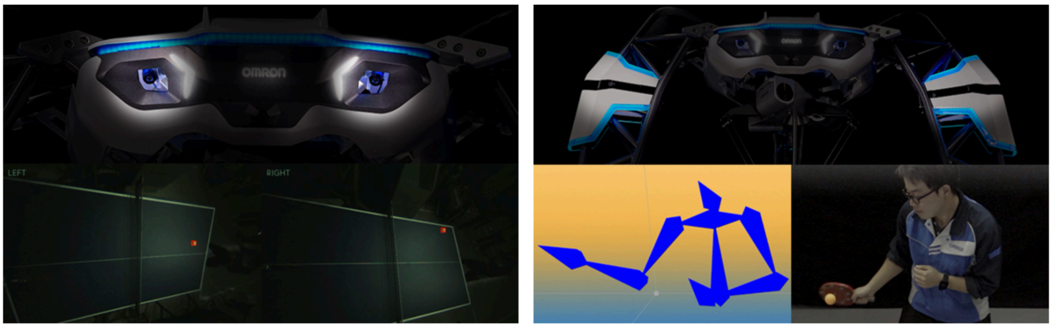


Figure 2.9 High speed camera sensing(left) and Motion sensor sensing(right) technology of Forpheus

Figure 2.10 A block machine for volleyball attack training

Chapter 3
Design

3.1. Design Overview

For discrete motor skill acquisition such as table tennis stroke practice, develop a recognition schema that pairs sensory information with the desired outcome is the key factor to improve performance and increase the accuracy of reproducing the movement.

In other words, the performer needs to be aware of the sensory information such as visual, audio, muscle sensation, and be able to distinguish the response outcome based on this information which means knowing the result is a success or not during learning. This theory is also proved during real training scenario that the trainee's performance gets improved under coach's real-time comments that enable trainees to accomplish self-confirmation or adjustment which is also the insight of the final design of this research.

This design aims at dealing with the dilemma that many beginners are facing with which is not accessible to regular professional training, meanwhile not capable of training themselves without a professional coach.

A machine learning method is selected to create a virtual partner that takes the responsibility of a professional coach to give a real-time evaluation of strokes for players. Most previous work within the context of "sports and machine learning" focus on human motion recognition with sensors such as high-speed camera, accelerometer, motion tracker and so on.

However, the data is interpretable to computers is hard to transfer into the form that human can easily process like visual and audio information. Thus, this design utilizes haptic data that represent the stroke sensation from the impact between ball and racket to realize the desired interaction.

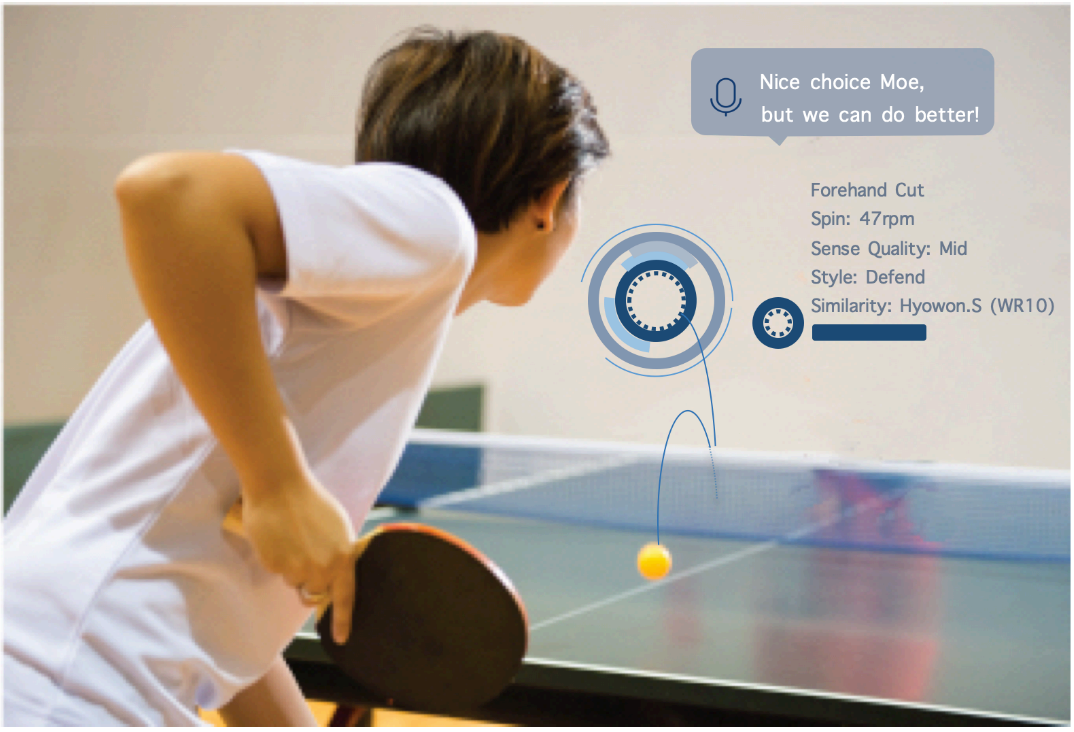


Figure 3.1 Concept Sketch of Future Table Tennis Partner

3.2. User Behavior Study

3.2.1 Non-participate Observation

A long-term observation study in VICTAS was carried out as a part-time staff for six months in order to get in touch with potential target users and address the problems in real life scenarios for them.

VICTAS is a multi-functioning table tennis shop which not only sales table tennis equipment, but also supports for equipment purchase by providing trials of various rackets and rubbers, and real-time speed testing for customers.

The insights from this observation study are addressed in following two aspects:

Ability Differential in Stroke Sensation Comprehension

The ability to distinguish subtle differences by "feelings" differs a lot from experienced players and beginners. The ability to comprehend stroke sensation shows mainly in the capability of telling the difference and assessing the quality which is significant to both training and competition.

During observation in VICTAS, a huge differential on this ability was revealed between beginners and experienced players. Equipment from different materials influences the users' performance and play experience to a great extent. In table tennis, mainly the rubber and wood material alter the play sensation and performance.

VICTAS produces various types of rubber and wood paddle to provide a wide range of racket selections for customers with different needs.

Figure 3.2 Performance comparison between two types of rubbers

However, only a few customers can tell the subtle differences in visual, audio and sensational feedback when they are trying different types of rackets, not to mention finding a suitable type for themselves based on the sensational differences. Usually, these customers are having or had the experience of professional training.

It is a common scene that even the beginners take a trial in between various rackets which contain carbons or not, using pips-on and pips-out rubber, all they show is only a confusing face and end up buying nothing or follow the shop staff's advice.

The proper understanding of stroke sensation is key to skill level improvement to players which is also possible to become a

Behavioral Change towards Speed Testing System

VICTAS is equipped with a real-time speed testing system for customers to experience playing the feeling of various types of rackets with different materials. This system aims to support customers' purchasing process. During the observation is that the real-time speed testing system encourages players to attempt different strokes in order to get higher speed no matter the experience of the player. The

Figure 3.3 Speed testing system in VICTAS

system works relatively more effective for experienced players as they understand the standard feeling of a "nice" shot which leads to a successful result in most situations. Thus they are capable to compare the feeling during trial play and to see to what extent the new racket can improve their performance.

