Universiteit Utrecht

Department of Information Computing Sciences

Game and Media Technology - Master Thesis

Rugbysense: Exploring Possibilities For Data-Driven Reflection on Place Kicking In Rugby Union

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Abstract

This thesis examines the feasibility of using accelerometer and gyroscope data in a feedback system for place-kicking in Rugby Union. Successful place kicks can decide matches when the score is close. This is why it is an important skill in Rugby Union. As it takes many hours to master a coach cannot always be present during these training sessions. During these sessions, players still want to gain insights on how to improve their technique. This thesis explores what is needed for a data-driven feedback system to help players gain insights into their place-kicking performance.
The study uses a user test with 12 participants an account of the users' experience with the system. This experience is defined in five themes: *Understanding Data*, *Felt Experience Versus Objective Measurements*, *Self-Directed Exploratory Learning Versus Guided Learning*, *Data Literacy and Self-Efficacy Needed for Data Engagement* and *Improvements for the System*. These themes show that the unprocessed accelerometer and gyroscope data from the IMU sensor is too abstract for the participants to grasp. Thus additional guidance, such as providing context and simplifying the data, is needed to improve their understanding. The findings can also be used for the design of a future user interface. The findings also show that users find measures, such as position or power metrics, more intuitive to gain insights into performance and training goals. The findings aim to serve as a foundation for future IMU-based data-driven feedback systems for sports performance.

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Contents

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Introduction

Rugby Union (from now on referred to as rugby) is a relatively small, but rapidly growing team sport. The sport has grown from 6.6 million world wide participants in 2014 [7] to 9.6 million players in 2018 [27]. It is a physical team sport where different body types are celebrated.

The most commonly played version of rugby is 15s, which is played between two teams of 15 players on a grass pitch (Figure 1.2) for two 40 minute halves. The team that has scored the most points after 80 minutes wins the game. There are several ways of scoring points. 5 points are awarded when a player grounds the ball in the opponent's in-goal area (Figure 4.3c). This is called scoring a 'try'. When a try is scored 2 more points can be gained by kicking a conversion kick through the poles. This can be done with a drop kick or place kick (Figure 4.3). 3 points are awarded for drop goals in open play and penalty kicks through the poles.

Figure 1.1: *Player in open play during a rugby match. Source: Jan Kaper*

In the game of rugby, players are not allowed to pass the ball forward, only backwards or laterally. Gaining ground towards the opponent's in-goal is done by running with the ball in hand, kicking the ball, or within a scrum of a maul. The defending team's goal is to stop the opponent from scoring and gain possession of the ball so they can attempt to score points. This is done by bringing the ball carrier to the ground with a tackle or contesting for the ball with the ball carrier on their feet (a maul). The two set pieces in rugby are line-outs and scrums. A line-out occurs when the ball or the ball carrier touches the sideline. Forwards line up a meter apart, perpendicular to the touchline and between the 5 and 15 m lines. A player from the team that did not play the ball into touch throws the ball in between the lines of players. Both sides compete for the ball. Lifting teammates into the air to gain an advantage is allowed. A jumping player is not allowed to be tackled until they are back on the ground. The second set-piece, the scrum, is a way of restarting the game after minor infringements such as accidentally passing or knocking the ball forward. A scrum is formed by the 8 forwards of each team. Both packs of players are bound together in three rows. On the ref's call, the front row

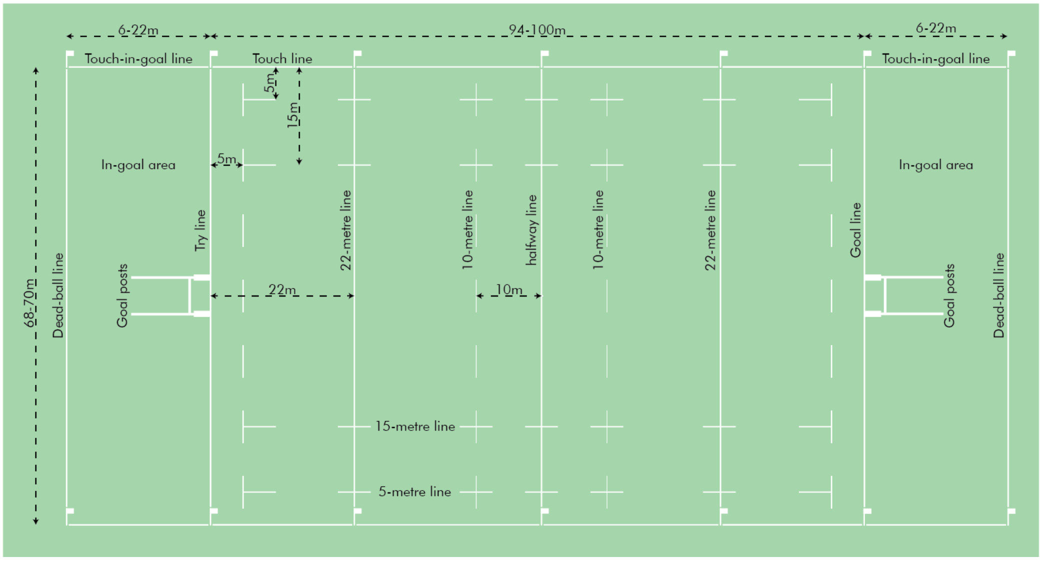

Figure 1.2: *Rugby pitch dimensions and lines*

binds on the opponent's front row. The scrum-half of the team that was awarded the scrum then feeds the ball and both hookers try to gain possession by hooking the ball backwards with their foot. At the same time, both packs try to push forward to help gain possession. The side that gains possession can either keep the ball in the scrum while moving forward toward the try line or transfer the ball to the back of the scrum where the scrum half or number 8 can pick up the ball and play it. For bigger offences, free kicks or penalty kicks are awarded. A team can then tap kick the ball and resume play, kick the ball from hand to gain ground or attempt a place kick at the poles.

(a) *Player grounding the ball in the opponent's in-goal area to score a try. Source: Jan Kaper*

(b) *Player attempting a conversion kick at the poles after a try has been scored. Source: Jan Kaper*

Figure 1.3

There are many different skills in rugby, from basic skills such as passing, tackling, and sidestepping to more specialist skills such as line-out throwing and different types of kicking techniques. This thesis will look at designing a system that supports players in improving their place-kicking technique with a data-driven feedback system. Successful place-kicking can decide matches when the score is close, which makes it an important skill to train for kicking specialists. Many of these training hours are done without a coach present. This is an area of the sport that is still underdeveloped within rugby in the Netherlands. A portable data-driven feedback tool aimed at players' personal development could fill this gap in development by allowing players to have more high-quality training hours even without a coach present.

(a) *A scrum before the bind. Source: Jan Kaper*

(b) *A line out with one team lifting a player to gain an advantage. Source: Jan Kaper*

Figure 1.4: *Set pieces in rugby.*

In this thesis, we present RugbySense, a data-driven feedback system designed to assist rugby players in their place-kicking training. Fitness trackers that are used to track training progress are increasingly popular. For rugby, such a system does not yet exist. The goal of this thesis is to investigate the possibility of such a system specifically designed for place-kicking in rugby. The system uses data from IMU sensors to give users a graphical representation of their performance. This can provide useful insights into their execution of the place-kicking technique. The aim of this system is to help players improve their technique, gain confidence, and become more consistent using a system that is easy to set up and use.

1.1 Research Procedure

Figure 1.5 shows the methodology used during the thesis and the structure of this report. Chapter 2 (Related work) shows the results of a literature study into the field of HCI and sports. At the end of this chapter, we have defined the scope of the research with multiple research questions. In Chapter 3 (Design & Implementation) we will discuss how we arrived at the system design. In the design process, we used a pre-study in combination with the related work section to define the design requirements and principles. These were then used to design the system. A prototype of the system design is then built. This process will be discussed in Chapter 4 (implementation). The prototype of the system design was then evaluated, which we discuss in chapter 5

(Evaluation). In the next chapter (Discussion) we will discuss the results of the evaluation and answer the research questions. We will also present the limitations of our work and how future work can build on this thesis. The final chapter (Conclusion) will summarize and conclude the thesis.

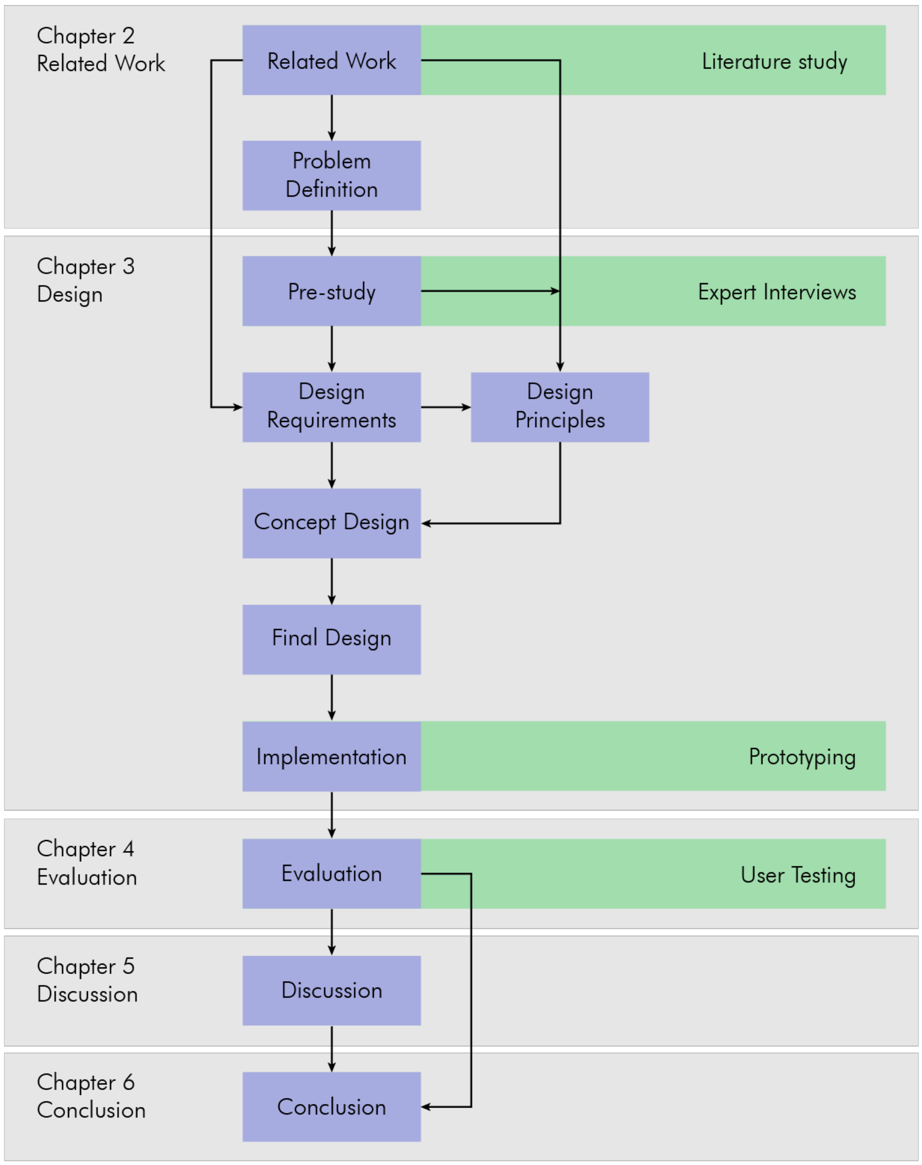

Figure 1.5: *Methodology*

1.2 Research Aim

This thesis explores if a sensor-based data-driven feedback system could be used to train place-kicking specialists to improve their place-kicking performance.

1.3 Contributions

This thesis entails three main contributions:
First, possible metrics for a data-driven feedback system for place-kicking were explored using expert interviews. This study among the first to explore such a system designed specifically for place-kicking in rugby. Second, an implementation of this system was built. Thus possible solutions for a prototype were explored and exposed to a training environment. Third, the system was evaluated with potential end users in a lab environment. The participant interviews provided important gaps for future work to explore.

