A Comparison of Alternative Motion Capture Systems for Postural Measurement of Rugby Union Scrums

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Hamish Simmonds

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Abstract

Much research has recently been published on the optimal posture in rugby union scrums. These use expensive motion capture systems to collect postural data during trials. There is a clear gap in technology between what is used for training purposes and what is used for research, with the latter being expensive and requiring lengthy calibration times. The method proposed here would remove these as issues to postural data collection by teams using their scrum machines.

The method uses a neural network to infer posture from simple a motion capture system that uses inexpensive sensors to return postural parameters such as the angles of the back, as well as the hip, knee, and ankle joints. The accuracy and precision of this method are compared to a commercial motion capture system.

The results show that the proposed method performs well compared to the motion capture system and is a suitable method for this type of application. Thus, a clear path for the future development of an instrumented scrum machine that incorporates the capture of postural angles.

Acknowledgements

This project required access to professional teams and coaches, as well as an understanding of scrum machine design requirements and scrum tactics. Tim Horgan from my sponsor company Powa Rugby was very helpful in providing valuable insight into these areas, which I really appreciate. I would like to thank my supervisors, Dr Morio Fukuoka for providing me with ongoing support throughout the project, and Dr Huub Bakker for giving me direction and assistance when needed. I would also like to thank my partner Emily for her love and support throughout this project. Lastly a big thank you to my family for their support during my studies.

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 What is an instrumented scrum machine

An instrumented scrum machine is a tool coaches and players use to gather useful data on players' scrummaging performance. The use of non-instrumented scrum machines is common among rugby union teams. While this is adequate for training technique and pushing power, it will often give little-to-none feedback on performance increase by the player over time. Instrumented scrum machines have become standardised in research to determine optimal stances for maximising forward-pushing power. Current instrumented scrum machines utilise force measurement devices such as weights and load cells to give accurate feedback (Bayne & Kat, 2016; Green, Kerr, Dafkin, & McKinon, 2015; K. L. Quarrie & Wilson, 2000; Wu, Chang, Wu, & Guo, 2007).

1.2 Research Context

This project integrates knowledge gained from research in the sports science area, with modern technologies from the Mechatronics Engineering field.

The output of this project is intended to create a user-focused system with which coaches can measure their players' scrum performance and technique. Although the idea of instrumented scrum machines and postural optimisation has been researched, this project will improve upon the automation engineering aspect of the machine and improve the cost of production of the platform. The cost reduction is in the hopes that the product produced based on this platform will be more affordable for lower-budget rugby teams and clubs to make it easier to compete with non-instrumented scrum machines. The background of the author is in electrical/software engineering, an effort to understand the biomechanical aspects of this research area has been made.

1.3 The Goal

The goal of this project is to develop an affordable method to capture the postural and force data in rugby scrummaging. This data can then be analysed to find the optimal scrum body position. This project will focus on comparing different postural data collection methods to evaluate which one would be the best fit for this type of application. While other research into this area has been focused on maximising forwards pushing power, this project will produce the knowledge for future development of a coaching tool for technique and personalised player development.

1.4 Research Question

Will making a more user-focused method for postural data collection bridge the gap between systems used in literature and those used for training purposes?

1.5 Project Aims

- Design an instrumented scrum machine to capture relevant forces produced by the player.
- Design and implement a method to capture the postural data of the player and extract key joint angles.
- Ensure the final design is both affordable and user-friendly.
- Use collected data to identify the optimal body position to maximise forward pushing power.
- Validate the method by comparing the optimal positions against past literature.

2 Overview of the Rugby Scrum

Rugby union (rugby) is played in over 120 countries and reportedly has over 8 million players participating in the sport. New Zealand alone has over 155 thousand players registered to play 15 aside rugby union (Rugby, 2019). Rugby is played by two teams over two halves, for a total of 80 minutes. This section provides relevant information to help the reader understand ideas, rules, and terminology relating to the rugby scrum.

2.1 What is a Rugby Scrum?

Points can be scored in four different ways; a try awards the scoring team 5 points and is achieved by placing the ball on the ground past the opposing try line. A conversion will award two points and is scored by kicking the ball between the two goalposts of the opposing team. A conversion opportunity is offered after each try is scored. A penalty kick is worth three points and can be scored by kicking the ball through the goalposts after a major infringement by the other team. Lastly, a drop-goal will earn the team three points and can be scored by kicking the ball through the goalposts during an attacking phase of the game. In rugby, there are two types of infringements, major and minor. A major infringement will result in a team being awarded a penalty. A minor infringement will result in one of three outcomes: a scrum, a lineout, or a free kick. In the scrum, eight players (usually jersey numbers 1-8) also known as the 'forward pack' from each team compete to win the ball by attempting to push back the opposing pack (Rugby, 2022).

A rugby scrum is used to restart play after a minor infringement, where the game is restarted is determined by who caused the infringement. The non-offending team will always be given the ball to throw in, except for a few cases where the ball can become unplayable, in which case it will be given to the attacking team (Rugby, 2022).
A scrum is won by whichever team successfully retrieves the ball from the scrum. The scrummaging process is known to be physically intensive, especially on the front row of each team as all of the pushing force generated by the pack is applied as a compressive force across the three front row player's backs.

2.2 Scrum Formation

In the scrum, the loosehead prop, hooker, and tight-head prop (players 1-3 respectively in Fig. 1) bind with the opposition players of the same position. In this bound position their heads are between the heads of the opposing players and shoulder-to-shoulder contact is made. The two locks then bind behind the front row (numbers 4-5 in Fig. 1), they then bind to the remaining two flankers and number 8. To bind effectively a player will grab onto either the shorts or jersey of the nearest player.