3.2.2 Participate Observation

This fieldwork was done in collaboration with Tactive[1]. A table tennis school located in Shibuya. I participated and observed two different sessions of the experience course which was designed for beginners. The training session for beginners contains several sections. Each section starts with the coach's oral instruction and stroke demonstration. They record video and give real-time oral feedback while the trainee practice under the coach's supervision. After each session, the coach watches the video replay together with the trainee and explain the failure reason and revise method.

Effects of Oral Instructions

Trainees would adjust their movement according to the oral feedback. The oral feedback works as an important role during training process to the trainees' mental condition and effectiveness of achieving the desired output. There are mainly three types of oral feedback that are: instructive feedback, positive feedback, and descriptive feedback.

There are chances that oral feedback would influence trainee's spiritual situation, urge behavioral changes that lead to a successful play.

3.2.3 Haptic Workshop with Forpheus

Another fieldwork that offered me inspiration is the workshop with OMRON FORPHEUS team. The project of Forpheus aims to create a smart table tennis robot that can play not only against human player, but also brings the potential out of every player and help them to improve their skills. Our goal in this project is to excavate the future goal of the robot and the approach to it. How to change

1 `http://www.tactive.co.jp`

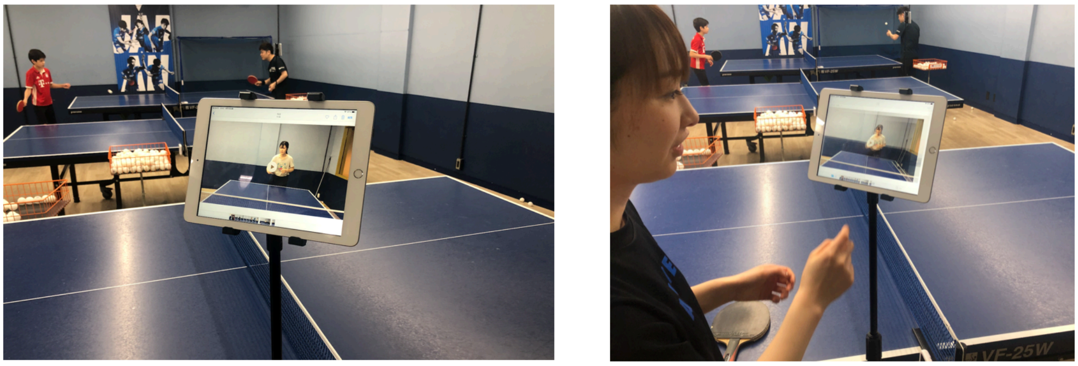


Figure 3.4 Training session in TACTIVE

the character of the robot from a playing partner to a coach, an opponent, and a friend? This is the main focus of this workshop. For the current phase, FOR-

Figure 3.5 Forpheus and Workshop with OMRON

PHEUS is functioning as a robot that is capable to carry on a simple rally with the player.

The team agreed on one out of several problems addressed during the brainstorming which is single direction communication between robot and human. The technology they are using right now is image recognition of human motion from two high-speed cameras. They use this technology to design the evaluation system and ball trajectory prediction algorithm for the robot the choose the best way to return the ball in order to continue the rally as long as possible.

This system enables the robot to understand the human motion and ball movement. However, this is a single direction for the computer and this kind of data is hard to interpret into massages that human players can actually understand and transfer into knowledge.

Differential in Producing Stroke Sensation

During the haptic workshop with Forpheus, we used TECHTILE as a real-time sensation transfer device by attaching a microphone and a vibrator separately to two rackets that composed a stroke sensation transmitter and a receiver. Table tennis experienced players and beginners in the Forpheus team participated in perform strokes with the transmitter racket in turn. The sensational differential could be transferred clearly to everyone who holds the receiver racket. This difference is produced by strong hitting power and rotation the rubber gives to the ball while impact. This workshop experience gives me insight and motivation to work on using haptic data to classify stroke types.

3.3. Interaction Design

3.3.1 Design Elements

Based on the literature review on the cognitive theory of discrete motor skill acquisition, the following key elements were defined for the design process:

1. **Dataset Selection:** A machine learning approach is selected in this research which makes the data acquisition an important part for building the whole system. In actual utility, the data acquisition method also decides the real-time feedback that the system could provide. In the whole developing process, several attempts were made to collect data from a different perspective.

2. **Interpretation of certain movements:** the knowledge of results is the basis for the performer to correct or alter a movement.

3. **Record and review:** the recording and replay of all the information involved in the training process enables performers to strengthen their memory.

3.3.2 Use Case

To support novice players to train without professional coaches' supervision, the key point is to explain everything and give instructions in a more intuitive and clear way. The concept is to use haptic data as a new language to interpret table tennis strokes. And instead of focusing on the format and the result in the traditional training method, it changes the training goal into getting closer to the right feeling. In order to support the beginner's self-training process, there are 3 aspects the system needs to participate in. First of all, to enable self-training without a coach, there should be an instruction to make the training method clear and simple for beginners to follow.

Secondly, real-time evaluation is the motivation and basis that beginners could follow on to continue self training. Therefore, giving the concurrent feedback on each strokes that enables beginners to be aware of the correctness of their movement is the main part of the training flow. To connect each training session and make the interval beneficial to beginners, it is rather crucial to create a access for trainees to review their own performance during last training session.

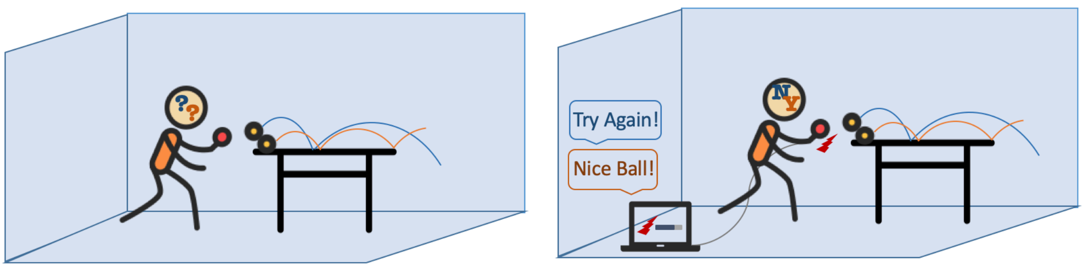


Figure 3.6 Use Case Example of Training Alone

3.4. System Implementation

A machine learning approach is selected to achieve the desired interaction described above. The figure below presents the overall system composition and flow which will be introduced in following sections.