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Related Work

A variety of subjects have been examined to better understand the research topic. In the field of HCI (Human-Computer Interaction) for sports, there are many areas of research that are useful for this thesis. The first subject I will look at is wearables in sports. These are electronic devices that people wear on their bodies. I will focus on wearables that are used in sports to track data for performance feedback and reflection. These wearables track different types of physiological data, leading to the next section, which will focus on a complex type of physiological data that is prevalent in HCI research: Electromyography (EMG) and its use for Electrical Muscle Stimulation (EMS). The subject I will discuss after this is augmented reality (AR) in sports. There are many different AR systems that are used in sports. The systems I will look at focus on real-time feedback. The final section will provide information on the use case. This section will go more in-depth into the rugby kicking movement we are looking to augment. Finally, I will summarize my findings and present my research questions and hypotheses.

2.1 Wearables in Sports

There currently exist many different types of wearable devices for consumers to track, analyze and reflect on sports performance. A common wearable for sports performance tracking is the smartwatch. These types of watches track parameters such as distance, speed, and heart rate in real-time. They also provide data on your sleep and recovery. These wearables often have a companion app for your smartphone to store the data and analyze it more deeply. Different studies have been done on the use of smart sports watches. One study showed that distance and heart rate data collected using a sports watch can give an indication of football players' fatigue [32]. Most smartwatches offer textual status information as real-time feedback. This paper investigates a different approach to real-time feedback visualizations on smartwatches. The information presented on the watch was more minimalistic and graphical than those on current consumer products [29].

There also exist commercial wearables aimed at tracking football performance with sensors on the player's shoe [1, 23] and research has also been done with textile pressure sensors on the shoe [36]. These sensors can be used to detect several football-related actions, such as shots and passes accurately [30]. Tennis stroke types have also been identified and classified using wearable sensors [6]. Further research presented a way to estimate ball speed and spin based on racket-mounted sensors [5]. This paper explores a rope-pulling detection system for climbing using a sensor attached to the bolt anchors and a camera [12]. The goal is to gain insights into climbers' behaviour throughout the day. This hybrid system performed better than a video-only system that was also tested. This shows the usefulness of sensor-based systems.

Many injuries occur due to wrong shoe choices or a bad running technique. Injuries can be prevented by increasing bodily awareness. RunMerge aims to give runners a better understanding of their running using existing hardware but improve the presentation of the data using visuals [16]. GraFeet augments running shoes to increase users' understanding of sensor data. The system visualizes kinesiological data about the runner's feet and gait using LED outsoles. The user can access this data after their run [34].

The work mentioned explores the use of wearable technology for tracking players' performance. Many solutions are designed with a specific sport in mind. No such wearables have been designed in the context of rugby. This gap in the literature provides an opportunity for this thesis research,

2.2 Physiological Data

There are many different types of physiological data. One type has been mentioned in the wearable section, heart rate, but some other examples are blood glucose levels, blood pressure, respiration rate, and body temperature. An interesting type of physiological data for sports is electromyography (EMG).

EMG: Electromyography

Electromyography measures the muscles' response to a nerve's stimulation. This data can give insights into the muscles' health and the state of nerve-to-muscle communication. This can be useful in the field of sports for the rehabilitation of injuries. However, it is difficult to get reliable surface EMG recordings [8]. This is a problem for medical diagnostics. However, a lack of precision is less of a problem in interactive applications such as games [15] or even prosthetics control.

An example of an interactive application of EMG is the MYO controller which uses eight EMG sensors to measure muscle tension and inertial sensors for hand orientation. The quality of the motion and muscle sensing is of sufficient quality for music expression, but the number of built-in classification actions is limited [24].

Another use for EMG can be to gain bodily insights, which can allow people to gain a deeper understanding of their physiology. This can be done by giving Electromyography-based biofeedback while performing physical activities. This system allowed users to improve their form during exercises. [14]

A problem with EMG is that the optimal settings are context-sensitive and expertise in signal processing and instrumentation is needed to use the data [8]. This indicates that a one size fits all solution is difficult to achieve.

EMS: Electrical Muscle Stimulation

Electrical muscle stimulation is also known as electromyostimulation, which more closely indicates its relation to electromyography. EMG measures muscle activity, while EMS activates the muscles. Electrical pulses are used to stimulate muscle contraction. Some common use cases of EMS are muscle strength training, testing neural and/or muscular function, or as a post-exercise tool for athletes. However, there are more creative ways to implement this technology.

EMS has been used to correct heel strike in running by stimulating the calf muscle. The method leads to significantly lower heel strike rates than traditional coaching [9]. Another implementation for EMS is actuated navigation for pedestrians. The idea is that the user does not need to pay attention to the navigation as the muscle stimulations steer the pedestrian in the correct direction [25]. EMS can also be used to help maintain the ready position in crossminton [10]. This system allowed coaches to effectively and immediately guide players.

EMS has similar drawbacks compared to EMG. The application can be tedious as individual bodies are different and the application is not completely one size fits all. For use in dynamic situations, the pads might also move which can influence their effectiveness. For this reason we opted to use a contactless sensor that measures the user's movement instead of measuring physiological data.

2.3 Feedback in Sports

There exist many ways to provide feedback to players. One way of providing feedback is by using augmented reality (AR). AR is self-paced/self-reflective for single-player training. Users can choose how quickly to progress and might feel less like they are being watched when a coach is not present.

It is also cheap and does not require the trainer to be present. AR can be used for different training purposes. Some examples are realistic simulations in motorsport, training with projected holograms, and obtaining data in a simpler and more effective way [28], but there are more approaches to AR and sports.

Subletee looks at vibrotactile, auditory, and visual feedback to provide real-time feedback on body weight balance and elbow bend during a golf swing. Vibrotactile and visual feedback improved golf swing, while auditory feedback was frustrating according to users [33]. Feedback systems that require the user to look at a display while in motion lead to incorrect posture. This system uses sonification and sound image localization to train correct golf swing [31].

MTBalance helps novice mountain bikers with balance and posture using real-time feedback. Vibrations are used as this produced the lowest cognitive load on users [3]. Clairbuoyance uses LEDs to give swimmers feedback on their orientation in open water. This research showed a different feedback preference between novices and proficient swimmers [17].

Proper training results in a faster increase in skill and fewer injuries. Slackliner uses projections to give real-time feedback on body position and improve the training quality [22]. Another system that uses projections to support athletes is VirtualLadder [19]. For this system, they found that while the projections were favored, a display in front of users partially had better results.

Another sport that has been explored in research is rock climbing. This research has looked into making the experience in VR more realistic using haptic feedback [20], made continuous climbing in VR possible using a climbing treadmill [18], and looked into the

importance of virtual hands in the VR climbing environment [21].
This paper focuses on the use of high-fidelity information gathered from a smartwatch and combines this to give real-time feedback on the player's performance using a Hololens. The system could be used for sports that focus on hand-eye coordination and precision, such as billiards, archery, golf, and table tennis [35].

2.4 The Place Kick in Rugby

The movement we will be augmenting in this project is the place kick in rugby. The place kick in Rugby is an isolated movement where the player attempts a kick at the goalposts. A place kick is awarded either in the form of a penalty kick when the opponent makes an infringement or a conversion kick after a try is scored. In rugby, a place kick at goal usually happens multiple times during a match. When a team is awarded a penalty they can choose to either play the ball, kick it out further up the pitch for a line out or make an attempt at goal. If this attempt is scored 3 points are awarded. A place kick is also awarded when a try is scored. In this case, it is called a conversion. This kick can be taken from 10 meters or more in a straight line back from the position the try was scored. A conversion is worth 2 points. Successful attempts of a place kick can be the difference between winning or losing a game.
In rugby, place kicking is a specialist skill. It takes many hours of practice. Most of these hours will be without a trainer present.
The place kick consists of four phases, the set-up, the run-up or approach, the kick, and the follow-through. The first phase is the set-up. During this, the kicker first places their tee facing the poles. Next, the ball is placed onto the tee with the 'sweet spot' exposed. The sweet spot is the bottom of the ball where the kicker wants to hit the ball. Often kickers place the ball with the valve either at the bottom or top of the ball, with the seam pointing towards the poles. If the valve points to the outside this could potentially influence ball flight negatively as there is more mass on one side of the ball, which can cause the ball to wobble. After the set-up, the kicker walks backwards from the ball to create a run-up. The run-up or approach differs per kicker, but a general rule of thumb is to have an angle of 45 degrees toward the ball when you make contact with the ball. This results in your leg swinging through in the direction of the poles and thus a straight ball flight. In the third phase, the kicker places their plant foot next to the ball while their arm on the same side is up. The other leg is backward and the body acts like the string of a bow, storing energy to be released into the ball. As the kicking leg moves forward towards the ball the opposite arm comes forward and swings across the body. The foot makes contact with the ball on the sweet spot at the back of the ball. The part of the foot that makes contact is the bone on the top of the instep of the foot. This is where the shoe laces are. The next phase is the follow-through, which means letting the momentum of the kick carry you forward. Correct follow-through results in the ball travelling further. For a good follow-through, it is important to look at the ball until the kick is done. Looking away from the ball often causes the ball to be hit incorrectly.
Pre-routine can be used to focus on the task at hand. The post angle is the best predictor of how difficult a kick is. A smaller kick angle is a strong predictor of concentration time

[13]. Our system should not influence the pre-routine and allow the users to concentrate.

Summary and Research Questions

Wearable technology is used in sports training to track, analyze and reflect on performance. These wearables, often in the form of watches, use sensors to gather different types of data, such as heart rate, speed, acceleration, or distance covered. Wearables can also track movements to gain insights into a player's technique. This data can then be analyzed and used to reflect on a user's performance. Data-driven reflection can help users to train smarter and thus improve at a higher rate.

An interesting type of physiological data used in HCI and sports research is electromyography (EMG). EMG is the measurement of the muscles' response to nerve stimulation. When electrical pulses are used to stimulate muscles this is called electromyostimulation or electrical muscle stimulation (EMS). We choose not to use EMG and EMS as it requires additional hardware that needs to be installed on a user's body. This installation needs to be tested as muscle fibres differ per person. During movement, noise can also occur and pads might move, causing even more noise. This reduces the effectiveness and reliability of the system.

Instead, we choose to use IMU (inertial measurement unit) sensors. The setup for these sensors is more simple and thus faster. A design needs to be made to ensure consistent placement of the sensors on the users.

The data collected from these sensors can be used to provide players with AR (real-time) feedback.

The use case for this research project is training the place kick in rugby. This specialist skill is often trained without the presence of a coach as it takes many hours to master. A data-driven (augmented reality) feedback system could provide a form of coaching when a real coach cannot be present. This feedback system could also allow trainees to have higher quality training anywhere and anytime. A data-driven system might also feel more objective to users than a coach's feedback, which hopefully results in more consistent training.

RQ: Can a data-driven feedback system, that uses wearable sensors to track player movement, effectively train players to improve their place-kicking performance defined by consistency, kicking distance, and player's confidence?

We based this research question on previous work using sensor data in a sports context to train users in movement patterns and apply it to the context of placekicking in rugby. The focus of performance improvement will be on the player's consistency (being able to hit the ball on target), kicking distance (being able to kick successfully from further away), and confidence (trusting themselves to be successful).

RQ.1: What movement-based parameters influence the success of a place kick?

RQ.2: How can feedback be presented to support players during their place kicking training?

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System Design

The design of the system was done using an iterative process. Figure 1.5 shows a general overview of the design methodology. In this chapter we will look at the pre-study which was done by interviewing experts, coaches, and players, to gain insights and get a clearer idea of how to coach rugby players, which aspects influence performance, and what data might be useful to improve kicking. Using the related work and this pre-study we have defined the design requirements and principles. Next, we will discuss the concept design that has been made using these design requirements and principles. This concept has been tested on its usability to arrive at the final design of the system.
Trainers are not always available at any time. But the system is available all the time and allows the trainee to train at their own pace. Putting in high-quality training hours will improve skills quicker in their technique than when a player trains without feedback.
The goal of the system is to allow players to analyze their kicking technique and performance in training. Players can change a ”variable” to see how this will influence their performance. This way of learning is called self-directed exploratory learning. We think this exploratory learning approach to training will allow trainees to gain insights into their technique and reflect on ways to improve their skills.
Another goal is to present the data to the user in a way that is encouraging and motivating (positive coaching). This allows for growth in their confidence, while also pushing them to get better.