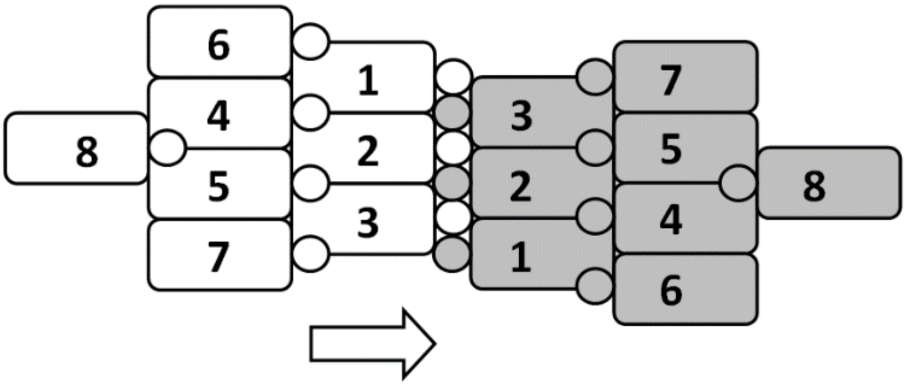

Figure 1: Scrum Formation

2.3 Scrum Engagement Phase

The engagement phase of the scrum is initialised by the referee using three calls Crouch, Bind, Set (CBS). Once both sides are standing square to one another in the formation shown in section 2.2 above, the referee calls “crouch”. The two front rows will then crouch down to a point where their heads are no lower than their hips. The referee will then call “bind”, the players will then bind to one another gripping either the shorts or jersey of adjacent players, including those on the opposite team. All players must maintain this bind for the remainder of the game. Now that the scrum is fully formed the referee will call “set”. The teams will then engage, this will create a tunnel for the ball to be thrown in between the two front rows. All three front-row players must start with both feet on the ground with at least one foot able to support their body weight.

2.3 Scrum Sustained Phase

The scrum contest begins only after the ball has been thrown in, at this point the teams may begin to push. The push must be straight and parallel to the ground. If the scrum were to collapse or the players are forced too far upwards the referee will signal to stop pushing. The referee will then, either reset the scrum or, award a penalty against the team that caused the scrum to break down. The scrum ends when one team can use their feet or lower leg to hook the ball to the back of the scrum, where the number eight or scrum half can collect the ball.

2.4 Rugby Terminology

CBS
The method the referee uses to set up and commence the scrum, “Crouch”, “Bind”, and “Set”, are sometimes referred to as the CBS method.

Forwards
Used to name a group of players, jersey numbers 1-8. These players also make up the scrum.

Front Row
Jersey numbers 1-3, these players are located at the front of the scrum. They include two props and a hooker.

Backs
Used to name a group of players, jersey numbers 9-15.

3 Literature Review

This section will give the reader an overview of previous research done on the advancement of rugby scrummaging. Section 3.1 will offer a brief history of the research into scrum performance. Section 3.2 will review the types of scrum machines used in previous experiments and draw ideas on how to improve the amount and quality of data gathered from the machine. Section 3.3 will review the postural data capture methods used and the optimal body positions concluded by previous research studies. Section 3.4 will investigate the types of injuries often caused by scrummaging to gain an understanding of how to avoid basic injury. These topics will then be summarised in section 3.5 where gaps in knowledge will be identified.

3.1 Prior Research into Scrummaging

Research began in 1979 when Cohen used an instrumented scrum machine (Cohen & Siff, 1979). In this study, the authors measured the average force output of a small sample of players. A steady stream of research into optimal scrum posture since this, with less of an emphasis on observing the players, and more on finding the optimal kinematics. Injury research gathered momentum going into the early 2000s and has become the most researched topic within rugby scrummaging.

Since rugby became a top-level professional sport, more funding in the area has led to more research on the topic. The research done in these papers has improved player technique as well as found issues with technique and scrum laws which create an unnecessary risk of injury. Good technique is very important as there are very high compressive forces acting through players' spines, with the combined forces often more than 6kN (Cazzola, Preatoni, Stokes, England, & Trewartha, 2014; Ezio Preatoni et al., 2012; K. L. Quarrie & Wilson, 2000). A large proportion of the research into optimising forward pushing force and stability is done using vision-based systems (Cazzola, Stone, Holsgrove, Trewartha, & Preatoni, 2016; P. D. Milburn, 1990; Sayers, 2008; Wu et al., 2007). These systems are often limited to being used in a laboratory or workshop setting due to motion capture technology requiring steady backgrounds and consistent lighting. Motion capture systems also cost tens of thousands of dollars to purchase putting them out of reach of smaller teams. Interviewing multiple professional scrum coaches from New Zealand made it clear that these laboratory-based systems did not lend themselves well to coaching and therefore were not used by players as a coaching tool.

3.2 Common Injury Caused by Scrums

As performance in the scrums continues to improve, the forces that are loaded onto each player also increase, and so do their chances of injury. In a study by Brooks, it was found that 11% of all injuries can be associated with scrummaging. Taylor, Kemp, Trewartha, and Stokes (2014) found that the risk of injury was higher in collapsed scrums, of which the front row is of the highest risk of injury. This is one of the driving forces behind continuously changing scrum laws, to reduce impact force and the chances of collapse.