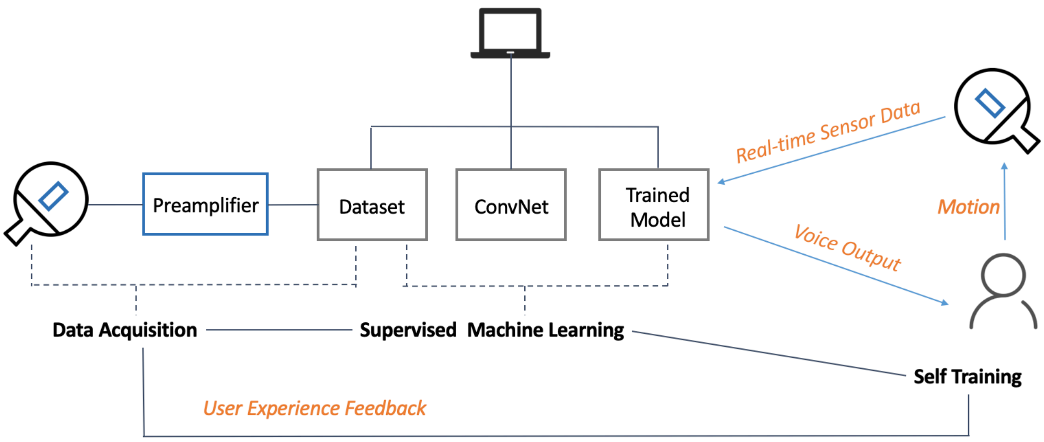


Figure 3.7 System Design

3.4.1 Hardware Implementation

For collecting the data of the stroke and the concurrent feedback system, I redesigned the table tennis racket with an embedded sensor to detect the impact on the racket. There are several sensors widely used for collecting haptic data. For example, TECHTILE toolkit used contact microphone to collect audio data as the haptic information [30]. However, the contact microphone receive not only the impact of the ball on the racket, but also background noise like people talking and also the ball dropping on the table without difference which will affect the accuracy of the classification system. That is the reason I choose the wearable skin vibration sensor using a pvdf film [2]. This sensor was used to pass on the subtle vibration on finger tips skin as digital signal which is much more sensitive but can isolate environment noise to some extent. Moreover, the weight of table

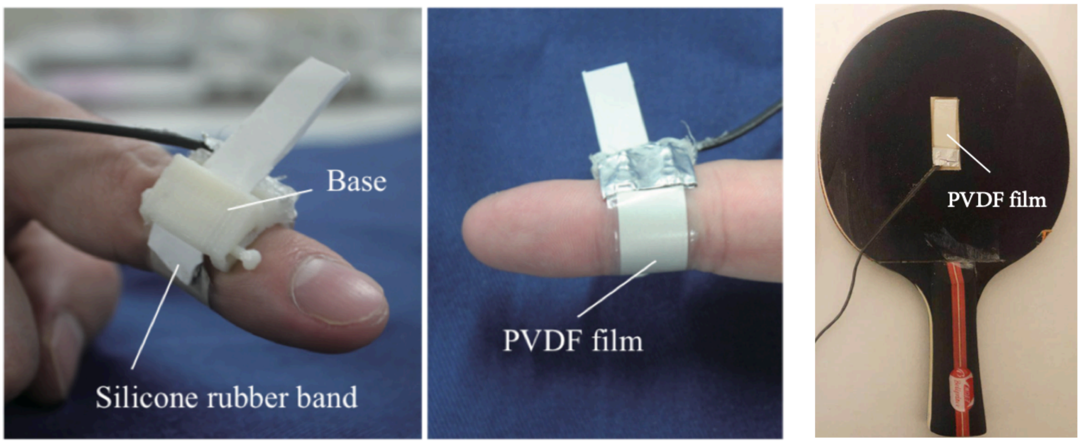


Figure 3.8 Usage of pvdf sensor [2](left) on racket(right)

tennis racket is extremely important to table tennis practice. On considering of minimizing the influence of the sensor to the racket, with the properties of thinness and light weight, the skin vibration is a better choice over microphone to be embedded in between rubber and wood paddle.

The impact of the rubber and the table tennis ball directly decides the action of the ball about the speed, spin. The position where the ball hitting on the racket also influences the quality of the stroke. On considering of these aspects, the piezo sensor should be placed in the center of the racket. To place the piezo sensor, the center of the wood paddle was engraved with a rectangular hollow sized 16 x 42(mm) using CNC machine as the figure shows. In order to alter the signal from piezo sensor is connected to a pre-amplifier [31] before the data was transferred to the system.

Figure 3.9 Redesigned racket with embedded sensor

Data Properties	
Data type	wav file
Data duration	1 second
Sampling rate	44.1kHz
Channel	Mono
Resolution	16bit

Table 3.1 Properties of collected data

3.4.2 Model Development Environment

Data Collection

In order to reduce the afterwards processing for the dataset, data samples were collected and pre-processed by a python script using the sensor-embedded table tennis racket. The data samples was automatically recorded when the sensor detecting signal amplitude beyond a threshold represents ball bouncing on the racket. All data samples are recorded in the format of one-second wave files.

Data Processing

Data processing and training were operated on Jupyter notebook[2] using Keras[3] with Tensorflow[4] as the backend.

Data processing is needed before the dataset is trained by the neural network. All the data samples pre-processing goes under the next steps.

- **Downsampling**: to save the computational power and enable faster training, the downsampling of all the data samples was operated before data processing.
- **Embedding**: embedding is to mapping discrete objects, here the audio files, into vectors in fixed size. For audio signal process, the mel-frenquency cepstrum(MFC) which is a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency.

  MFCC encoding is widely used in audio classification among scenarios like speech recognition and audio scene classification. I choose to using mfcc to transfer data samples into vectors as well.
- **Saving vectors**: computing MFCC is a time-consuming process, thus, it is better to operating once and organize and save all the vectors into numpy files before feeding them into the neural network.
- **Separating training and testing set**: using sklearn library's function train_test_split to separate dataset into training and testing set for further model evalutaion.

Building Training Network

CNN(Convolutional Neural Network)is built in this research. Step 1 - Convolution Max pooling dropout convolutional layer max pooling Step 3 - Flattening dense