3.1 Pre-study: Expert Interviews

We used semi-structured interviews [4] with both coaches and players to gain insights into their experiences. These interviews were conducted in person or via Teams. We used open-ended questions to create a conversational interview and discover aspects we might not have considered so far. We tried to keep the questions general enough to not push the interviewee’s answers in a certain direction. Our focus when interviewing coaches was to learn more about how to coach players and what aspects influence performance. When interviewing players we focused on their experience when training on their own and what could help them train more effectively. The questionnaire can be found in Appendices 7.1 and 7.2.

Procedure

We greeted the participant and started to collect demographic data (i.e., XX, YY). We then started to ask participants about their experience in playing rugby and the challenges they encounter during their training sessions. The last part of the questionnaire focused specifically on training place kicking.

Data Analysis

The recorded audio data material will be transcribed verbatim. Then the data will be analyzed using the pragmatic approach to thematic analysis as described by Blandford et al. [4]. The first three interviews will be open-coded by two coders to obtain an initial set of codes. This code tree is discussed and adjusted. The student will then analyze the remaining data using this adjusted code. After coding the whole data set the code will be discussed with the supervisor and refined to the final code tree. Based on this analysis we will identify common themes.

3.2 Design Requirements& System Design

Based on the thematic analysis from the data analysis section and the literature study we derive design requirements and principles that inform a usable experience to analyze place kicks. The basis of the design requirements is the themes derived from the previous interviews. Based on the design requirements and principles a prototype will be designed and built. This prototype will be used to perform user testing with potential users.

Design Requirements

The following requirements are either based on the literature study or based on discoveries made during the prototyping phase.

1. The hardware needs to be protected from damage during testing.
2. The communication of data between the data collectors (sensors) and data presenter (a portable device with a screen) needs to be wireless.
3. The system needs to function properly for different users with different body sizes.
4. The prototype should not hinder the kicking movement.

System Design

The system is then designed to adhere to these requirements. This design process will iteratively explore different options to arrive at a design that will be used for testing. The design of the system has two aspects: hardware and software. The focus for both will be on functionality.

3.3 System Implementation

Based on the design we build a working prototype that can be used during the testing phase. The implementation has a physical component that collects sensor data and a digital component that analyses the data and presents a graphical representation of this data to the user on a portable device with a screen (smartphone/tablet/laptop).

Sensing Exploration and Prototype Design

The previous interviews informed about desired metrics for coaches and players to reflect on. Based on these metrics a hardware solution is chosen. The previous interviews also provided insights that can be used in the design of the graphical representations. Further user testing with concept designs could be useful to iteratively improve these graphical representations to fit users' needs.

Metrics

The following desired metrics were discovered during the pre-study interviews:

1. Explosiveness of kicking movement (quick acceleration)
2. Consistency in set-up, run-up, approach and kicking movements
3. Follow-through after kick
4. Hit point of foot on ball
5. Hit point of ball on foot
6. Keeping head down during kick (looking at the ball/staying in the kick)
7. Foot placement relative to the ball and tee.

We have decided to track the movement of the kicking leg. This movement is recorded using an IMU sensor attached to the leg or foot.
It is important that the sensor is attached such that it will not hinder the movement of the user or easily break due to impact with other objects. The housing of the sensor should be strong enough to protect the electronic components when dropped. The prototype needs to stay in position during the movements performed during a training session such as walking, running and kicking.
The metrics we can gather with this are

Physical Prototype

Internal Electronics

The internal electronics of the prototype had to be small, but powerful enough to accurately sense the movement. The base of the prototype was an Arduino Nano RP2040. This microcontroller board is widely available and has built-in modules that were useful for our purpose. These are a 6-axis IMU sensor for collecting the movement data and a WiFi and Bluetooth module for wireless connectivity. The board has a width of 18mm and a height of 45mm. It also weighs only 6 grams. This small footprint in combination with the built-in modules and a powerful processor made it a good fit for our prototype.
To power the prototype different options were explored. An alkaline 9V battery was too heavy and bulky, which made the prototype move around while kicking. Another

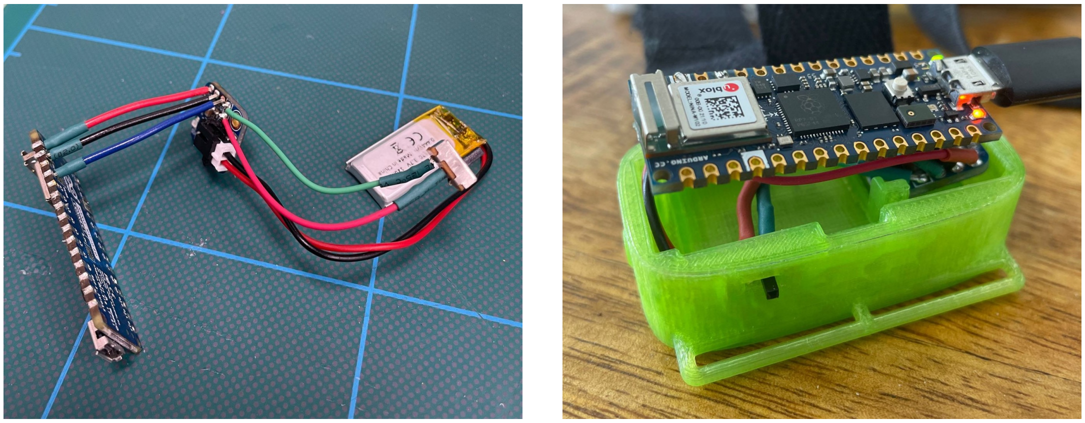
Figure 3.1: *The prototype with the straps attached on one side.*

problem was that most 9V batteries cannot be recharged. In the end, a LiPo battery was chosen, as these are more energy dense than alkaline batteries and could be recharged. This meant a smaller battery, which also weighs less, could be used. Overcharging, over-discharging or short-circuiting LiPo is dangerous thus using a protection board to prevent damage to the batteries is necessary. A DC conversion is also needed to give a stable input to the microcontroller. This meant the LiPo battery cannot be connected directly to the microcontroller's power input. AdaFruit's Li-Poly backpack provided the smallest solution to this problem.

Software

Without software, the prototype was just a microcontroller with a power source. The prototype's software was written in Arduino Studio. It uses the following libraries:

- LSM6DSOX: This library takes care of reading the accelerometer and gyroscope data from the built-in IMU sensor. The library has a set range for both the accelerometer and gyroscope. This is 4G for the accelerometer and 2000 degrees per second for the gyroscope. For our purpose, the accelerometer range was too small thus we changed it to the maximum possible value, which was 16G. This bigger range can accommodate a more rapid movement of the sensor, which is necessary for explosive movements such as kicking. The frequency of the sensor output was set at 104HZ,



(a) *The internal electronics connected by soldering wires.*

(b) *The internal electronics are connected to a micro USB cable while inside the housing. This is how the battery is charged.*

Figure 3.2: *The internal electronics: an Arduino Nano RP2040 connected to an Adafruit Li-Poly Backpack with a button and 120 mAh lipo battery.*

which is enough for our prototype.

- SensorFusion: The output data of the accelerometer was influenced by gravity. To remove this influence from the data sensor fusion is needed. The Madgwick filter was used to get the orientation of the sensor in quaternions. Quaternions can be used to interpolate between two rotation values and avoid gimbal lock, which is a problem when using Euler angles. With a simple formula, an approximation of the gravitational acceleration per axis was made and then removed from the data.

- WiFi Nina: With this library, the microcontroller can connect to an existing Wi-Fi network or set up a Wi-fi network and act as an access point for other devices. It can also do both at the same time. A Wi-Fi access point was needed to send the data from the prototype to a computer. An ESP32 microcontroller was programmed to function as the access point. The Arduino Nano RP2040 was programmed to connect to this network and reconnect when the connection was lost.

- WiFiUdp: Packages can be sent via Wi-Fi using UDP, which stands for User Datagram Protocol. These datagrams are sent to a specified IP address and port. The other device, in this case, a pc, then listens for these packages on the specified port. How this data is then saved will be discussed in the section about the digital prototype.

- avr/dtostrf: This library was used to convert the floating values of the IMU data to chars. Chars take up less space than strings, which made the UDP packages smaller.

- stdlib: This library was used to access the sprintf function. This function made it possible to send strings as chars, which made it possible to use udp.write() instead of udp.print() to add values to the udp package. Using write instead of print made the code run much faster. This made it possible to achieve a package frequency of about 104HZ, which is the same as the data frequency of the IMU sensor.

Housing

To protect the electronic components and connect the prototype to a player's leg a housing was needed. 3D printing was used as the production method as this provides possibilities for rapid prototyping. A part can be modelled, printed and tested within a couple of hours to a day. This made it possible to test different ideas quickly and fix issues easily. The standard nozzle size of 0.4 mm provided enough precision and detail while printing quicker than a smaller nozzle. A bigger nozzle size of 0.6mm was too big to print the housing properly. This was mostly an issue when printing the strap holders and the hole for the power button.

To attach the prototype to the body two straps were used. These straps used velcro sown onto a sturdy cotton strap to easily attach and remove the prototype. An elastic material was used in between the velcro parts to provide more comfort when wearing the prototype. To make the elastic material stay in place better it was sprayed with non-slip coating.

Digital Prototype

Python was used to write two programs to create a graphical representation of the data. The first program was used to listen on a port for UDP packages and write the data to a .csv file. The seconds program was used to load these .csv files and create a figure with 6 graphs representing the 6 data streams of the IMU sensor. Peak finding was used to place the kicking motion at the same spot in each graph. This made graph comparison easier, as the biggest peak for each graph, which represents part of the kicking phase, lined up.

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Evaluation

4.1 Study Design

During this part of the research project, we will test the working prototype with potential end-users; place kicking specialists. This will be done by asking the participants to perform tasks that simulate a training session. Participants are asked to share their thoughts by thinking out loud. After these tasks are performed, the participants are interviewed about their experience with the system. The goal is to see how these potential end-users experience the system and whether it helps them improve their place-kicking skills, and/or become more consistent, and/or gain confidence in their place-kicking abilities.

Participants

A group of intended end-users was asked to participate in these user tests. To fit the profile of the end-user participants had to have previous experience with conversion kicking in matches. The participants were recruited using snowballing using the author's own network. Whatsapp was used to reach potential participants. A recruitment message was sent in multiple rugby-related group chats and some potential subjects were messages privately to ask if they would be willing to participate. A detailed profile of the twelve participants can be found in Table 4.1.
Four participants had problems occur during the user test which was due to the system and not their use of the system. During tests 3 and 4 there was a problem with the data transmission. This meant that 2 out of 3 graphs did not show the correct time frame. These graphs missed crucial data on the kicking motion. They were not able to compare the three graphs and relate them to their performance. It was also more difficult to identify the phases as the graphs were incomplete. However, both participants provided interesting input for improving the data representation. That is why part of their interviews was still used in the thematic analysis. The prototype's battery had problems with retaining its power, which caused the device to turn off during tests 10 and 11. What caused these battery issues is still not completely clear. However, connecting it to a power source via a USB cable for a couple of seconds would fix the problem temporarily. Restarting the device reset the time which resulted in data points accidentally having similar time stamps. This caused strange artefacts in the form of horizontal lines in the graphs. Thankfully not all three graphs were affected by this and the participants could still provide interesting input. These participants were also still able to see enough of the graph to do all tasks, besides properly comparing the three kicks.

PID	Gender	Age	Experience with fitness/sports performance tracking
P1	Male	18-24	No experience
P2	Female	18-24	A lot of experience
P3*	Female	25-34	No experience
P4*	Female	18-24	No experience
P5	Female	25-34	A lot of experience
P6	Female	25-34	No experience
P7	Female	25-34	No experience
P8	Female	18-24	Some experience
P9	Female	18-24	Some experience
P10†	Male	18-24	A lot of experience
P11†	Female	18-24	Some experience
P12	Male	25-34	Some experience

Table 4.1: *An overview of the participants interviewed in the study. The table reports basic demographic data such as age, gender and their (self-identified) experience with fitness/sports performance tracking. Participants marked with an asterisk (*) were not able to compare the three graphs due to problems with the system's data transmission, while participants marked with a cross (†) had artefacts (horizontal lines) in their graphs due to battery failure.*

Materials & Design

The experiment was done using a high-fidelity prototype of the system. This prototype has two components. These are the hardware that collects the data and the graphical representation of this data presented on a laptop screen. The tests were performed on a rugby or football pitch considering most rugby pitches were closed for the summer. We provided the participants with 3 balls. The balls were inflated at the correct pressure (around 9 psi). The participants used their own kicking tee, but backup options were brought to the test in case they forgot their own. The type of kicking tee players use is a personal preference thus we wanted to give them the option of using their own. We wanted to limit a negative influence on performance due to changes in their usual kicking routine and set-up. Changing the kicking tee could have had an influence on their kicking performance and could also have distracted the participant from focusing on the tasks.