3.2.1 Neck Injury

One of the main three types of scrum-related injury is to the neck. During the scrum, players can place high axial compressive loads on the neck. The risk of severe neck damage is increased during a collapsed scrum (K. L. Quarrie & Wilson, 2000). Measures to prevent neck and back injury have included changes to laws on the scrum procedures, these measurements reduce the peak loads through the neck and reduce the number of collapsed scrums. Law changes have been implemented to remove axial loading, this now means players are not allowed to load and push through their heads (Rugby, 2022).

The forces on engagement have the potential to exceed axial neck load and bending movement tolerance limits. Cazzola et al. (2014) found controlling a player's engagement, specifically through the prebind method, reduced forces on the player by about 20%. This new method had no observed impact on the sustained force in the scrum but did show promising results in improving stability, which would reduce the number of collapsed scrums.

3.2.2 Spine Injury

The harm that Rugby has on a player's spine has been the focus of a lot of papers over the past three decades. Not all of these are from the scrum, however, Kenneth L Quarrie, Cantu, and Chalmers (2002)states that the scrum accounts for 40% of all rugby spinal injuries. Reboursiere et al. (2018) found that the rate of catastrophic spinal injuries decreased significantly in the decade between 1996 and 2006. This happens to be around the same time that scrum laws were continuously changing to become safer, and the same time that New Zealand introduced "Rugby Smart". "Rugby Smart" is a course that coaches and referees must take that informs them on reducing and managing injury.

The education of referees can help to reduce the amount of collapsed scrums. Taylor et al. (2014) found that the risk of spinal injury was highest during collapsed scrums. P. D. Milburn (1990) analysed the scrummaging of high-school rugby players and found that the hooker experienced the highest lateral shear force acting on the spine, this was identified as being a leading mechanism in degenerative changes in the cervical spine. This finding was corroborated by Wetzler, Akpata, Laughlin, and Levy (1998) when they found that 78% of US rugby players who obtained cervical spine injuries were hookers. These issues leading to injury have led to rule changes which attempt to reduce impact force and improve stability, to reduce the number of collapsed scrums.

3.2.3 Ankle Injury

During the scrum, a player will have all their generated force transferred through their ankle. This creates a high chance of injury, particularly for professional players who often have rigorous training and playing schedules. In a study containing 300 forwards and 246 backs, Sankey, Brooks, Kemp, and Haddad (2008)found that ankle injuries accounted for 11% of all match injuries and 15% of all training injuries. Sankey et al. (2008) also found that while the incidence rate for injury during a match was similar, the incidence rate during training was higher for forwards compared to backs. The severity of the ankle injury was also higher for forwards.

3.2.4 Law Changes Due to Injury

As research into the forces generated in the scrum is continually advancing, the realisation of the high rate of injury due to the scrum has led to rule changes occurring. In New Zealand, the Accident Compensation Corporation (ACC) has collected information on all rugby-related injuries since 1974 ("Accident Compensation Corporation,"). Reviews of this data found that even though more injuries occur during tackles, scrums are the most dangerous phase of play due to the severity potential of the injuries caused over the short period of the scrum. Kenneth L Quarrie, Gianotti, Hopkins, and Hume (2007) analysed ACC data and found that between 1976 and 2000 48% of permanently disabling spinal injuries occurred during the scrum, but this was reduced to 12.5% from 2001 to 2005 after rule changes and preventative measures were implemented. Many studies into scrum-related injuries inform World Rugby on effective rule changes to introduce. The data shows that these rule changes are working as New Zealand’s scrum-related injuries have fallen by 97% in recent years (Kenneth L Quarrie et al., 2007). Table 1 shows the key scrum law changes that have occurred.

Table 1: Law change History

Year	**Law Introduced**
2007	"crouch", "touch", "pause", "engage"
2012	"crouch", "touch”, "set"
2013	"crouch", "bind”, "set"
2022	Brake foot

In 2007 World Rugby introduced the "crouch", "touch", "pause", "engage", method to commence a scrum. This was aimed to reduce the gap between the two front rows, as up until this point there was no need for the front rows to start within touching distance of each other. In 2012 the law was changed to replace the "pause", "engage", step with “set”. Removing the “pause” stage helped to speed up the scrum. One season later the law would change again to replace the “touch” stage with “bind”. This reduced the gap between the forwards even further and reduced the impact force.

3.3 Comparable Scrum Machines

Forces that can be observed in the scrum are lateral, vertical, and compressive forces (Cazzola et al., 2014; P. D. Milburn, 1990; Ezio Preatoni, Stokes, England, & Trewartha, 2013; E. Preatoni, Stokes, England, & Trewartha, 2015). The compressive forces generated by players have been the focus of most research papers to date, this is due to the forward pushing power being one of the main ways to win a scrum. However, the vertical and lateral forces are sometimes measured in literature due to vertical forces and lateral forces causing scrum collapse and wheeling, respectively. The direction of these three forces is shown in Figure 2.