2 https://jupyter.org

3 https://keras.io

4 https://www.tensorflow.org

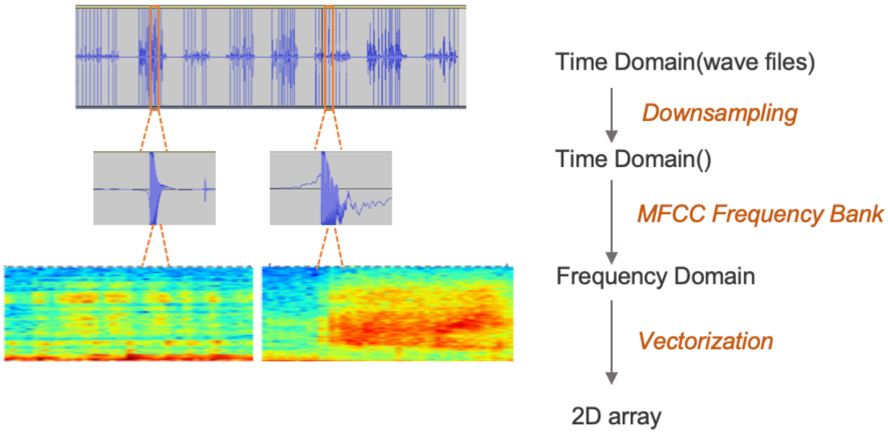


Figure 3.10 Data Processing Process

dropout dense Step 4 - Full connection

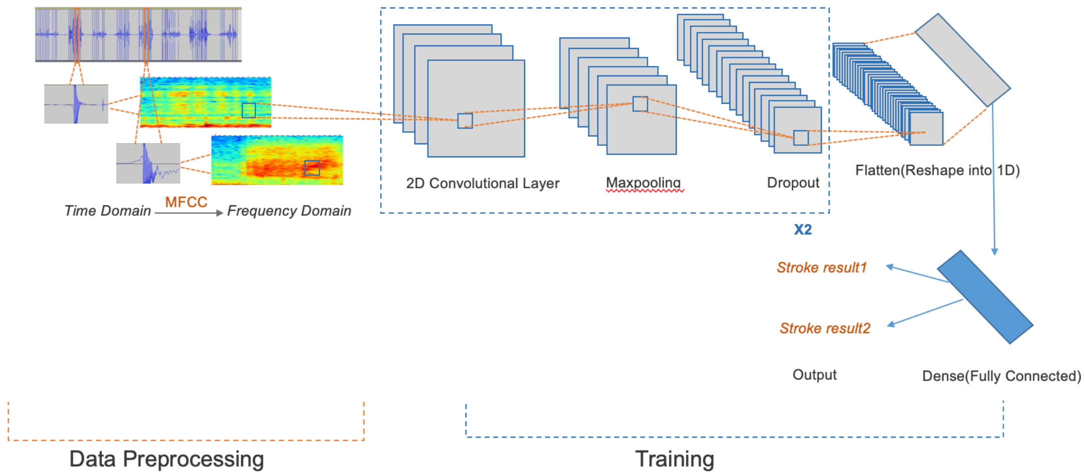


Figure 3.11 Convolutional Neural Network Image

3.5. Model Design

3.5.1 Stroke Classification Model

Distinguish and develop the basic recognition towards different stroke types is extremely important in table tennis. Understand the presence of sensation on behalf of different spin, speed, and hitting position is the first step for beginners to master table tennis basic skills.

The first model is developed based on the thought of supporting beginners to recognize various basic stroke types. On the other hand, as the first model