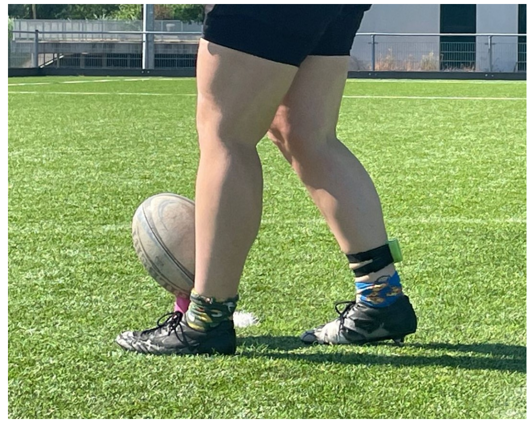
Procedure

At the start of the experiment, the participant will be provided with the necessary background information on the research. They will then get an overall explanation of the tasks they will be performing in written text. After this, they will be asked to give their consent to participate in the study as described. Before starting the tasks participants are asked to do a warming up.

The participant performed the following tasks in the described order:

1. The participant is asked to read the consent form. After consenting to the research the participant is asked some demographic questions, such as their gender, age and experience with fitness/sports performance analysis systems.

(a) *The participant has the prototype attached to their leg while waiting to start the user test.*



(b) *The participant is setting up the ball during the user test. The prototype can be seen attached to their right leg.*

Figure 4.1: *The prototype was attached to the participant's kicking leg using the user test. Two straps with hook and loop tape were used to attach it.*

2. Next they are asked to perform a warming up to prepare their body for the kicking movement.
3. The participant is asked if they have any questions and feel ready to perform the test.
4. The participant is asked to attach the prototype to the back of their kicking leg as close to the shoe as possible without the prototype hindering their movement.
5. Perform three kicks with a focus on their technique and power.
6. After these three kick the participants are asked about their performance per kick.
7. The data is then processed to be presented to the participant.
8. The participants are asked to draw and explain what they expect the data of their kicks will look like.
9. The participant is presented with graphs that shows the accelerometer and gyroscope data of the kicks performed in the previous step.
10. They are then asked questions about this graph to test their understanding of the data. They are asked to relate their experience of the three kicks to the provided graphs. They are also asked to identify the four kicking phases: approach, kicking, ball contact, and follow-through[2].
11. The participant is then asked how this kicking data could be presented such that it would provide them with insights into their performance. They are asked to draw a visualisation. If they have no ideas we show them an example of data visualisation in sports.

Figure 4.2: *A video still of a participant wearing the prototype during the user test.*

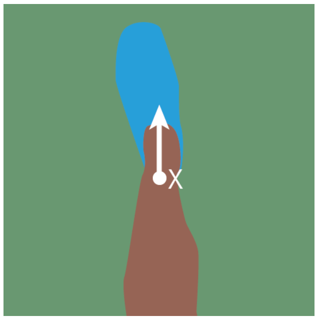
12. The user test ends.

Data Analysis

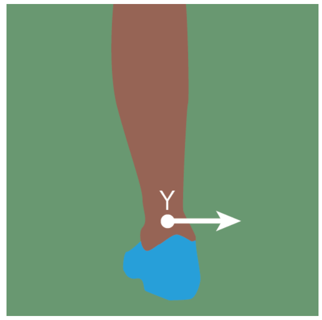
The twelve interviews (3h in total) were transcribed verbatim. The student coded the interviews using an inductive open coding approach. After the first three interviews were coded the codes were discussed with the daily supervisor. This resulted in an extra layer of detail in the codes. The next nine interviews were then coded by the student using the same level of detail. Having coded the entire dataset, themes were derived from the codes by identifying common patterns. This was done during a session together with the daily supervisor. During this session, we derived four themes that described the participants' experience with the system.

4.2 Results

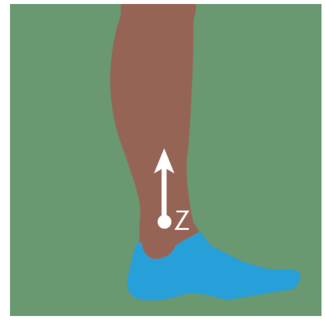
Here, we present the findings of the thematic analysis that was performed on the twelve coded transcripts. The five themes described in this section are: *Understanding data*, *Felt experience versus objective measurements*, *Self-directed exploratory learning versus guided learning*, *Data literacy and self-efficacy needed for data engagement*, and *Improvements for the system*. The results are illustrated with quotes from the interviews. These quotes are marked with the participant ID.



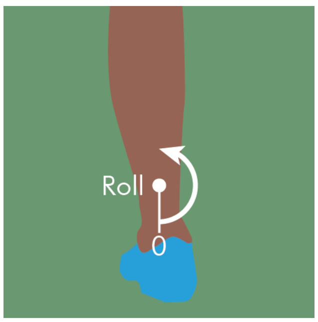
(a) *Ax: acceleration in X direction, which relates to forwards and backwards movement.*



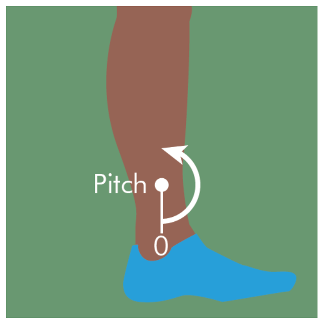
(b) *Ay: acceleration in Y direction, which relates to sidewards movement.*



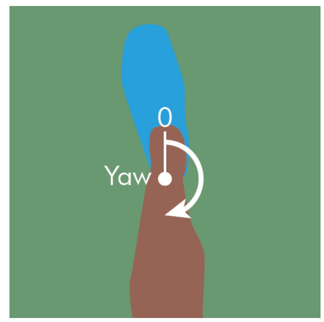
(c) *Az: acceleration in Z direction, which relates to upward and downward movement.*



(d) *Roll: rotational velocity around the X axis.*



(e) *pitch: rotational velocity around the Y axis.*



(f) *yaw: rotational velocity around the Z axis.*

Figure 4.3: *A visual representation of the six directions of movement that the prototype measures. These images were shown to the participants as an explanation of the data.*

Understanding data

This theme describes how the participants interpreted the data. The participants were tested on their understanding of the kicking data by asking them to draw their expectations and identify the four kicking phases [2].
11 out of the 12 participants expressed that they experienced difficulties when asked to draw what they thought their kicking data would look like. They expressed this by saying literally saying *"This is difficult"* or phrases such as *"This is a good one. This is a very good question, indeed."* as said by P2 or mentioning that they had to *"think really hard"* about it or that they were *"trying to visualize it"*. When asked why they struggled with the task P9 gave *'a lack of spatial understanding'* as their reason. They described their problem as follows:

> *"I just wouldn't know how to draw that. I don't know how to visualise that. It's also a problem with this one that I don't know how I should visualise that in a graph." - P9*

Participants admitted that they had not thought about their kicking movement in this manner before. P6 even said that *"You never actually think about it, which is kind of* *funny in itself, and I kind of have my own movement in my head, but not necessarily what that looks like when you break it down into x, y, z, roll, yaw and pitch."* The participants also often asked clarifying questions or looked at the provided graphics to check their understanding of the six directions and how these translated to the movement of their bodies. Phrases such as *"So what was this one again?"* were uttered often.

Often the participants would describe the kicking movement in depth but then start doubting themselves because they had a hard time with the complexity of the task. P10 suddenly exclaimed: *"I don't know. I'm just going to do something."* Often they would also talk negatively about their drawing skills and try to lower the expectations by describing their work as *"just a rough approximation'* (P3) or saying *'it's not the most scientific graphics I've ever seen"* (P10) and *'I screwed up the graph a bit.'* (P2).

All participants broke up the movement into easier-to-understand parts to make the task less complex. They described how their kicking leg moved during different parts of the kick. In the following example, P10 identified different parts of the kick such as the *backswing*, *impact of the foot on the ground* and *follow-through*:

> *"As my foot comes back down, yeah, that would be the tail there. So that's the backswing. That's impact on the ground, that's follow through, that's just standing." - P10*

Many participants would describe changes in the direction of the movement by using opposites such as backward versus forward, left versus right, and up versus down.

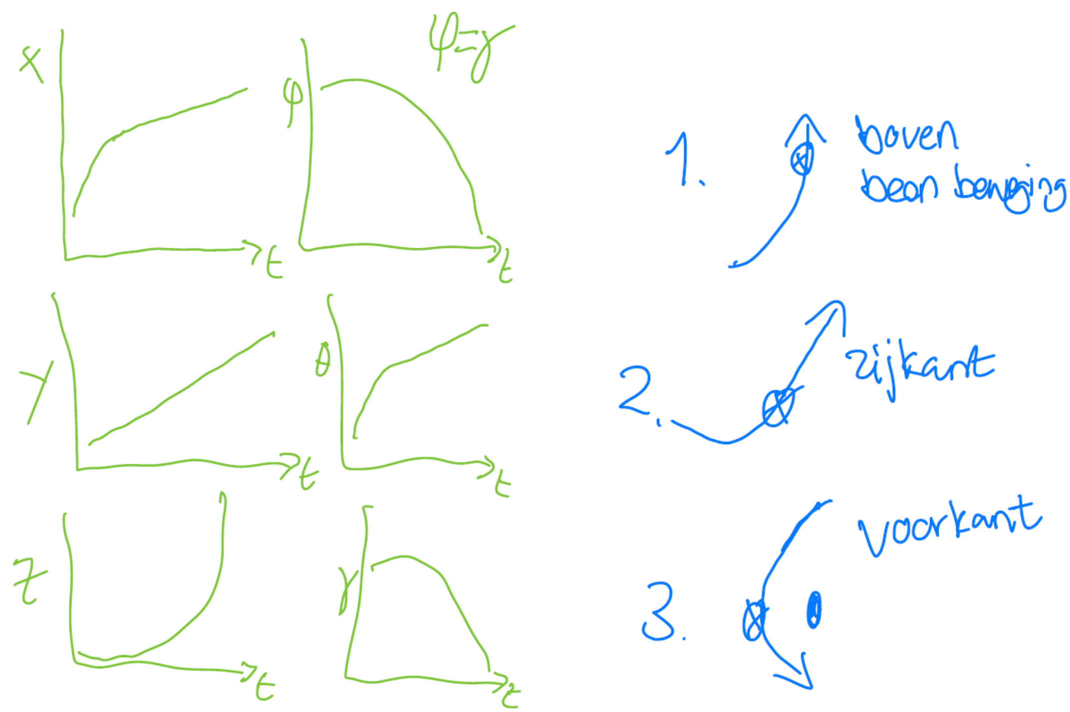
> *"So that one goes forward first, then backwards and forwards. The Y. That was sideways so it goes first in that curve and then to the left because I make that swing. Z. That goes... So I walk... The same height. Then I pull it to the back. Then that one goes back up and then back down and then back to... So then it comes back to the ground." - P12*

P2 was the only participant that drew an interpretation of the whole kicking movement from approach to follow through split into the six directions, see Figure 4.6. The other participants stuck to more simplistic interpretations. For two examples of this see Figure 4.4 and 4.5. P2 also started out by drawing X and Y as simplistic interpretations of the path of the leg but then moved on to drawing a more detailed interpretation of the acceleration and angular velocity. They put markers on the graphs to show when they expected the point of impact with the ball happens. They described their drawing as follows:

> *"We have the high points. Then you kicked the ball there, then here the ball is gone. And then you go back, and then it goes back straight where you started something like that." - P2*

Even though they were asked to draw the acceleration and angular velocity of their lower leg many of the participants drew what they described as a *'change in position'* or the *'trajectory of their kick'*. See figure 4.4a for an example of a drawing of the leg's trajectory.