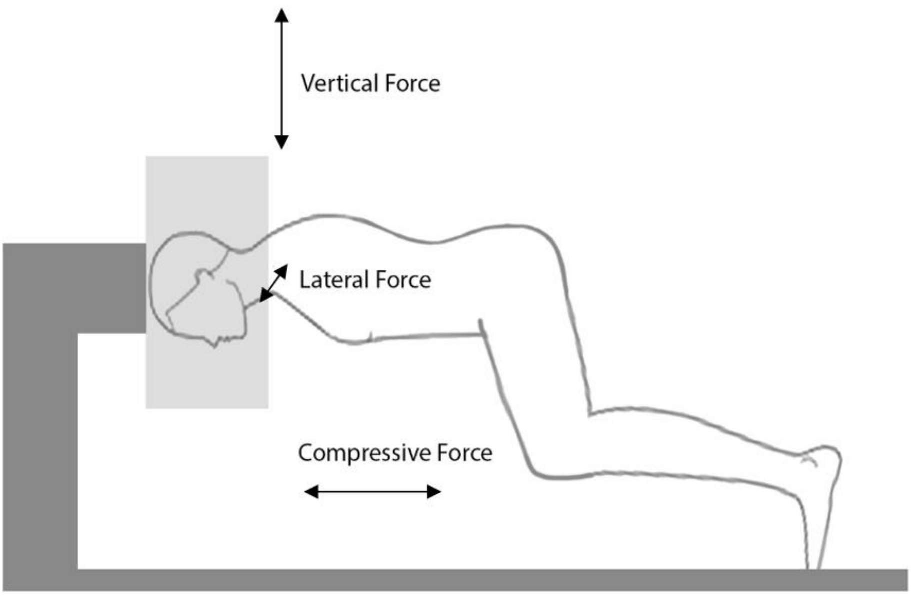

Figure 2: Forces during the scrum

Studies which measure the forces of a player in a scrum scenario generally use a variation on an instrumented scrum machine. K. L. Quarrie and Wilson (2000) used strain gauge force transducers attached to each of the shoulder pads on a scrum machine to measure the forces through each shoulder. Wu et al. (2007) used a single uniaxial load cell to measure total compressive forces. This approach of adding load cells to the shoulder pads is a popular approach for force measurement and is used in almost all the research in this area. These instrumented scrum machines with a single load cell attached to each shoulder focus only on the compressive forces. The scrum machine used by Wu et al. (2007) is shown in Figure 3.

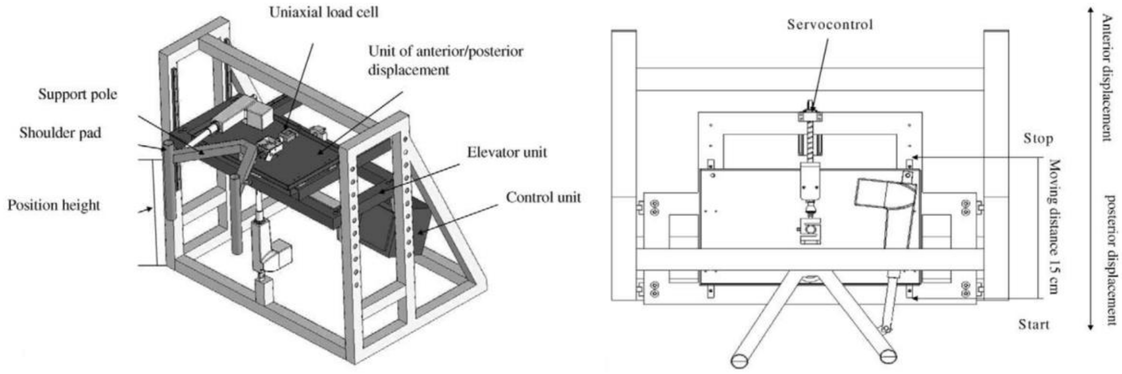

Figure 3: Example of an instrumented scrum machine. Reproduced from (Wu et al., 2007) with permission from the Journal of Strength and Conditioning Research.

Lallemand et al. (2020) used the French National teams "L'Atelier de la mêlée" instrumented scrum machine to conduct their study. This machine can measure relevant forces and able to simulate an adverse pack. Green et al. (2015) used a custom-built scrummaging ergometer which has 4 s-type load cells at each corner of a square bracket to which the pads are attached. This configuration allows the authors to measure not only the compressive forces but also some of the lateral and vertical forces.

Comparing the results of natural turf footing against synthetic matting and indoor settings alongside an instrumented scrum machine shows a clear increase in force results for the artificial grounds. The synthetic/indoor footing results average in the 3 to 4kN peak force range (Mensaert, Sharp, & Vanwanseele, 2015; Sharp, Halaki, Greene, & Vanwanseele, 2014). Whereas the natural turf average is in the 2 to 3kN range (Green, Dafkin, Kerr, & McKinon, 2017; Green et al., 2015; Green, Kerr, Dafkin, Olivier, & McKinon, 2017). This is not too important as these studies are used to analyse technique and if the surface is noted clearly on the study, then performance metrics can still be drawn from the results. In some ways, it is better to have the synthetic option as it removes one variable from the study making the optimal posture more influential in the results. Mills, McMaster, and Smith (2019) used a ladder-style foot block to ensure all players in the study would have equal footing for their research. This option strays further from the natural turf, although because Andrew Green, Samantha Kerr, et al. (2017)and Bayne and Kat (2018)both concluded that the parallel foot stance offered the highest force output, training technique with the ladder option would force players to have parallel feet.

3.4 Player Postural Data

This section will cover the various methods used in previous studies to capture scrum posture. It will also summarise the optimal positions found in literature for scrumming.

3.4.1 Motion Capture Methods

Literature shows that there are three main methods of collecting positional data on the player these are annotated images, inertial sensing, and multi-camera motion capture.

P. D. Milburn (1990), K. L. Quarrie and Wilson (2000) and Bayne and Kat (2018) are examples of studies that all use annotated images to gather positional data. All three of these examples use a single video camera positioned in the sagittal plane a few meters to the side of the player, at about waist height. Once the trials have been run the images can then be annotated to create a 2D biomechanical model of the player. This option for motion capture is very cheap compared to standard motion capture and gives accurate results with K. L. Quarrie and Wilson (2000) stating that all joint angles had an error of ±4°, this was found through repeated sampling of the video records.