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 19, 10, 64)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 9, 5, 64)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 9, 5, 64)          0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 8, 4, 32)          8224
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 4, 2, 32)          0
_________________________________________________________________
dropout_2 (Dropout)          (None, 4, 2, 32)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 258
=================================================================
Total params: 41,698
Trainable params: 41,698
Non-trainable params: 0
_________________________________________________________________
```

Figure 3.12 Detail of trained CNN model

developed, this is also a trial to explore the role that haptic can play in stroke type classification.

There are 8 main stroke types in table tennis which can be distinguished based on the racket angel, hitting position(relationship between racket and table), "Yin-pai"[5]direction. Among those, there are 4 basic strokes that need to be mastered by beginners before they move on to more complicated skills which are forehand drive, forehand block, backhand drive and backhand block. There are the 4 stroke types that I chose as the labels of the classification model.

Figure 3.13 Hitting posture of 4 Basic Strokes

The dataset for stroke type classification model was collected from one semi-professional player and a amateur player. The two of them were asked to hold the racket attached with sensor to play the four basic stroke types repeatedly. Over 100 data samples were collected for each stroke and the mistakenly played strokes were picked up from the data samples.

There are 421 valid data samples were collected and 80% of the data samples

5

were used as the training set to build the model and the rest of them were used as validation set to evaluate the model accuracy.

The training accuracy and evaluation accuracy of the model are 97% and 92%.

System Evaluation

The system accuracy of the stroke type classification model is evaluated under the same condition of the data collection setting with the same players who contributed to the data samples. Each player were asked to play 4 basic stroke types repeatedly to check the accuracy that the system provides.

Feedback

The stroke classification model is my first attempt to explore the role of haptic data in table tennis strokes. The result shows the possibility for further research, so I followed up and interviewed a experienced player to discuss the usage in real training scenario. In order to explore and clarify the role of this model during beginners' training process, I contacted an experienced table tennis player for comments. The interviewer is a player who had the experience of training and compete in a Chinese province team for 8 years about the possible usage of the stroke classification models during actual training and gaming experience. Followed are part of the comments and discussion from the interview.

For experienced player, the spin direction and speed can be felt on the stroke feeling in real time.

The decision of hitting position and ball direction should be made based on the ball coming from opponent in real time during game.

If it is possible to record the stroke data for both sides, this will be a strong support for coaches during techniques training.

The data record and analysis during training is very important because it can be used to analysis the player's play habit and style. Especially if it is possible to know the opponent's serving and returning habit, the chance to win a game would be significantly higher between a technically tied game.

Usually players are judging the ball spin direction according to the opponents' movement based on their experience.

However, there are many "fake" movements in table tennis that even for a same move flow of one's body, only by slightly change the hitting position and timing, the ball spin and trajectory could be totally different.

Even though stroke classification is crucial in table tennis competition. It is not the easiest way for beginners to get improved of their skills. Moreover, the classified result could be used more on training process data analysis rather than concurrent feedback.

Discussion

As the very first trial, the stroke classification model proved that it is a valid method to use haptic data collected on the racket to classify different stroke types which also inspired me to go further with this method. There are also several directions pointed out to be considered for revising next prototype on both the system improvement perspective and the user experience improvement perspective:

1. Interactivity: the stroke classification model lack concurrent feedback for trainees to receive and process the system's output.

2. Interpretation: stroke type is not an optimized perspective for beginners to understand the basic strokes. This model is more effective used in later-on analysis rather than real-time instruction.

3. Dataset: during the testing, the generalization of real time haptic data is not as expected. In consequence, the accuracy in testing period is significantly lower than the evaluation accuracy in training period which reveals the defect of dataset in both quality and quantity. This refers to revision of classification method and also harder effort in data cleansing and collection.

3.5.2 Personal Instruction Model

The participate observation in Tactive mentioned in previous section was carried out after I received advises about the first model. The personal instruction model was built due to the insight from this fieldwork.

Data Collection

With certain accuracy reached by the evaluation mode, a model with more defined classifications was designed based on personal experience and individual difference. The novice player who contribute to the novice data samples of evaluation model took part in the training session from a professional coach in TACTIVE. After the training session, the coach picked up three most made mistakes of this player to guide the data collection for the personal model. The aim of personal instruction model is to give detailed instructions according to the haptic data recieved in real time. In this case, the haptic data is interpret as a specif condition of strokes, such as when hitting a edge, and hitting with a bad angle and hitting at a bad timing. The data was collected with one player, the whole playing process was recorded for labeling afterwards. The model was trained under the exact same network environment.

System Accuracy and Discussion

The training accuracy of the personal model is lower than the previous stroke type classification model. Only 82%of evaluation accuracy was achieved during the training phase. In reference of the previous model accuracy, I assume that the actual performance would be even lower. The data quality required for the personalized data is even higher and considered to be difficult to accomplish under current system. For the similar reason as the stroke classification model, the data samples in different labels are not distinguished as expected. To look for other options, literature review on motor skill acquisition were done after this. With the insight from Schema theory for discrete motor skill learning which was introduced in previous chapter, and the experience from fieldwork in VICTAS. The finalized model was built and will be described in following section.

3.5.3 Stroke Evaluation Model

The stroke evaluation model was built based on the feedback from the users and the expert about the stroke type classification model. The main points of the revision from the first model is to improve the real-time interaction and also alter the focus on interpretation of the strokes for beginners. In order to improve the system performance, increase the sensor type and number was considered as a powerful choice at first. But with further discussion about the final goal of this research, it is refined that the focus is on effective utility in self training. Thus, in order to maintain the system simplicity as much as possible, instead of changing or increasing the sensors, increasing the data differential among each label is another option to put effort in for the system performance.