> *"The ball is over here and I'll just draw the trajectory of my kick, of my foot actually, then I think those... I arrive a little bit from the side of course. I arrive a*

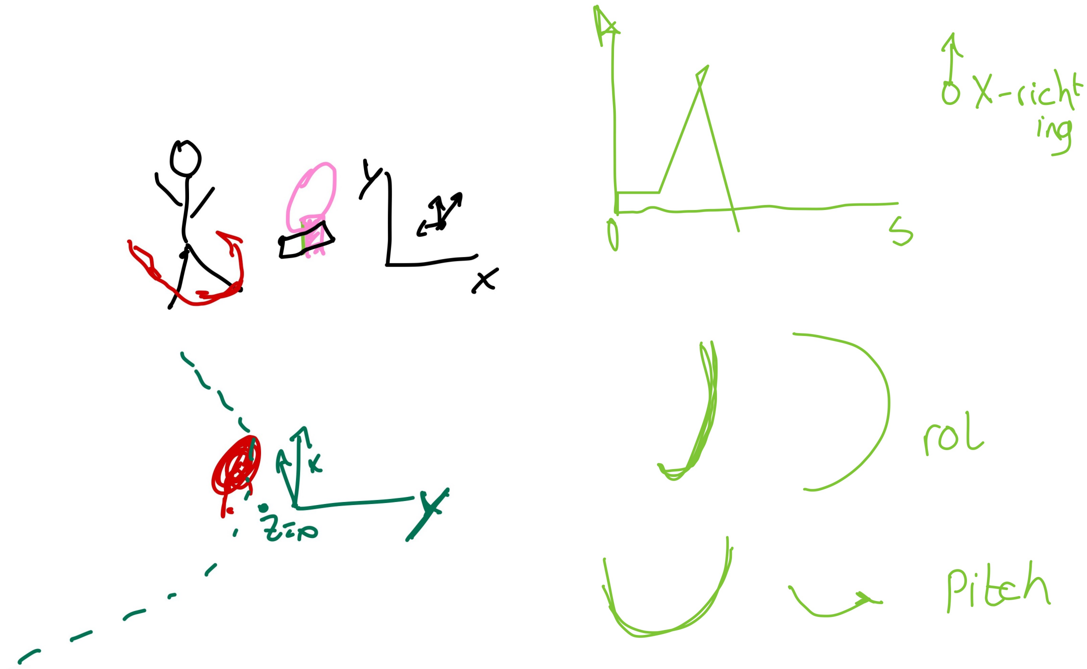


(a) *Expectations of the data drawn by P3. This participant drew the movement of the leg over time in a graph format.*

(b) *Expectations of the data drawn by P7. This participant drew the movement (trajectory) of the leg from 3 perspectives.*

Figure 4.4: *Two examples of more simple drawings of expectations of the data. Both participants only focused on part of the kicking phase.*

little bit from the side and then I hit the ball here and then I continue a little bit like that." - P11



(a) *Expectations of the data drawn by P11. This participant drew the movement of the foot in relation to the ball. They referred to this as the trajectory of their kick.*

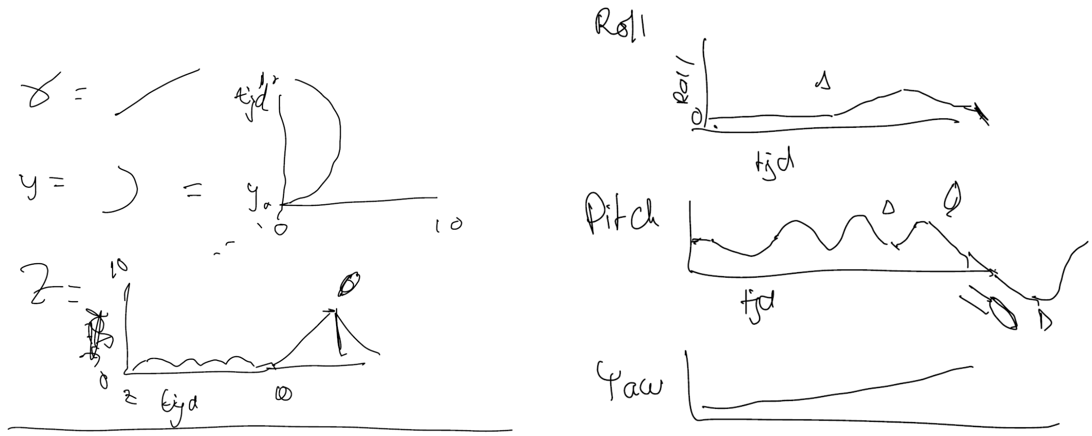
(b) *Expectations of the data drawn by P9. For roll, they drew J and C shapes, which are common descriptions of the leg's path in the XY plane during the kicking and follow-through phases.*

Figure 4.5: *Two examples of drawings of expectations of the data. Both participants drew the leg's trajectory during the kick.*

Effectively this meant that participants used the path of their leg as their starting point and tried to reason towards velocity and acceleration from there.

"you have to think, alright okay. So when I kick... One leg makes, a bit of a sweeping motion. So it doesn't go straight forward, so your hip turns with it so I already have that, that I don't whack my leg forward, but in a semi-circle actually. And then from the side." - P7

Describing the movement in velocity was doable for some participants, but being able to describe the movement in acceleration was too abstract for the participants. Some participants related the movement to previous knowledge about place-kicking techniques. One participant mentioned the often used J and C shapes to describe the kicker's trajectory. Where a J shape is considered a better shape as the final movement is towards the target, while with the C shape the kicker's final movement is at an angle away from the target.



(a) ***(b)***

Figure 4.6: *P2 started drawing only the kicking phase as a simplistic interpretation for X and Y. They then drew the kick from approach to follow-through for Z, roll, pitch and yaw.*

"But I think, at least with this one, that instead of moving in a J shape, I'm moving in a bit of a C shape." - P9

After drawing their expectations the participants were shown the graphs describing their three kicks. Eight of the participants expressed problems with understanding the graphs. One problem was that roll, pitch and yaw were not intuitive to understand.

"If you say roll pitch and yaw, I would have no idea what it is and will have to look at a picture every time." - P2

Another issue was that one participant did not understand which sideways direction was positive or negative.

"What the negative and the positive mean exactly, so which way that is, because that's a certain direction from those perspectives but you don't know if that's to the left of the right, for example." - P5

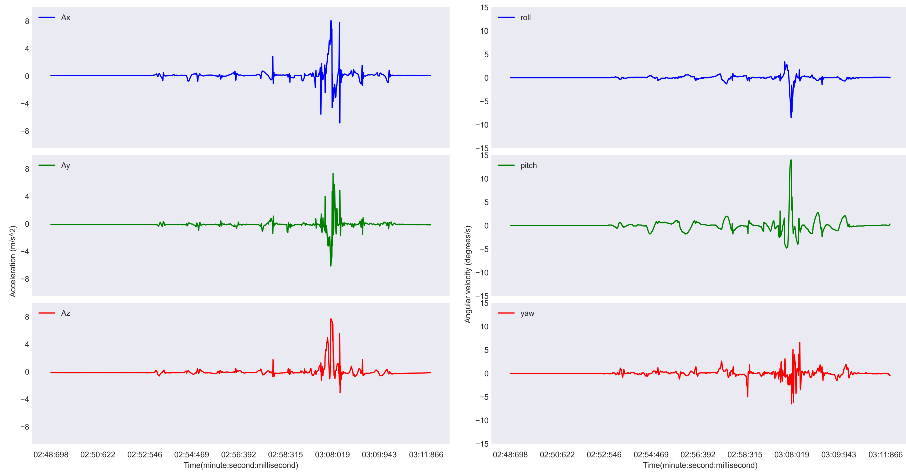
P8 expressed that they did not understand what certain peaks or throughs in the graphs meant. The graphs representing their second kick can be seen in Figure 4.8.

"I don't know what happened here. That is simply an Iceberg, but I wouldn't know either." - P8

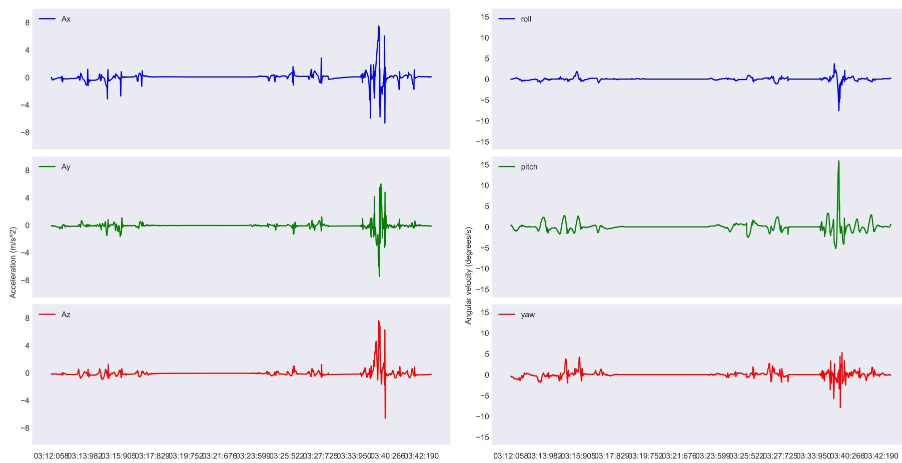
P6 thought splitting the movement into 6 directions was difficult to understand.

"That whole movement, broken down into six movements is obviously very difficult for a human being to understand." - P6

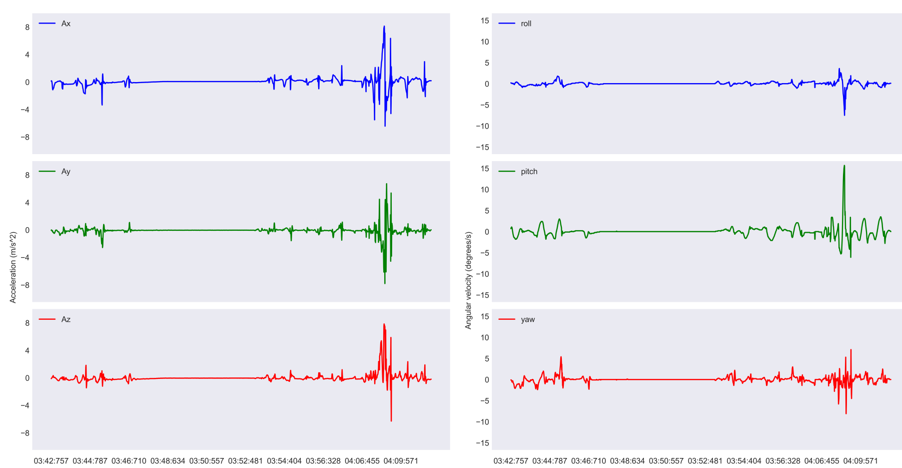
Six participants clearly expressed they doubted their ability to understand the data. P2 said they *'doubt it'* when first asked to identify the four kicking phases. Another



(a) *The six graphs of P12's first kick.*



(b) *The six graphs of P12's second kick.*



(c) *The six graphs of P12's third kick.*

Figure 4.7: *P12's three kicks in six different*

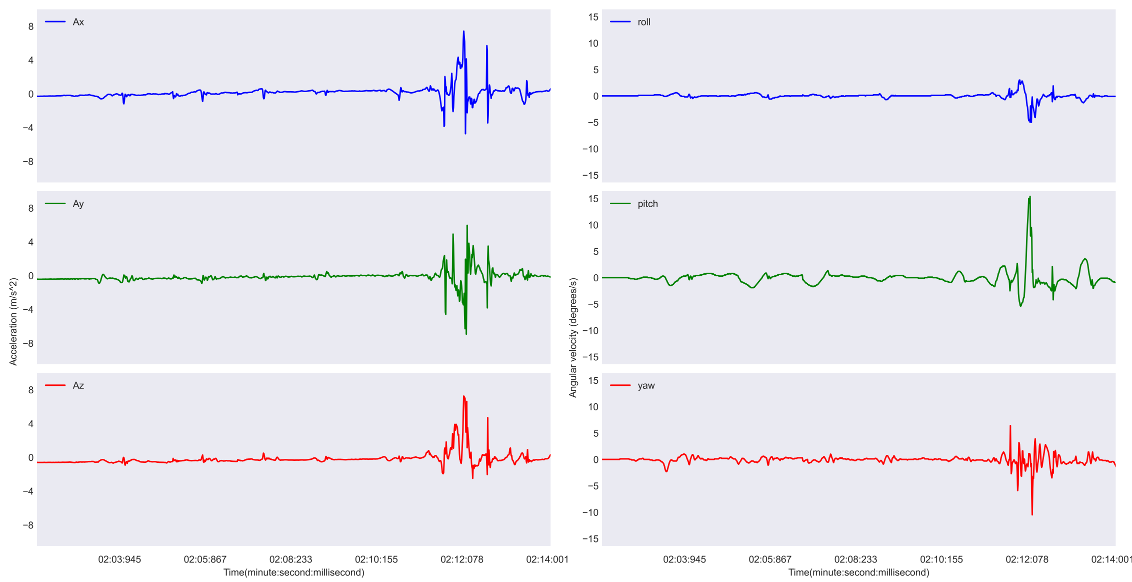


Figure 4.8: *The six graphs representing P8's second kick.*

participant cut themselves off because they were afraid of understanding the data incorrectly. P9 even said: *"No, never mind then I'll say it incorrectly."*
Five participants compared all three graphs, and three of these participants remarked that they thought the shapes of the graphs were consistent across the three kicks.