Multi-camera motion capture equipment is considered the "gold standard" for this sort of research as the results are very accurate, and once set up there is no need for annotation. This makes it a good fit for laboratory-based research. Wu et al. (2007), Mensaert et al. (2015) and Andrew Green, Samantha Kerr, et al. (2017) all utilise a 6, 4, and 18 camera motion capture configuration. This gives the authors precise results and captures rotation of limbs which single camera image annotation would not. However, after speaking with multiple high-level coaches from New Zealand, it was concluded that there was a large divide between what is used in research and what is used as training tools by teams. The long calibration time, complex software and temperamental lighting conditions make these motion capture systems impractical for teams to use.

Swaminathan, Williams, Jones, and Theobald (2016) uses 6 inertial sensors placed down the spine of the player to get 3D positional data during trails. These sensors are improving rapidly in terms of size and data that can be collected. With the rise of awareness around concussions in sports and players wanting information on their playing habits, motion tracking options such as wearable body suits with inertial measurement units embedded in them are becoming popular options. These can track indoors or in the field but do sacrifice precision.

Another option for motion capture is to use a standard camera and pose estimation software. These software use trained neural networks to estimate the position of the body. A network such as Open Pose (Cao, Simon, Wei, & Sheikh, 2017) can give sufficient results under normal circumstances, however, due to the player having their head occluded by the scrum machine, and only having a view of one side of the body, this method will struggle to find enough identifying key points on the player to give a reliable result.

3.4.2 Optimal Scrum Positions

Optimal scrum posture has been studied frequently to improve force output and reduce the odds of injury. Du Toit, Olivier, and Buys (2005) state the coordinated force applications of individual players are necessary to have good team scrummaging performance. To improve individual scrummaging instrumented scrum machines can be used to isolate a player's data compared to gathering data on a whole forward pack. Many have found the basic scrum posture to be used as a straight flat back(Mills et al., 2019; K. L. Quarrie & Wilson, 2000; Rodano & Bulgheroni, 1992; Wu et al., 2007). Studies have shown a strong correlation between the vertical squat position and the horizontal scrum position(Mills et al., 2019). Wu et al. (2007) found that the Optimal scrum position was when the player's back was at roughly 40% of their body height. Multiple sources found that the knee flexion angle should be between 105 to 115 degrees (Mills et al., 2019; K. L. Quarrie & Wilson, 2000; Wu et al., 2007). Sayers (2008) found that 125 degrees of flexion in the knee provided more forward force output. However, after interviewing multiple coaches and observing game footage it is apparent that the players are more unstable when their feet are further back from the body and provide less stability to the scrum often leading to a collapsed scrum. Often research studies into maximising the force output split the scrum into two phases; these phases are before and after the impact. These two phases, before and after impact, are often referred to as the "engagement phase" and "sustained push" respectively. As shown in Figure 4 there is a clear peak in the force at impact, then there is a small trough in the force where there is a clear rebound before the force stabilises into the sustained push phase. Figure 4 shows that the impact force can quite often be higher than any other part of the sustained push. This is a large reason why many of the recent scrum Law changes have been to reduce the distance between players to reduce the peak impact force.

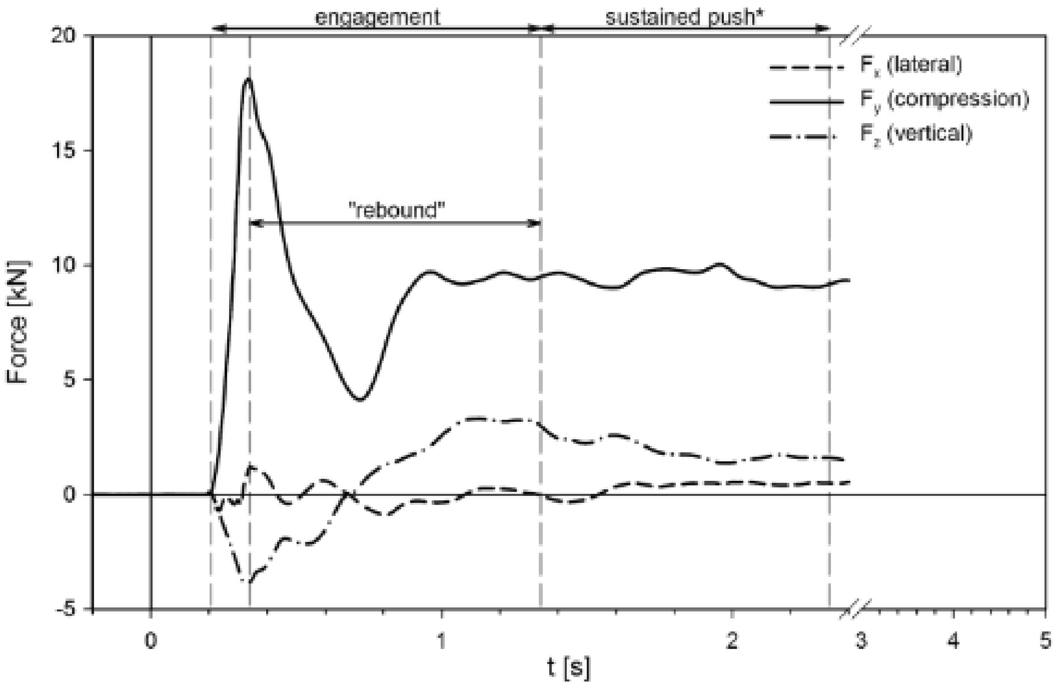

Figure 4: Scrummaging force vs time. Reproduced from (Ezio Preatoni et al., 2013) with permission from the British Journal of Sports Medicine.