Data Collection

After the stroke type classification model and the ideation between with experienced player and coach, the concurrent feedback of the classification system was raised as the key topic of next model design. For the third model, I want to build a tight relationship between sensation and a determination that enable novice to distinguish sensory information. I decide to collect haptic data from players with different play experience. Finally, the dataset was collected from an experienced player and a novice player. They were all asked to do forehand drive with a standard format repeatedly. Over 250 data samples were collected for the new model. After training, the training accuracy and the evaluating accuracy are 99% and 94%.

System Evaluation

To test the accuracy of the stroke evaluate model, two participants contribute to the evaluation of system accuracy. Each of them played for 10 minutes with the system. The play process was recorded with not only the haptic data but also the video data. The actual evaluation of each stroke was done by a 10 years experienced player to compare with the result that the system provided.

User Test and Feedback

Two participants took part in the first test of the stroke evaluation model. They were asked to play freely with the system. One participant was told about the

Actual \ Predict	Bad	Nice	Accuracy
Bad	28	14	66.7%
Nice	3	32	91.4%
Overall Accuracy	90.3%	69.5%	81%

Figure 3.14 System accuracy of stroke evaluation model

goal of this experiment and another was not. The first participant is 25 years old male player, a table tennis amateur without systematic training experience.

Performance during test. At first, the player feels confused about the standard of a “nice ball”. He then started to try different strokes, like returning the ball in backhand, giving the ball a side spin, or changing the power when hitting the ball. When his new trial successfully gives a “nice ball” result, he shows a satisfying face. After several times of trial, he starts to conclude the pattern of when the system gives a “nice ball” feedback and continue to repeat the way where he get the feedback he wants to make sure that his conclusion was right.

After 10 minutes training session, he was asked to convey the pattern of a “nice ball”. He felt confused when he was playing with the system. Then he was showed the video and synchronized haptic replay, the recognition of the patterns that lead to a different result start to change in he’s mind. First of all, he commented that even though not sure about the feeling towards haptic review, but from the video replay that he got insight of what makes a better stroke.

Even though the effect of haptic review needs further discussion, it is clear that this user test gave positive feedback on the system performance and it’s effect on supporting self training and help trainees too understand strokes better. I decide to carry on further evaluation using this trained model which will be introduced in the next chapter.

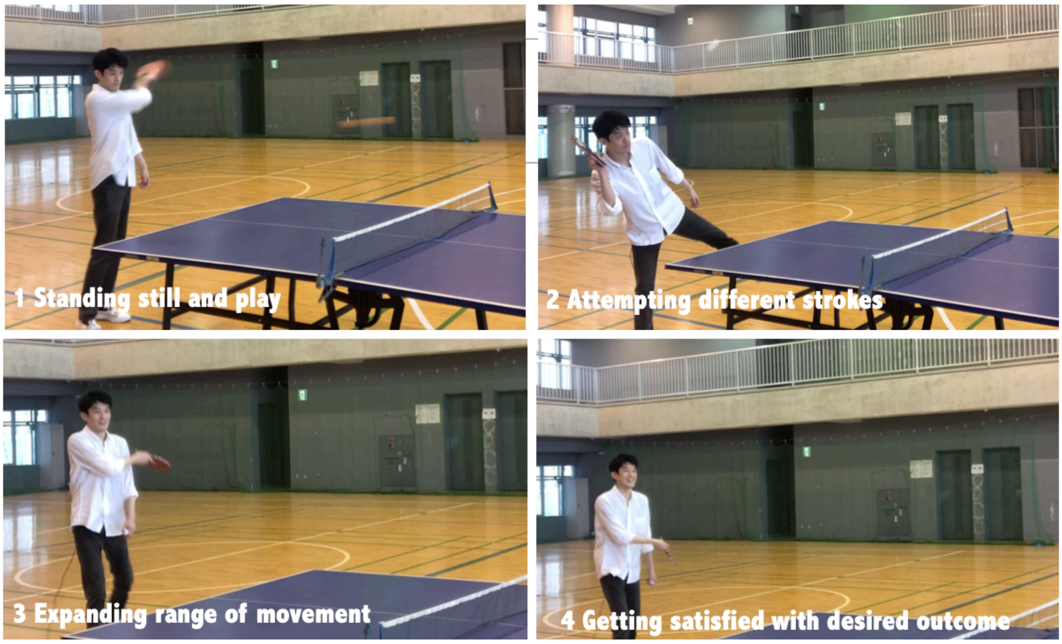


Figure 3.15 User Test Scenarios

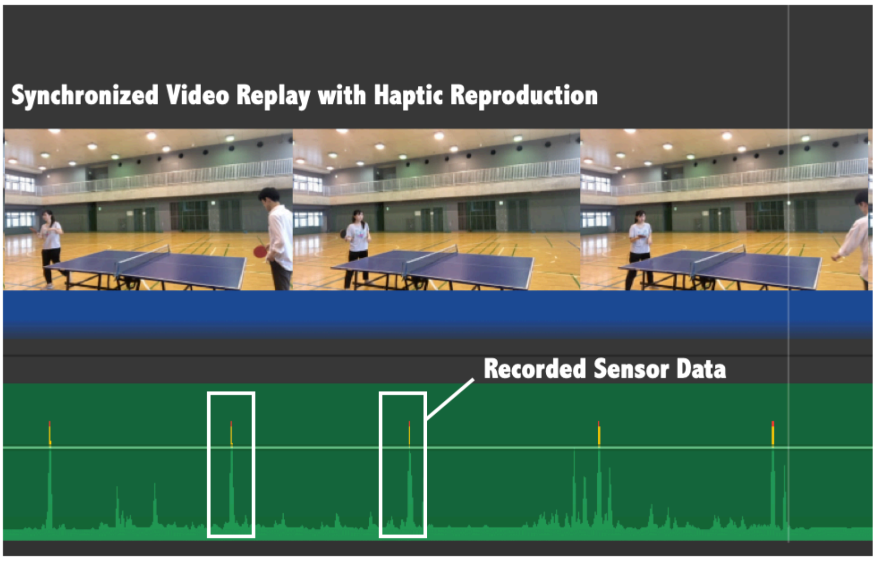


Figure 3.16 Synchronized Haptic Replay with Video

Chapter 4
Evaluation

In the previous chapter, the steps taken from building the concept to developing the final prototype was described in detail. During the development process, the performance of the system were already evaluated and discussed. The results present positively on system effectiveness of supporting table tennis self training.

To further evaluate the system accuracy and usability of the design. A more detailed experiment was carried out which would be discussed in following section.

There are three purposes of the experiment which are:

1. Evaluate the overall system accuracy and the system performance under circumstance of training alone and training with accompany;
2. Validate the user experience of training with the system;
3. Assess the user performance during and after training with the system.

4.1. Experimental Setup

The scenario of the system utility is a relatively private context for novices to train themselves together or alone without the professional coaches' supervision. Consequently, the experiment was tested under two conditions: training alone and training with another novice partner.

Equipment needed for the experiment are a PC, sensor embedded racket, normal racket, a camera or a smart phone for recording and a table for practice.

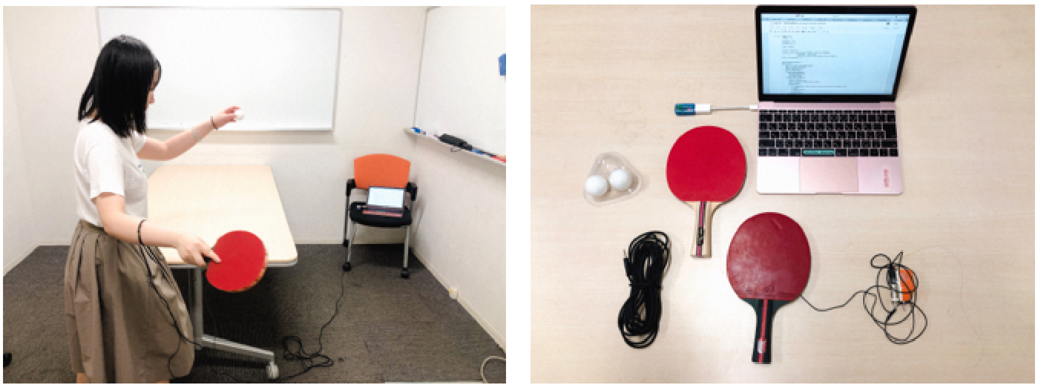


Figure 4.1 Experiment Devices and Setup

4.2. Evaluation Procedure

4.2.1 Experiment Procedure

- Warming Up: For the records of personal initial condition, the participant was asked to play with normal rackets for 3 minutes. The participant was asked to continue forehand rally as long as possible for the first 2 minutes and play freely for another 1 minutes.

- Training session: After warming up, the participant will start training with the feedback system. On considering of the individual differential on learning speed and initial level, a task that achieving 20 nice ball determination instead of a time limit was set to end the training session.

- Experience Assessment: After the training session, a questionnaire-based experience assessment of the system was carried out in order to evaluate the subjective feeling on the system usage.

- Self Assessment: The video replay of participants' training process was prepared for a after-training self assessment to test the user's comprehension towards a specific stroke.

- After-training Comparison Test: An afterwards play test with normal racket was carried out in order to compare the short-term effect of the training system.

4.2.2 Analysis Procedure

The whole experiment process was recorded with video for the purpose of afterwards data collecting and further performance analysis.

- System Verification: The system accuracy was calculated based on data collected from user test period from experiment. In order to check the correctness of system determination on each stroke, the participant's test experiment videos were cross checked by two experienced players. The strokes that marked differently were removed from the result.

Stroke Quality Double Check Table							
Participate1	1	2	3	4	5	6	7
Judge1	+	+	-	-	+	+	-
Judge2	+	+	-	+	-	+	-
Final	+	+	-	/	/	+	-
System	+	-	-	-	+	+	+
System Correctness	T	F	T	/	/	T	F

Table 4.1 Example of Stroke Quality Double Check Table

- User Experience: the data from the questionnaire was collected and discussed in combining with the information of user differential on play experience, play style(grib style, forehand or backhand) and system accuracy.

- User Performance: the user performance during and after training with the system were evaluated by observation.

Figure 4.2 Video Screen Shots of Accompanied Training(upper) and Solo Training(lower)

4.3. Evaluation Result

4.3.1 System Verification

There are 7 participants varies from beginner to experienced players contribute to the user test in total. Followed are the detailed data of overall system accuracy and individual participants data. The results were recorded and checked manually as described refers to table4.1.

Overall System Accuracy			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	161	44	
Low(System)	76	177	
Accuracy	67.93%	80.09%	**73.80%**

Figure 4.3 Overall System Accuracy

There are 458 effective strokes result were taken into calculation and the overall accuracy reaches 73.8%. The accuracy on determine a low quality stroke is higher than high quality stroke which are 80.09% and 67.93% respectively. Individual results fluctuates from 55.88% to 83.78%.