> *"Other than that, apart from having slightly more outliers here, it does look the same in terms of shape." - P6*

They would comment on small differences between the graphs when asked to relate the data to the way they experience the kicks, but found that overall "you do really see the same shape in it." (P6). The similarity of the graphs of the three kicks by P12 can be seen in Figure 4.7.

> *"Looking at it this way, two and three are more similar there. Basically, I think they are pretty similar." - P12*

Often they were looking for something in the graphs that could be used to back up their perception of their performance.

> *"That second one, that kick that didn't go as well, really does have a bit of a higher peak than the other two over there." - P7*

> *"With the Y, you do notice that it has the biggest spike compared to the others, and that is the movement to the side. So I think that's why this kick is also better because my leg makes less of a sidewards movement." -P9*

Only two participants related the graphs to their previously drawn expectations. P2 commented *"That's not at all what I drew"*, while P6 said:*"Oh that's interesting! I was really expecting there to be some kind of acceleration and deceleration."*

Eleven participants expressed that some kind of extra context was needed to better understand the data and gain insights about their performance. One way to gain context was by comparing a bigger dataset of kicks. P7 remarked that *"you might also be able to detect a trend"* when there is more personal kicking data to compare. Four participants mentioned the use of video to add more context to the graphs. Five participants wanted to know what their graphs would look like compared to an ideal image of a kick. Mentioning that without a reference *"you don't actually know what your goal is, what you want to achieve"*. The participant that did not express a need for more context could not think of any possible improvements besides being able to change the time frame shown in the graphs to get a better understanding of the data.

Two participants mentioned that another way of adding context could be by adding a measure of how the kick felt to the data.

> *"I do think it's good to always have some kind of combination between how the kick felt and what the data that comes out of it looks like. That you can give your kick a score, from one to ten, so to speak. Because I think your feeling also plays a big role in that." - P11*

This combination of how a kick felt and the results of the measured movement will be discussed more in-depth in the next section.

Felt Experience Versus Objective Measurements

Another recurrent theme in the collected data describes how participants related how they experienced the feeling of the kick to the objective measures provided by the prototype. The participants reported that how a kick feels is an important form of feedback they use in their kicking training.

> *"Well, I actually find them very similar. The difference is quite small as well, but I think it's more the feeling of where I hit the ball than that it purely is the movement." - P11*

As mentioned in the previous section, two participants remarked that they wanted to add their experience of the kick to the data for added context.

> *"I personally feel that you should then also add your personal experience to the data, and indeed you could then substantiate when something went well or did not." -P6*

Knowing which body movements and thus graph shapes resulted in a good kick could provide players with more information on their consistency. Adding a score to kicks could allow also allow players to think about what they should adjust when their movement deviates from their usual form.

"And then if I know like okay, this trajectory of my foot resulted in a good kick and I see that sometimes I deviate really super far from that and another time I get really close, you can also see a bit of consistency in your kicking and yes, and the next step then is maybe some kind of interpretation in reverse from there. Suppose I deviate from it a certain amount, what can I adjust in my kick?" - P11

Self-Directed Exploratory Learning Versus Guided Learning

This theme describes the difference between training on your own and having a coach or system that guides you. We perceived that the participants had difficulties figuring the data out on their own and wanted help with the interpretation.

When asked if they were talking about wanting a coaching element added to the data P11 remarked: *"I think so, but maybe that's also in combination with someone who can interpret then."* P3 and P4 both also mentioned a need for someone to interpret and guide them through their performance data.

"I think making it visual is great, but I also think if you can just explain it clearly like right now, you're stretching your leg too much, too fast. Right now you're moving your leg inwards really fast, and you don't have to do it like that, I think that could also help a lot. But do it in a way that data is already interpreted for you because people aren't very good at that by themselves. So if someone has simply done that for you already. That could either have already been done visually or just someone, a person, doing it. That would make it very useful." - P4

Both participants wanted this interpretation to guide them in what to change in their body position to improve their technique. A visual of the movement of certain joints during their kick and what it should look like instead was considered more useful, than having to figure it out by yourself from the presented graphs.

"And of course, you're not going to say 'Oh kick less in an acceleration of this or that in this or that joint', because nobody understands how that works. Or at least that's very difficult to imagine, but if someone says to you, 'You need to move your knee outward a bit more during kicking', that's more useful information that you can really do something with and seeing that visually, I think that makes it more manageable for most people, and also for myself, than having to figure something out from this." - p3

One participant doubted if acceleration data could provide them with the insights they needed to improve their performance. At the same time, they did mention that looking at the data they knew when their leg stopped moving, but they did not understand how this could relate to useful tips. Having acceleration data was considered useful to know how powerful the kicking motion was, but it provided them with no clear insights into their body position during the kick.

"So you can now see at what second your foot stopped. But not whether you're following through, so it's useful to know some kind of acceleration so you know how powerful you're kicking, but you can't really change much about that. Because of course, you put all your power into it. Because that's kicking. But little tips like follow through more, or hit it in a good position, you're not going to find those with the acceleration I feel like." -P2

Data Literacy and Self-Efficacy Needed for Data Engagement

This theme describes how there is a need for data literacy and self-efficacy to have participants engage with the provided data. Five out of the twelve participants self-identified as having no experience with fitness/sports performance tracking. P7 self-identified as having no experience but then talked about their fitness watch and its data presentation during the interview. This could indicate that self-identifying as experienced does not necessarily indicate a lack of data literacy.

Only one of the participants mentioned not having any experience with applications related to fitness or sports performance tracking during the interview. This participant also self-identified as not having experience with fitness applications or performance analysis in the survey. This participant struggled with engaging with the data the most. They only made short remarks on the graphs and were not able to relate them to how they experienced their kicks. They never went into more depth than pointing at the data and saying the phases.

"I think it can be seen the easiest in the Z axis. This will just be the run-up. And, I then think this is the backswing and this is the follow-through." - P1

Only when asked direct questions they would give slightly more detail on their interpretation of the data. When asked what they thought the first peak in the Z graph meant when they pointed at it they would not say more than *"That you just slam your leg back and then forward, I think"*.

When asked if they could think of potential visual changes for the data he said:

"I have never used that (fitness applications). I really have no idea." - P1

As mentioned in *Understanding data*. P9 remarked that spatial understanding was needed to be able to visualize the data. In their opinion, they had no spatial understanding and thus struggled with visualizing the data.

When participants lost trust in their ability to get through the task on their own encouragement such as "a lot of people find this difficult", changing the phrasing of the question that was asked or answering clarifying questions would help. Most participants got over the mental hurdle of thinking they were not able to figure it out.

P1 even went from expressing doubt in their ability to identify the kicking phases to confidently saying:

"I expect I can identify it in the data. Okay. In fact, it should make a lot of sense, because the pivot point of pitch... If pitch is stationary, that means if it (the device) is at the back of your foot and you make another swing that is extremely big. And then stop. That's my... should I point it out?" - P1

Later on, they started doubting themselves again saying they were ”totally bluffing” when pointing out their steps in the data. Then they started looking at the data a bit more and confidently confirming their earlier statement.

”These are steps because every time you put it (your foot) down. Then you see a bump and then we don’t move for a bit longer, because your last step is slow.” -P1

Another participant showed careful confidence in identifying the approach because they found the pattern of steps was easy to spot in the data.

”The approach. I think maybe here you can very easily spot it because here your leg does... I think those are just steps I’m doing.” - P9

Improvements for the System

The final theme describes how the participants want to improve the system. 8 participants mentioned wanting to know the position of the leg over time. Some participants knew exactly what that would look like. P3 explained that they wanted to see how their joints moved in comparison to how they should move.

”so then I would actually prefer to just kind of see a knee, and see ’Oh you move it like that’ and you should move it more like that. That’s what I would prefer to see, I think.”- P3

P2 took inspiration from the social sports performance tracking app Strava. Their idea was to have a visualisation of the kicking set up in a certain plane, instead of one axis. The position of the leg in the visualisation then changes based on the chosen moment in time. The time can then be changed with a scrollable time bar. They drew how they wanted this data visualisation to look, see Figure 4.9. They explained their idea as follows:

”Well on Strava, you have for example when you run that you can see the little icon of a person running with your time bar. Now this is on the millisecond, but it is possible because then you can indeed see if it’s faster... Then you have the acceleration, but you also have position in it. ”- P2

Some participants struggled more with coming up with a way to present the position to the user. P11 knew they wanted to be able to see the trajectory of the foot. According to them this positional data would be easier to interpret when shown in the perspective of different planes.

”I think for, say interpretation it might be easy to look in one plane, but then maybe that you have one plane from behind or something and one plane, kind of from the side.” -P11

P7 also wanted to be able to see positional data of the motion of the leg but could not formulate a way to then present this data to the user.

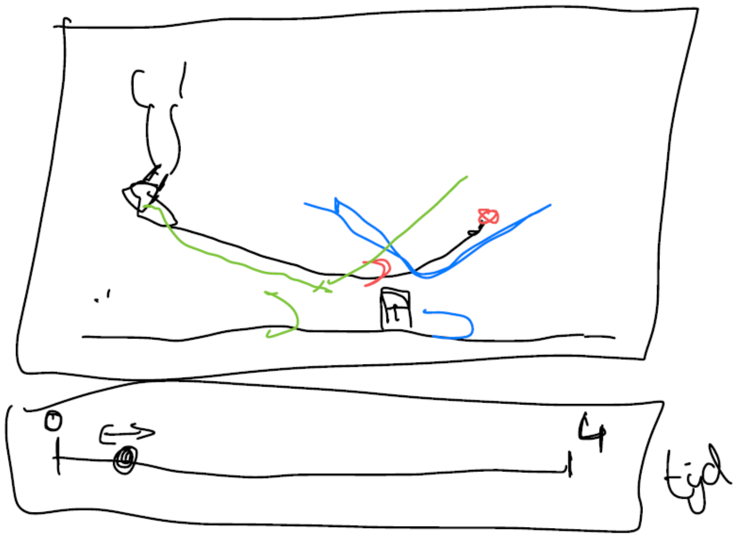


Figure 4.9: *P2's drawing of a data visualisation with a scrollable time bar and position as a metric.*

> *"I think indeed the motion, so the movement. Then again, I have it in my head but I don't know how to visualize that then in an app or something. I don't know that precisely."-P7*

Eight participants said they wanted to know how powerful their kick was. According to three participants, this power metric is the velocity of their leg when their foot makes contact with the ball, while according to three different participants, power is their leg's acceleration when they hit the ball. Three of these participants described this as their *impact on the ball*. Three participants described power as the force their leg produces. One of these participants also described power as acceleration, while the other two only refer to power as a force. P6 explained how they wanted their power metric to look:

> *"I would maybe like to see some kind of strength diagram. That you say, for example, in certain images whether your force is now say more focused like this or more focused like this, then you might actually be able to see a little bit of whether your loss of force is in the right direction." -P6*

For some of the proposed metrics, it is needed to change the position of the sensor. 3 participants had an interest in having a sensor on the standing leg. According to P11, their feeling of whether a kick went well relates more to the position of their standing leg than their kicking leg. They think their kicking leg movement is similar each time but the standing leg has an impact on where they hit the ball. They explained it as follows:

> *"I actually think the difference in what I feel then is mainly in my left leg. Yes, because if I am further away from it or actually closer, then, of course, I have to kick closer too." -P11*

P2 also explained that they needed data about the position of the standing leg and the position of your non-kicking foot influences where you hit the ball with your kicking foot. P10 remarked that with a sensor attached to the standing leg's foot, it would be possible to get the length of the last step. This metric would be of interest to them.
Three participants wanted to attach a sensor to the kicking foot. P2 said that their kicking performance is influenced more by their foot's position than their lower leg's position. P6 thought this as well, remarking how rotating your foot inwards slightly changes the ball's path greatly. P7 explained their interest in attaching a sensor to their kicking foot as follows:

> *"Because then you can also see to what extent your foot changes so indeed in terms of that rotation or in terms of that tension." -P7*

Another sensor position of interest to 2 participants was the upper part of the kicking leg. According to P6 having just upper leg data is of much use. The data needs to be in relation to the lower leg. They said the following about relating upper and lower leg data:

> *"I think a thigh, for example, provides a lot less information. But if you put for example your thigh information next to your lower leg information, then you can think about also kind of how much does my leg actually sway, because I think the movement is really coming from your hip and your upper leg and the looser your lower leg is, the more noise you get on your data, of course." -P6*

P8 also wanted to relate upper and lower leg data to each other. They remarked that they were interested in knowing the angle of their knee during the kicking phase. However, they also remarked how attaching a sensor to the upper leg was probably uncomfortable and that perhaps the sensor could be attached just below their knee instead to get data this data.
Two participants said they would like to have data on their non-kicking leg side's arm. According to P7, their arm's position can show whether their body position is how they want it to be. P12 also said that their opposite arm is used for keeping their body balanced.
Two participants wanted to attach a sensor to their chest to track their body positioning. P7 was interested in knowing how long it would take to get back into their normal, upright position, while P12 was interested in how much they were leaning forward or backwards.