During the machine-based testing, it was identified by K. L. Quarrie and Wilson (2000) and Wu et al. (2007) that a lower more extended position would maximise the force produced. This may not work in a real-world scenario though, as this position would lead to instability and more force loaded onto the lower ankle region (Flavell, Sayers, Gordon, & Lee, 2013). Measuring the forces in the vertical axis could provide data to find the optimal position while still considering the vertical stability of the scrum.

Flavell et al. (2013) found that attacking scrums have a higher force output compared to defensive scrums, this is due to a larger displacement of the hips when defending scrums. This finding is supported by the other optimal position findings and explains why Wu et al. (2007) found that the optimal position was in a lower, more extended position, as this would be the body position of a player when they are attacking a scrum. Likewise, the other authors found that a slightly more compressed body position was optimal and would be closer to that of a defensive stance during a scrum.

3.5 Professional Scrum Coaches

During the early stages of the project, interviews were conducted with high-level professional rugby coaches to determine what they look for in players' techniques, how they train to scrummage, and what they would want in an instrumented scrum machine that is to be used as an everyday training tool.

After interviewing multiple coaches, it became clear that a lot of the training tips that they would teach their players were based on experience rather than data. Hurricanes scrum coach Dan Cron said that “for every degree that the back is not parallel to the ground, the player loses 1% power”, to which he admitted he had no quantitative data to back it up(Cron, 2021). However, rules of thumb like these appeared in a lot of interviews. This shows the need for coaches to have access to instrumented scrum machines as then they would be able to back up their theories and be more definitive when talking to players. Cron (2021) also stated that there was no one “best” exercise for training scrum technique and that squatting in the team’s powerlifting gym was probably the closest exercise to train the muscles used in scrummaging, Mills et al. (2019) backed this up in their research stating that the back squat closely follows the joint kinematics of scrummaging.

Both All Blacks scrum and forwards coach Greg Feek, and Dan Cron gave a very similar list of four key measurements that they would like an instrumented scrum machine to be able to provide (Cron, 2021; Feek, 2021). These were:

- Impact force at engagement
- Force over time (known as “stay strong”)
- Force percentage drop over time
- Stability of the player

3.6 Gaps in Knowledge

Although research into proper form during scrummaging and maximising output force has been happening for decades, there is a clear gap between what is used for research and what is used by teams for practice. There is an opportunity to create a method for postural and force capture that coaches could use more readily in general practice. This disconnect between research equipment and training equipment is generally down to two factors, cost and ease of use. The state-of-the-art motion capture equipment used in some of the studies from section 3.3.1, can cost tens of thousands of dollars, and can often require lengthy calibration for each player. As well as technicians to operate the software and extract useful data. The design of an inexpensive method that will give reliable results without the need for individual player calibration is the clear way to bridge this gap. If a method like this were to be used often by teams, then there will essentially be an ongoing study into optimal postural position, with much larger sample sizes than previously used in any research.

Another space where there is a knowledge gap is gathering force data individually from both shoulders of the player. Until this point all studies have focussed on the average forward push of the player and, in the case of Bayne and Kat (2018), even studied the average vertical push of the player. However, interviews with coaches from top New Zealand teams, tell us that each person in the scrum can have very different roles to play. Each player can often be required to push with most of their force down a particular shoulder, and even apply upward or downward force depending on their side of the scrum. To be able to record this data while the player is training would be useful to improve their game.

4 Scrum Machine Development

During the year before this project, Powa Rugby worked with Massey University to develop an instrumented scrum machine. This prototype went on to inspire this research into ways to improve the use of the machine. This section outlines the steps taken to create a new instrumented scrum machine to capture all the force data for this project. It recaps the previous prototype from Powa Rugby and discusses improvements that could be made to the design.

4.1 Previous Experience with Scrum Machine Design

This prototype was very useful for finding out what worked well in terms of the physical design of the machine. The annotated initial prototype is shown in Figure 5 below.

The machine worked well as a proof of concept. It offered reliable force results for the left and right shoulder. The foot ladder gave the player a range of footing options, this did remove the option of a staggered stance and forced the player into a parallel foot position. However, in the literature review (section 3.4.2) Andrew Green, Samantha Kerr, et al. (2017)and Bayne and Kat (2018)both concluded that the parallel foot stance offered the highest force output. The right and left handle offered the player a long and short bind position, this was good as the machine needed to cater to all positions in the scrum.

Figure 5: Previous initial prototype

The use of bushings to guide the pads into the machine would often bind and cause a lot of friction. This would mean that the player would have to adjust the way that they were pushing to move the pads. The load cells were also located behind the shocks and arms, this means that all the friction losses were not observed in the data. The shocks being in front of the load cells would also alter the force readings. Although the observed work done by the player should be the same with the shock placement, as the springs would store the energy put into them, they would cause a damper on the peak engagement force.

The use of only one spring above the ram created the issue of torque being applied at the pad. This created more friction in the bushing, adding further error to the results and reducing the ease of use. Only using one load cell on each side meant that only the left and right forces were able to be captured. To get a 3-dimensional force vector at least two load cells are required on each side.

4.2 New Scrum Machine Design

This section shows the steps taken to create the instrumented scrum machine to capture the force data for the experiments. It also provides in-depth documentation of the inner workings of the machine.

4.2.1 System Specifications

The new system specifications were created to outline the core functionality the new scrum machine required, while also addressing the issues found with the old prototype.