There are three participants(participant5,participant6 and participant7) who plays penhold grib, the system accuracy on two of them are extremely low at around 55% to 60%. The other participant's accuracy reaches 83%. The comparison between two styles is as followed figure4.6 which show a huge performance difference.

The grib style of this system is limited from the data acquisition period because only forehand drive strokes were collected for the final model by both shakehand style players.

The system accuracy of practicing with accompany is slightly higher the solo practice.

The system accuracy on different participant skill level were calculated as following figure.4.8 The training accuracy among amateurs are the highest, followed is the beginner group and the result of experienced player is the lowest.

Participant1: Beginner, solo practice, shakehand, forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	16	4	
Low(System)	8	18	
Accuracy	66.67%	81.82%	**73.91%**

Participant1: Beginner, accompanied practice, shakehand, forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	20	4	
Low(System)	11	24	
Accuracy	64.52%	85.71%	**74.58%**

Participant2: Experienced, accompanied practice, shakehand, forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	33	5	
Low(System)	9	8	
Accuracy	78.57%	61.54%	**74.55%**

Participant2: Experienced, solo practice, shakehand, forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	28	3	
Low(System)	10	4	
Accuracy	73.68%	57.14%	**71.11%**

Figure 4.4 Participants and Individual Test Results

4.3.2 Qualitative Feedback

A self assessment questionnaire was carried out for every participants after the training session to see their feedback on the evaluation system and their understanding about stroke qualification. There are 7 players took part in the questionnaire.

Followed are the linear scale(1 to 5) answer result for following 4 statements:

1. I feel the voice feedback confirms my judge during play.

Participant3: Amatuer, accompanied practice, shakehand, forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	32	14	
Low(System)	3	28	
Accuracy	91.43%	66.67%	**77.92%**

Participant4: Amatuer, accompanied practice, shakehand, forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	22	2	
Low(System)	12	35	
Accuracy	64.71%	94.59%	**80.28%**

Participant5: Amatuer, accompanied practice, penhold, backhand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	4	10	
Low(System)	20	34	
Accuracy	16.67%	77.27%	**55.88%**

Participant6: Amatuer, accompanied practice,penhold,forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	16	18	
Low(System)	4	19	
Accuracy	80.00%	51.35%	**61.40%**

Participant7: Beginner, solo practice, penhold, forehand			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	5	2	
Low(System)	4	26	
Accuracy	55.56%	92.86%	**83.78%**

Figure 4.5 Participants and Individual Test Results

2. I feel the voice feedback confuses me.
3. I feel guided by the voice feedback.

Penhold Grib Accuracy			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	25	30	
Low(System)	28	79	
Accuracy	47.17%	72.48%	**64.20%**

Shakehand Grib Accuracy			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	136	14	
Low(System)	48	98	
Accuracy	73.91%	87.50%	**79.05%**

Figure 4.6 System Accuracy on Different Grib Style(Penhold and Shakehand)

Solo			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	42	7	
Low(System)	18	22	
Accuracy	70.00%	75.86%	**71.91%**

Accompanied			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	114	45	
Low(System)	39	140	
Accuracy	74.51%	75.68%	**75.15%**

Figure 4.7 System Accuracy on Different Training Condition

4. I gradually understand how to get the desired output("nice ball") during play.

The individual results were concluded in the following graphs in "Confirmation, Confusing, Guidance, Comprehension" 4 terms respectively.

Beginner			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	36	8	
Low(System)	19	42	
Accuracy	65.45%	84.00%	**74.29%**

Amateur			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	54	16	
Low(System)	15	63	
Accuracy	78.26%	79.75%	**79.05%**

Experienced			
Stroke Quality	High(Actual)	Low(Actual)	Overall Accuracy
High(System)	61	8	
Low(System)	19	12	
Accuracy	76.25%	60.00%	**73.00%**

Figure 4.8 System Accuracy on Different Skill Level

The average of "Comprehension" is 3.5 points. 5 out of 7 participants gave a result over 3 points which refers to that during training session, most of the players gradually understand the patter of how to get a desired output. Two participants who played using a penhold grib style gave results of 3 and 3.5. Both of them find it confusing sometimes during training session which shows a relevance that the system accuracy influences the player on finding the pattern and understanding how to perform a good stroke. For overall inclination, the higher the system accuracy reaches, the easier the player could understand the pattern of a good stroke.

Participant3 and participant4 are similar players with the same grib style and both reached the accuracy around 80%, however, giving fairly different results. The participant3 find the system less confusing and the pattern was easy to recognize while participant4 thinks even though it confirms his own judge most of

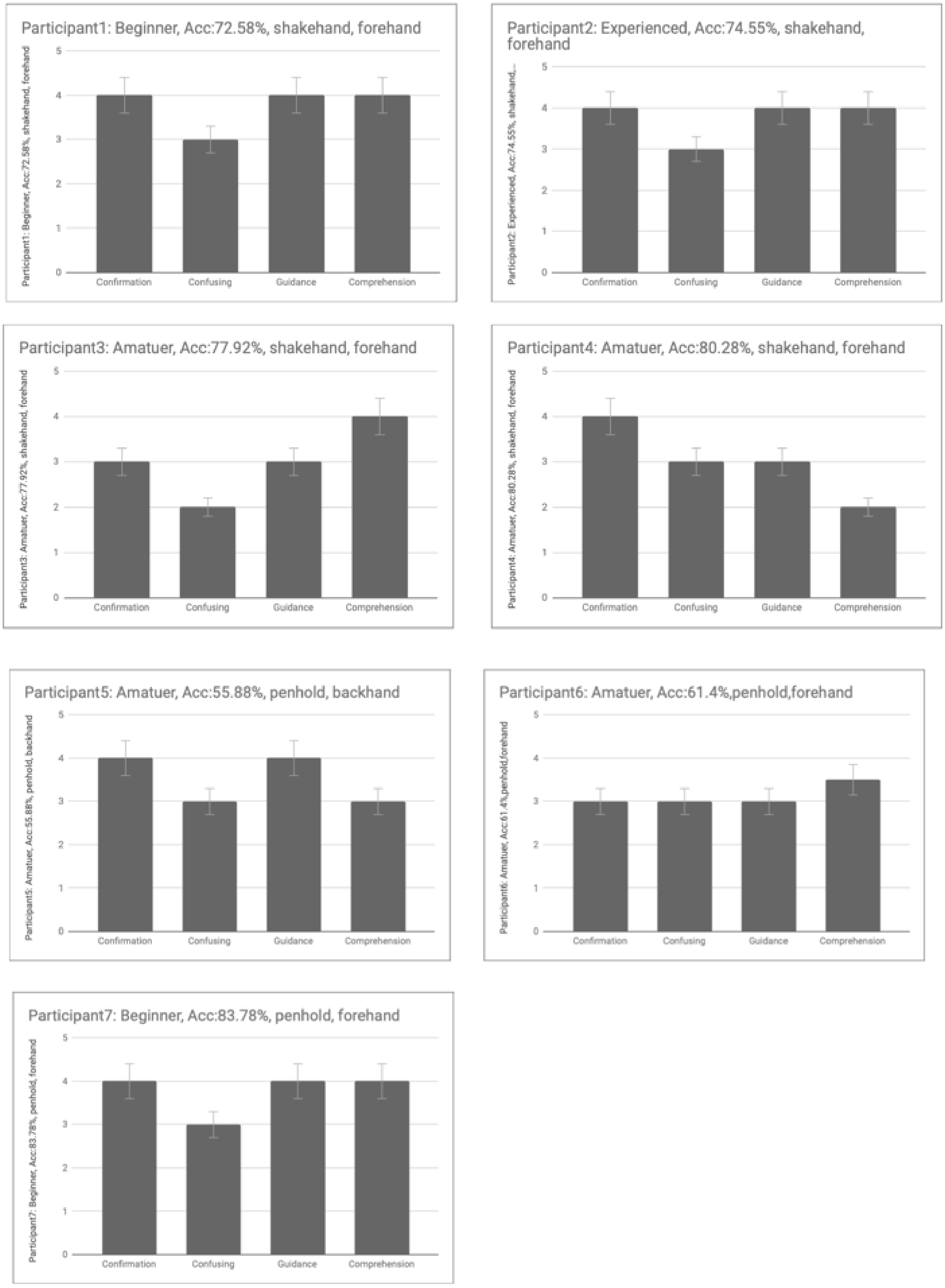


Figure 4.9 User Experience Self Assessment Result

the time, it is not clear of how the good stroke output was determined. Overall, participants show positively about understanding the system mechanism.

There are 4 out of 7 participants gave a score of 4 in terms of system performance on guiding. All the 4 participants also gave a score of 4 in terms of confirmation and 3 of them marked 4 on comprehension as well. This result reveals that when the player get confirmed by the system more frequently, he or she will feel guided by the system more.

4.4. Discussion

4.4.1 Expanding Training Scenarios

Usually, table tennis is trained with the instruction from experienced player or professional coach. The concept of training without supervision is proved from various perspective. The system accuracy and user experience evaluation shows no huge difference between solo training and training with accompany which proved positively on the usability for training alone. Two participants that took part in the solo practice experiment commented positively on the usage of the system indoors in daily scenarios. Moreover, for experienced player could also benefit from the system to carry out multi-ball practice with serving robot.

4.4.2 Encouraging Deliberate Practice

Deliberate practice is necessary for skill acquisition which was observed during experiment that participants thinking actively and making attempts to get better result. During the warming up session, participants tend to focus on the result of ball which sometimes lead to continuous failure for not changing their movements. Unlike the warming up session, in order to get the desired outcome, most participants presented a inclination of trying to play differently during training session.

Take participant7 who is a beginner with almost no past experience of playing table tennis as an example, her stroke performance in the warming up session was fairly poor that most of the strokes failed to bring out a desired output. During the early part of the training, the successful rate of a high quality stroke from the system is around 10% percent which even discouraged the player sometimes. However, after several rounds, the player start to observe the connection between the ball and her own movement, noticing the ball was bouncing too high while she hit the ball with a over racket angle. She then start to change her own wrist angle while hitting to see if the outcome could change.

When failed to return the ball on the table for the most of the time, she suggested to practice serving instead. These attempts contributed the the improvement of successful rate of the upcoming rally practice.