> *"Then I'll say your upper body. So what position it's in, whether it's leaning too far forward or backwards"-P12*

P10 wanted to know more about the movement of all major joints. They explained how then you could know exactly what part of your body is used to get your power. He explained it as follows:

> *"They have it in soccer where they have one on each of the major joints and you could see how much was coming from my hips, how much from my back and stuff. Because I felt like on the second one, I was pulling from my back more than from my legs.*

Participants also came up with solutions related to improving the current visualization of the data. Three participants mentioned that using colours in relation to the values of the measures could make the data easier to perceive. They said this while drawing in their expectations or when asked how they would improve the current visualisation. P7 compared the graphs to the visualisations in their FitBit app and said the following:

> *"Those colours make it very organized and perceivable at a glance. I think that is important." -P7*

!

Discussion

In this section, we summarize our findings and consider how our results impact our understanding of how a place-kicking feedback system can effectively train players. This understanding is then used to formulate requirements for future systems.

5.1 Contributions

The study looked into gasps in current literature and in doing so made the following contributions. First, possible metrics for a data-driven feedback system for place-kicking were explored using expert interviews. This study is among the first to explore such a system designed specifically for place-kicking in rugby. Second, the system was implemented. Thus possible solutions for a prototype were explored and exposed to a training environment. Third, the system was evaluated with potential end users in a lab environment. The participant interviews provided important gaps for future work to explore.

5.2 Lessons Learned

Kicking Data Is Difficult for Users to Visualize

The study tested participants' understanding of kicking data by asking them to draw their expectations and identify the four kicking phases. Out of the 12 participants, 11 experienced difficulties when asked to draw their kicking data, mainly due to a lack of spatial understanding. They often asked clarifying questions or looked at provided graphics to check their understanding of the six directions and how these translated to the movement of their bodies. Participants often described the kicking movement in depth but started doubting themselves due to the complexity of the task. They broke up the movement into easier-to-understand parts, describing how their kicking leg moved during different parts of the kick.

Some participants used the path of their leg as their starting point and tried to reason towards velocity and acceleration from there. Some participants related the movement to previous knowledge about place-kicking techniques, using J and C shapes to describe the kicker's trajectory. Overall, the study highlights the importance of understanding and visualising kicking data to improve performance and understanding of kicking movements.

The results discussed above might suggest that splitting the kicking movement into the six defined directions is too abstract for most users to understand. Thus, different ways of describing the movement data might be more intuitive for users to grasp.

Users Need Simplification and Context

The participants were presented with graphs describing their three kicks, which were difficult for them to understand. The graphs were difficult to understand due to the lack of intuitive descriptions of the data. Some participants also expressed difficulty in understanding what peaks and troughs meant in the graphs. The participants also expressed doubts about their ability to understand the data and the shape of the graphs. The collected data also highlights the importance of participants' experience of the kick in their training, as it provides valuable feedback. Participants found that the feeling of the kick is more important than the movement itself. They also expressed a desire to add their personal experience to the data for added context. Understanding which body movements and graph shapes resulted in a good kick can provide players with more information on their consistency. Adding a score to kicks could help players adjust when their movement deviates from their usual form.

The participants also sought to understand the data to support their perception of their performance. To better understand the data and gain insights, eleven participants suggested comparing a larger dataset of kicks, using video to add context, and adding a measure of how the kick felt to the data.

These results suggest that the presented data was hard to grasp, which future iterations of the systems would need to address. They also demonstrate that placing the data in a clearer context could help users better understand the data.

Missing Measures and Alternative Sensor Placement Possibilities

Participants in the study expressed interest in understanding the position of their legs over time, as well as the trajectory of their feet. They also wanted to see a power metric, which they described as the velocity or acceleration of their leg when their foot makes contact with the ball, as well as the force their leg produces when they hit the ball. Some participants also wanted to know the position of the standing leg, as their feeling of whether a kick went well relates more to the position of their standing leg than their kicking leg. They also wanted to attach a sensor to the kicking foot, as their kicking performance is influenced more by their foot's position than their lower leg's position. They also wanted to relate upper and lower leg data to each other, as they wanted to know the angle of their knee during the kicking phase. They also wanted to attach a sensor to their chest to track their body position, as well as to know more about the movement of all major joints.

The data contributes a clearer understanding of what measures users want from a place-kicking feedback system and how different sensor positions can help achieve this.

Guiding Players Through Their Analysis Is Necessary

Data literacy and self-efficacy are crucial for participants to engage with data provided in fitness/sports performance tracking. Five out of twelve participants self-identified as having no experience with fitness/sports performance tracking. However, one of them mentioned their fitness watch and its data presentation during the interview. This suggests that self-identifying as experienced does not necessarily indicate a lack of data literacy. Only one participant mentioned not having any experience with applications related to fitness or sports performance tracking during the interview.

This participant struggled with engaging with the data the most, only making short remarks on the graphs and not relating them to how they experienced their kicks. They only gave slightly more detail when asked direct questions and did not provide more detail when asked about potential visual changes to the data.

Participants in the study expressed a desire for help with the interpretation of their performance data, stating that they had difficulties figuring it out on their own. They also mentioned the need for someone to interpret and guide them through their data. They believed that visual representations of joint movements during a kick would be more useful than having to figure it out by themselves. They also expressed doubts about the potential of acceleration data to provide insights into their performance, as they did not understand how it could relate to useful tips. They also mentioned that they could use acceleration data to know how powerful their kicking motion was, but it did not provide clear insights into their body position during the kick. The study suggests that a coaching element could help guide participants through the interpretation of their data and provide guidance on how to improve their technique.

Understanding data is essential for participants to visualize the data effectively. When participants lost trust in their ability to understand the data, changing the phrasing of questions or answering clarifying questions could help. Most participants eventually showed confidence when identifying the kicking phases. The pattern of steps in the data was easy to spot, and participants showed confidence in identifying the approach.

Visualisations and Interacting With the Data: Improving the User Experience

We observed that the users in our study had a need for data that is more visually appealing. This could be done by adding previously mentioned extra context in a visual form. A participant suggested labelling the graphs with the different kicking phases could help guide them through the data. The participants' drawings and verbal insights could be used as inspiration for a better user interface.

Visualizations were also mentioned in relation to the suggested measures participants wanted to know. They mentioned wanting to see an abstract visualization of their leg to better understand what their movement looked like. This could be done by showing different perspective planes of the leg, for example from behind and from the side.

Participants also suggested improving data visualization by using colours. One participant compared the graphs to FitBit app visualizations and suggested using colours to make data easier to perceive. They wanted a scale of colours to represent a measure's range of values. An example of this is a faster acceleration being red, while a slower acceleration is blue or green.

5.3 Requirements for Place Kicking Feedback in Rugby

From the lessons learned, we can deduce requirements that can be used for future feedback systems for place kicking in rugby. The requirements are as follows:

- The kicking phases should be labelled on the data.
- Colors should be used to make the data easier to read.
- The ball should be tracked and this data should be looked at in relation to the current data.
- The system should guide the user through the data.
- The data should be simplified into easier-to-understand measures, such as the power of the kick and the position of the leg.
- The data should be visualized to more closely resemble the real-life situation. For example by using a graphical representation of the body.
- The system should combine data from sensors on multiple body parts. For example The standing leg, chest, standing leg side arm and the upper part of the kicking leg.
- It should be possible to see an overview of a bigger dataset of kicks to detect possible trends.
- The kicking data should be looked at in relation to an accuracy score.
- The kicking data should be looked at in relation to a score of the player's 'felt experience'.
- The kicking data should be compared to the kicking data of other players.

5.4 Limitations

The work in this thesis was conducted in a controlled setting with predefined steps the participants needed to adhere to. We recognise that this inquiry is prone to certain limitations. First, this controlled test set-up is not what a normal training session would look like. Evaluating in situ [26] while the user interacts with the prototype as it is intended would be ideal. This would also involve the user using the prototype over multiple sessions, while we observe their interaction with the system. However, as this is an exploratory study and the prototype was not sophisticated enough for this type of research, a controlled setting was used.
Second, as most rugby fields were closed for summer maintenance we were not able to use rugby pitches for most participants' user tests. Instead, we used football pitches and asked participants to aim their kicks over the top of the goal. Using a football goal instead of rugby poles during kicking training is done by players when no other options are available but not ideal. We recognise that this might have impacted the participants'

performances. However, we think that is not an issue because their reflection on their performance in combination with the data is still possible in this situation.

Third, as rapid recruitment was necessary convenient sampling was used. Due to the author's strong connection with Dutch women's rugby, the majority of participants were women. This is not the general demographic of rugby players. However, the participants were more diverse in terms of experience and skill level. Some participants were relatively new to rugby, but had prior football experience, while others have played for many years and one participant even played for the Dutch national team for multiple years. Only one of the participants had a nationality other than Dutch. This could create a bias in a certain direction because of cultural norms.

Fourth, the data was presented in a more ambiguous manner as this can encourage close personal engagement with the system [11]. This ambiguity allows participants to interpret things differently and give meaning to different aspects of the data without nudging them in a certain direction. For most of the participants, this resulted in interesting insights and engagement with the presented data. However, For one participant this ambiguity resulted in a lack of engagement with the data.

5.5 Future Work

Future work should build on this work by studying the use of the system in situ. This different approach to studying the system could garner new insights for the design of such systems. The current study should in future studies be conducted on rugby pitches instead of football pitches to remove the possible impact on performance. Another direction for future work should be to study a system that has been designed using the requirements derived from this research. This would remove the ambiguity, but could further validate the results of the current study. A long-term study could investigate whether players improve their place-kicking to a greater extent when they use a feedback system compared. This study should compare this to a control group that does not use the system but follows the same training plan. Another direction for future work could be to study the use of the system in a different sports performance context. This could be a different rugby skill or a different sport.

!

Conclusion

In this thesis, we investigated the feasibility of a feedback system for rugby place-kicking. Through conducting a user test with 12 participants, we built an account of their experience in five themes: *Understanding data*, *Felt experience versus objective measurements*, *Self-directed exploratory learning versus guided learning*, *Data literacy and self-efficacy needed for data engagement*, and *Improvements for the system*.

Our findings show that the unprocessed IMU data presented was too abstract for participants to understand. They require additional guidance in order to achieve a better understanding of the IMU data. This can be accomplished by providing context for the data as well as simplifying and visualising it. The sketches drawn by the participants can be used for a future user interface design. Using more intuitive measures, such as position or a power metric, could assist users in gaining insights into their performance while placing the data in a clearer context can assist users in understanding the implications of the data on their training goals. We hope that the findings of this study will serve as a foundation for future IMU-based data-driven feedback systems for sports performance.