The new machine must meet the following specifications:
- Support use by one player at a time.
- Measure forces on the vertical and horizontal axis.
- Capable of withstanding many hits by professional players.
- Be safe and intuitive to use.
- Offer the player “push-back” on the horizontal axis.
- Must not use bushings to provide alignment to the pads.
- Have the primary load cells in front of the springs (or another damper method).

4.2.2 New Design

The new design addresses the key issues with the previous prototype and adds the means to capture force and displacement data. The new revision of the scrum machine addressed the main issue of friction in the bushings by using a four-bar linkage to support the rams.

The new design kept some of the features that worked well in the last design, these included the foot ladder and the handles. The load cells to measure the shoulder forces were also placed directly behind the pads. The use of two load cells spaced vertically means that the shoulder placement location on the pad can be estimated through the proportion of the loads. The front link of the four-bar linkage is split and joined together using an s-type load cell. This gives data on the vertical pushing forces generated by the player.

Due to the large radius and small angle that the four-bar linkage can move, there is negligible vertical displacement caused when the player is pushing. There is also a magnetic precision encoder placed on each side attached to the linkage, to capture the angle of the linkage. This data can then be used to find the horizontal displacement of the pads during the push.

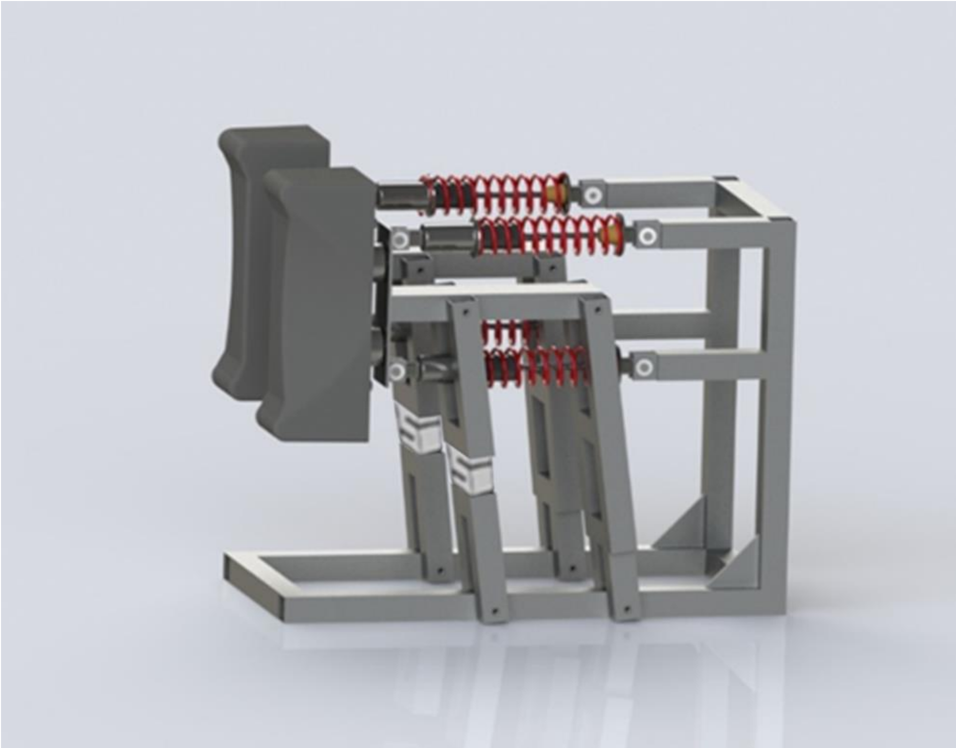

Figure 6: Assembly view

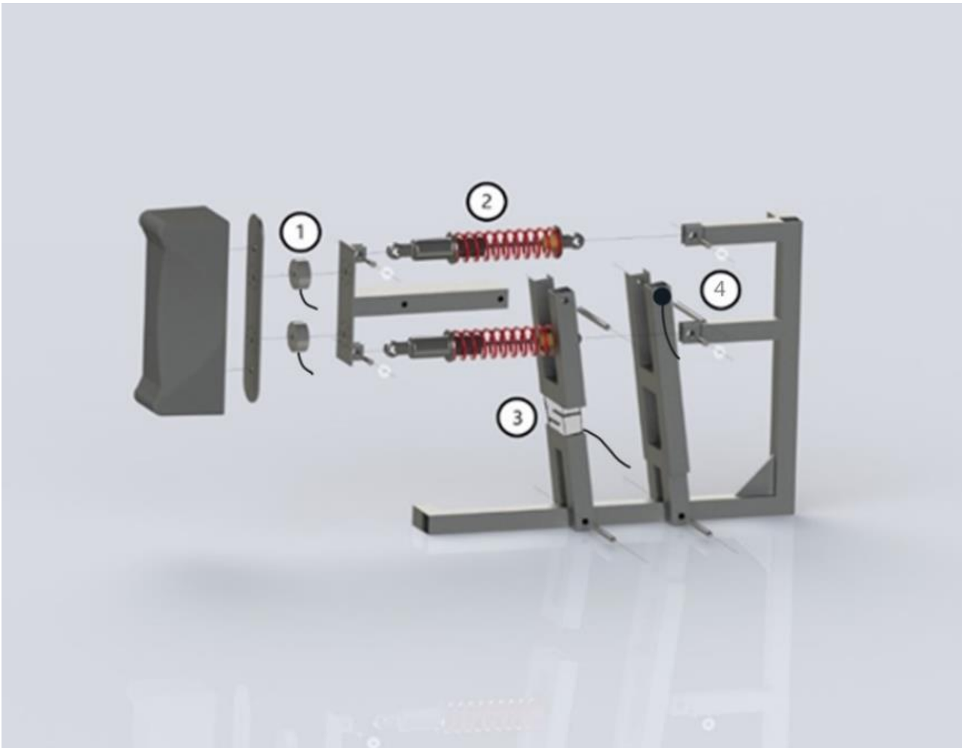

Figure 7: Exploded view

In Figure 7 above the numbers annotate the following key parts:

1. 250 Kg Pancake load cells
2. Rally shocks with 60 Kg coil-over springs
3. 1-ton s-type load cell
4. Magnetic precision encoder

4.2.3 System Electronics

This section shows a simple wiring diagram as well as a schematic for the layout of the components on the PCB used for testing.