In overall, when the participants start training session with the partner system, they all tend to adjust their movement positively. No matter what are the results of these attempts, they all contribute to necessary experience to build up comprehensive recognition towards the relationship of movement parameters to the determination of an outcome.

4.4.3 Habit Forming

After training session, the participants were asked to play with normal rackets again. It is observed that participants have the inclination to repeat confirmed strokes during training session unconsciously which is a sign of the habit forming.

Participant3, who is an amateur player prefer to return the ball with backhand at first, when he notice that the system gave better outcomes when he try to perform a forehand drive, he started to repeat and adjust his motion to give a better spin. After the training session, even though playing with a normal racket, he obviously increased the times of returning the ball with his forehand.

Participant7 who I mentioned above also changed obviously in the usage of the racket as showed in figure4.10 which presents 6 strokes to return the ball from a similar position. In the warming up session as showed in the first row, she returned the ball with a stiff wrist which made her missing the hitting timing for several times, and hold the racket downwards which would easily strike the ball bouncing too high and results in failure in returning the ball; In the second row, she tried to change the racket direction and angle that urged her wrist to stretch in order to get a desired outcome and it worked out; After the training session, it was obvious that her hitting habit was different from the warming up session that she returned the ball with an appropriate angle and a more relaxed body condition.

These kind of behavioral change and habit forming phenomenon happened more or less to almost every participants even only after one training session. The further effect of long-term training could be expected.

Figure 4.10 Improvement of Racket Usage Before(1st row), During(2nd), After(3rd) Training with the System

Chapter 5
Conclusion

The goal of this research is to enable novice players to get improved during self training without supervision and instruction from professional coach by being motivated to deliberate practice, continue the repetitive basic skill training for novice players to learn table tennis and get improved.

This research proposed an evaluation system for table tennis novice player utilizing the audio classification method with haptic data collected from players in various skill level. There are mainly three aspects of work bestowed insights for the final prototype throughout the design process which are fieldwork in various real life training conditions, interviews and ideation with experts in training and table tennis, technical reviews by myself and suggestions by mentors. Throughout extensive fieldwork and background research, it is revealed that building an intrinsic connection in mind between sensory information and the knowledge of results about a certain movement is the fundamental of motor skill acquisition. After multiple trials of different dataset collection and user tests, the final design of the evaluation system was developed based on this theory.

The system performance and effectiveness on self training without professional instruction were verified in experiments in multiple experiment conditions. It is positively proved that this training partner enables beginners to carry out self training alone or with accompany. Several behaviors such as changing the racket angle, enlarging the range of standing position, increasing the range of arm movement that are beneficial to table tennis learning during training process with the partner and performance improvements after training especially among beginners were observed during experiments. Besides, the method of utilizing haptic data as a feature to interpreting motor skills offers a brand new perspective to define the role of haptics in sports training.

Overall, the system performs well on the stroke types in the range that the dataset covers and have effects on improving novices' self training to some extent. Nevertheless, it still needs improvement both in technical part and the experience design part to achieve more overall training support.

First of all, because of the hardware limitations and dataset size limitations. The system accuracy is not high enough to substitute a professional coach's supervision, and its evaluation is valid only to specific conditions of shakehand grip style and forehand drive for current phase which I believe could be improved by enlarging the number of data samples. Moreover, the audio cable used to transfer real time sensor data from racket to the system interferes the play experience slightly. It should be considered to make the device wireless in future improvement.

For future development, enlarge the dataset coverage and seeking more tech is key to improve the system performance. Seeking more technical aspects and features of recording data such as resolution and distortion ratio should be carried out in future development. Also, it is mentioned from part of the user comments that simple output is not enough. Thus, feedback other than audio output could be considered in future design to provide more information to the trainee. To seek a balance in output design between providing clearer instruction and keep the incentive of voluntary thinking would be a direction for the future design.

Moreover, it is a unique feature that haptic data could be reproduced in formats such as vibration which is an intuitive way for human to perceive. This feature could build up a two-way communication between the system and the user that could be used in scenarios such as sharing professional player ' s knowledge, reviewing the training history together with the replay video to strengthen memory and so on.

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Appendices

A. Questionnaire

Self assessment for user test

1. **I am a table tennis _____**

   Mark only one oval.

   - Beginner
   - Amateur
   - Experienced player
   - Professional player
   - Not sure

2. **I know what is a forehand drive.**

   Mark only one oval.

   - Yes
   - No
   - Maybe

3. **I know how to perform a nice forehand drive.**

   Mark only one oval.

   - Yes
   - No
   - Maybe

After training session(before review)

1-5 disagree to strongly agree

4. **I can tell a good stroke from a bad one before the system gives me feedback.**
   Mark only one oval.

	1	2	3	4	5	
Never	◯	◯	◯	◯	◯	All the time

5. **I have no idea before the system gives me feedback.**
   Mark only one oval.

	1	2	3	4	5	
Never	◯	◯	◯	◯	◯	All the time

6. **I feel the voice feedback confirms my judgement during play.**
   Mark only one oval.

	1	2	3	4	5	
Never	◯	◯	◯	◯	◯	All the time

7. **I feel the voice feedback confuses me.**
   Mark only one oval.

	1	2	3	4	5	
Never	◯	◯	◯	◯	◯	All the time

8. **I feel guided by the voice feedback.**
   Mark only one oval.

	1	2	3	4	5	
Never	◯	◯	◯	◯	◯	All the time

9. **I gradually understand how to get the desired output("nice ball") during play.**
   Mark only one oval.

	1	2	3	4	5	
Disagree	◯	◯	◯	◯	◯	Strongly Agree

Self Assessment(with video)

Compare your performance between "nice ball" and "try again", choose the possible reasons of failure

10. **Standing posture**

Mark only one oval per row.

	Too high	Too low	No difference	Not important to the result	Not sure
Standing Posture	○	○	○	○	○
Arm Position	○	○	○	○	○

11. **Racket Angle (with horizontal surface)**

Mark only one oval.

- ○ Too big
- ○ Too small
- ○ No difference
- ○ Not important to the result
- ○ Not sure

12. **Hitting timing**

Mark only one oval.

- ○ Too fast
- ○ Too slow
- ○ No difference
- ○ Not important to the result
- ○ Not sure

13. **Others**

____