!

Appendices

7.1 Protocol for semi-structured interviews with coaches

Introduction

Ten eerste, bedankt dat je mee wil werken aan dit interview. Dit interview focust op jouw ervaringen als rugby coach. Met dit interview wil ik een beeld krijgen van coaching binnen rugby. Deze data wil ik gebruiken om het onderzoek van mijn thesis verder te vormen. Hoe meer je vertelt hoe beter en geen enkel antwoord is verkeerd. Verschillende perspectieven is juist waar ik naar op zoek ben.
Om je een beeld te geven van mijn onderzoek. Ik ben bezig met een onderzoek in de richting van human computer interaction en sport. In deze richting wordt technologie op verschillende manieren ingezet om wat toe te voegen aan een sport ervaring. Denk hierbij bijvoorbeeld aan sporthorloges of VR/AR systemen. Aangezien ik zelf rugby speel heb ik voor deze richting gekozen. Ik zal onderzoek doen naar een digitale feedback tool waarmee getraind kan worden op een secifieke rugby skill.
Ik zou graag het interview willen opnemen om later terug te luisteren en het interview te verwerken. Alle data zal anoniem verwerkt worden. Heb ik hiervoor je toestemming?
Heb je nog vragen voordat we beginnen?

General questions

- Hoe ben je begonnen met het coachen van rugby? Hoe lang coach je al?
- Hoe zou je jezelf als coach en je coachingsstijl omschrijven?
- Hoe zou je jouw rol als coach omschrijven en wat voor invloed heb jij op jouw team(s)?

Questions about skills

- Wat voor vaardigheden zijn belangrijk in rugby? Welke vaardigheden zijn moeilijk om aan te leren? (waarschijnlijk doorvragen, waarom moeilijk, hoe pak je dit aan)
- Welke vaardigheden hebben veel invloed op het spel? Welke vaardigheden hebben de meeste invloed op de uitkomst van de wedstrijd?
- Wat voor middelen gebruik je op dit moment om de voortgang van je team te monitoren?

Questions about place kick

- Hoe belangrijk vind jij place kick in rugby en waarom vind je dit?
- Hoe train jij spelers op place kicking? Waar loop je tegenaan wanneer je spelers traint op place kicking?
- Hoe kunnen spelers hun place kick verbeteren?
- Wat zijn fouten die spelers maken wanneer ze place kicking zelf trainen?
- Hoe groot is de rol van zelfvertrouwen bij de place kick? Hoe train je spelers hierin/hoe laat je dat groeien bij spelers?
- Hoe belangrijk vind je het dat spelers actief reflecteren op hun performance? Hoe zie je deze reflectie voor je? Hoe zie je deze reflectie voor je voor place kicking?
- Waarover zou je meer data willen vergaren? Welke data zou de meeste invloed hebben op performance? Welke data zou belangrijk zijn om te reflecteren op place kicking?

7.2 Protocol for semi-structured interviews with players

Introduction

Ten eerste, bedankt dat je mee wil werken aan dit interview. Dit interview focust op jouw ervaringen als rugby speler en in het speciaal conversie specialist. Met dit interview wil ik een beeld krijgen van jouw ervaring hiermee. Deze data wil ik gebruiken om het onderzoek van mijn thesis verder te vormen. Hoe meer je vertelt hoe beter en geen enkel antwoord is verkeerd. Verschillende perspectieven is juist waar ik naar op zoek ben.
Om je een beeld te geven van mijn onderzoek. Ik ben bezig met een onderzoek in de richting van human computer interaction en sport. In deze richting wordt technologie op verschillende manieren ingezet om wat toe te voegen aan een sport ervaring. Denk hierbij bijvoorbeeld aan sporthorloges of VR/AR systemen. Aangezien ik zelf rugby speel heb ik voor deze richting gekozen. Ik zal onderzoek doen naar een digitale feedback tool waarmee getraind kan worden op een secifieke rugby skill.
Ik zou graag het interview willen opnemen om later terug te luisteren en het interview te verwerken. Alle data zal anoniem verwerkt worden. Heb ik hiervoor je toestemming? Heb je nog vragen voordat we beginnen?

General questions

- Hoe ben je begonnen met rugby? Hoe lang speel je al?
- Hoe zou je jezelf als speler en je speelstijl omschrijven?
- Hoe zou je jouw rol als speler omschrijven en wat voor invloed heb jij op jouw team(s)?

Questions about rugby skill

- Wat voor vaardigheden zijn belangrijk in rugby? Welke vaardigheden vond jij moeilijk om aan te leren? (waarschijnlijk doorvragen, waarom moeilijk, hoe pak je dit aan)
- Hoe ben je gecoacht in de dingen die je moeilijk vond. Wat werkte hieraan wel en niet?
- Welke vaardigheden hebben veel invloed op het spel? Welke vaardigheden hebben de meeste invloed op de uitkomst van de wedstrijd?
- Wat voor middelen gebruik je op dit moment om je voortgang te monitoren?

Questions about place kick

Place kickHoe belangrijk vind jij place kick in rugby en waarom vind je dit? Hoe train jij op place kicking? Krijg je hier ook begeleidde training in? Waar loop je tegen aan wanneer je place kicking alleen traint? Wat is voor jou het verschil tussen alleen en gecoacht trainen? Hoe kunnen spelers hun place kick verbeteren? Waar werk jij aan met place kicken? Hoe reflecteer je op jouw place kicking performance? Welke data zou belangrijk zijn om te reflecteren op place kicking? In hoeverre speelt zelfvertrouwen voor jou een rol bij place kicking? Hoe train jij jezelf hierin?

7.3 Interview protocol for user test

Ik ga zo een aantal vragen stellen over je kicks en de data die hieruit komt. Geen enkel antwoord is fout. Ik ben juist geïnteresseerd en hoe jouw ervaring en interpretatie.

- Kun je per kick omschrijven hoe je vond dat ze gingen?
- Het systeem meet de lineaire acceleratie en hoeksnelheid van je beweging. Ook afbeeldingen geven met uitleg.
- Hoe verwacht je dat de data van je kicks eruit zal zien? (laten tekenen op papier
- (welke momenten versnellingen en vertragingen. Pieken etc?)
- (wat verwacht je niet te kunnen zien? Wat zou je in de data willen zien?)

Laat data zien.
Er zijn meerdere fases bij een kick. 1. De aanloop (approach) 2. De kick (kicking) 3. Het balcontact (ball-contact) en 4. Door de bal heen kicken (follow-through).

- zou je in de data de verschillende fases kunnen identificeren en hardop kunnen beredeneren. Laatste deel van de test. Hoe zou de data beter te begrijpen zijn?
- Zou je kunnen tekenen hoe jij de data (visueel) weergegeven zou willen hebben? (kunnen ze niks bedenken. Laat dan voorbeeldafbeeldingen zien.)

7.4 Consent form for user test

You are invited to participate in evaluating our Rugby kicking feedback system, RugbySense. RugbySense was designed to collect data about your kicking to gain insights into your performance. The data collected is three-dimensional acceleration and three-dimensional angular velocity. The sensor collects datapoint about every 10 ms. During the study, you will be asked to perform a set of tasks. These tasks consist of kicking while wearing the RugbySense system, answering questions about your personal kicking data and answering more general questions about data visualisation in this context. This will help us to evaluate the design of RugbySense. We are not evaluating you or your performance in any way.

As you perform multiple kicks with the system, your actions and comments will be recorded, through video recording and audio recording. You will be asked to verbally describe what you are doing and voice any thoughts you may have about the system. After this, you will look at your kicking data and are asked questions relating to your kicking performance in relation to the data and your understanding of the data. You may be asked questions during and after the evaluation, in order to clarify our understanding of your actions and view of the system. At the end, you will be asked to think of ways to improve the system and the presentation of the data. The evaluation session takes around 30-60 minutes.

The information you provide will be processed anonymously. Your name will be removed and only a subject number will be used to identify you during analyses and any written report of the research. The evaluation will be recorded, and all data stored securely, viewed only by experimenters.

Your participation is voluntary and unpaid. You are free to withdraw from this study at any time without providing a reason.

- I give consent
- I do not give consent

7.5 Coding results of user test

Codes

Name	Files	References
breaking down the movement	12	40
developing a routine	1	1
drawing the kick	12	76
expectation	10	34
important data	4	6
improvements	12	204
adding metrics	11	66
2D visual	3	4
3D model	2	2
accuracy as metric	3	4
add felt experience to data	2	4
angle of leg swing	1	1

Name	Files	References
ball trajectory	1	1
height of back swing	1	2
hit point on ball	2	2
hit point on foot	1	1
Impact on ball	3	4
leg position in relation to ball	1	1
length of last step	1	1
position as a measurement	8	19
power as metric	5	6
power of kick	7	8
rhythm of steps	1	1
time of kick	2	4
velocity of ball	1	1
Data in context	10	29

Name	Files	References
combining data streams	1	1
compare performance over multiple sessions	4	4
compare with others	2	3
having a reference to how it should be	4	7
relate data to accuracy (scoring)	2	3
relate data to heart rate	1	1
using video	4	5
what is the ideal kick	3	5
data visualisation	9	27
animation of movement	1	1
Force diagram	1	1
have a clear overview	2	7
kicking phases shown on graph	2	2

Name	Files	References
make data more visual	2	3
more dimsions in one visual	3	4
moveable time bar	1	1
multiple timesteps	1	1
use of colors	3	5
visualisation of body	1	1
zoomed in on kicking phase	1	1
Interpretation of data	8	21
coaching on body position	4	6
expert interprets for you	2	3
knowing what to work on	1	1
more explanantion of data	1	1
personalized	1	1
simplify data	4	9

Name	Files	References
Sensor position	5	7
different sensor positions	3	6
sensor just below knee	1	1
sensor on all major joints	1	1
sensor on arm (non kicking leg side)	2	2
sensor on chest	2	2
sensor on foot	3	4
sensor on other leg	1	1
sensor on upper leg	2	2
Wants data about standing leg	2	2
injury prevention	1	2
Kicking Goal	1	1
movement forward	5	5
movement pattern	10	48

Name	Files	References
arm position	1	1
Body position	3	6
foot position	5	17
leg movement	6	10
movement from hip	4	4
negative about provided measures	2	4
Problems understanding	8	16
reflecting on kicking performance	9	50
correct hit point on foot	2	2
feeling of kick	1	2
First kick	3	5
General improvement areas	1	1
Get more power from hips	1	1
less power loss on contact	1	1

Name	Files	References
more power in approach	2	2
not enough concentration	1	1
not enough height	1	1
positive about performance	2	3
rushed	2	2
second kick	3	7
somewhat positive	5	6
third kick	1	1
too much focus on more power	1	1
unhappy with performance	3	5
wrong hit point on foot	3	3
trouble visualizing	11	30
understanding data	12	290
analysing movement	11	30

Name	Files	References
comparing three graphs	5	6
confident in ability to understand data	8	14
consistent graph shapes	3	6
doubting abbility to understand data	6	14
Graph is hard to read	1	1
highest peak	5	6
kicking phases	12	119
approach	12	28
Steps	9	10
ball contact	9	21
follow-through	10	20
kicking phase	12	37
leg swing	11	18
Peak	7	13

Name	Files	References
Relating data to performance	8	19
relating graphs to drawings	2	2

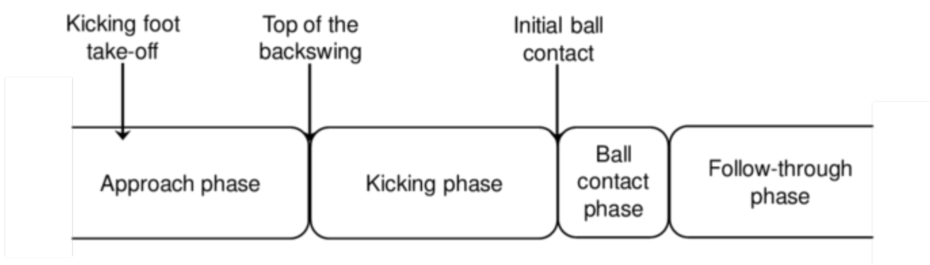


Figure 7.1: *The four phases as defined by Alexandra Atack in her Thesis called The Biomechanics of Rugby Place Kicking [2].*

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