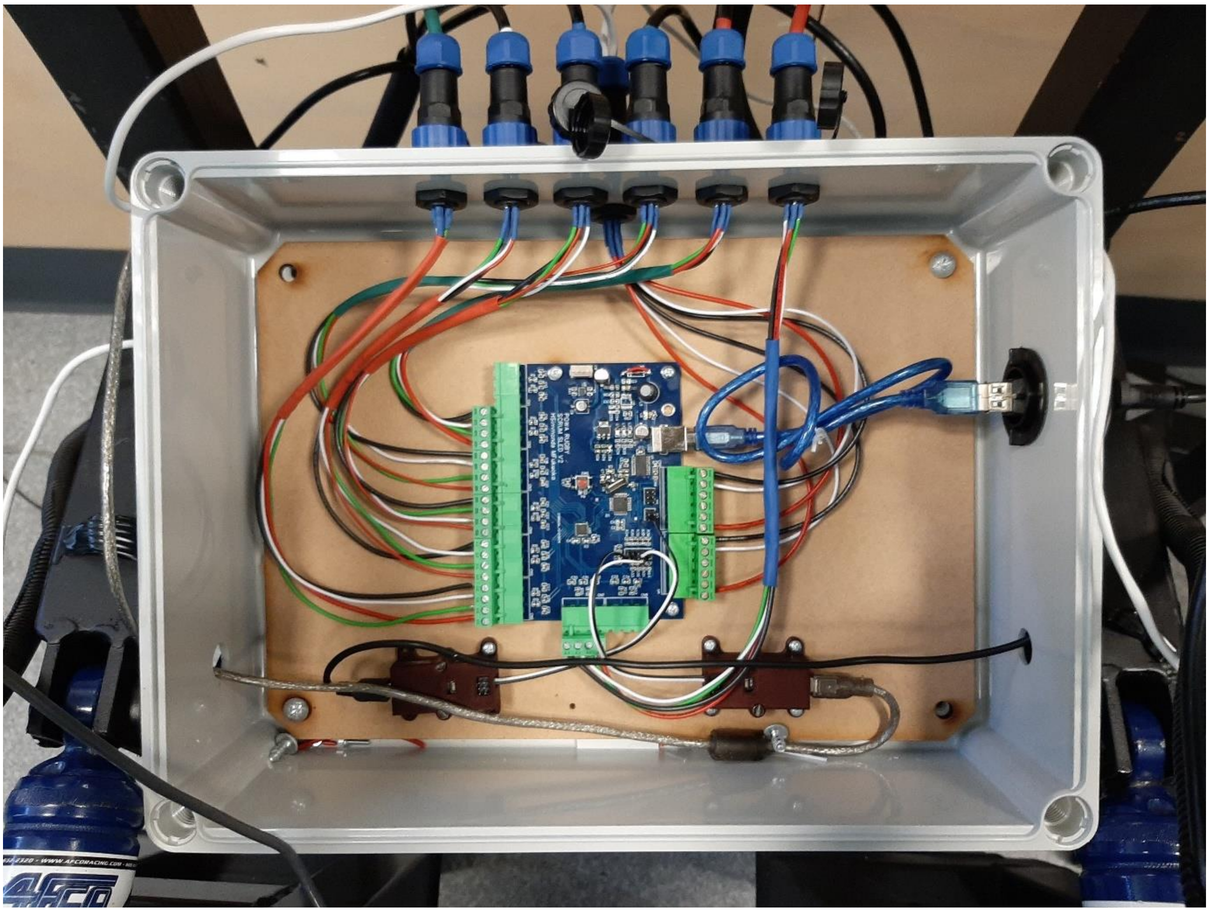

Figure 8: Scrum Machine Main Board Layout

Table 2: Sensors

Sensor Type	Use	Description
Universal Pancake Load Cell	Measuring the Horizontal force produced during the scrum	Four 250kg rated load cells.
S type Load Cell	Measuring the vertical force.	Two 1-tonne rated load cells.
Encoder	Measuring the angle of displacement in the linkages.	Magnetic precision encoder.

The main printed circuit board (PCB) is used to connect the sensors to the PC. The PCB uses an ADC to read the signals of each load cell and then outputs raw data to an Arduino microcontroller embedded into the board. The Arduino on the board connects to the ADC via SPI communication, this takes in the raw SPI data and converts it into force data. The Arduino reads the ADC data at a rate of 50 Hz. The data can then be sent to the PC via USB serial. The PCB also has a set of header pins that give prototyping access to 5 GPIO pins and 5 pins which offer grounds and varying voltages.

4.2.4 Software

There are two main sections of the software, the embedded code to read the sensors and output the serial data to the PC, and the graphical user interface (GUI) code to take the serial data on the PC and display it to the end user.

The embedded software uses a simple timer interrupt routine to poll the ADC at a frequency of 50 Hz. This data is then output to the serial port delimiter with a comma. This data can then be read by the GUI.

The GUI offers the user a range of functionality. Once the data is read by the PC it displays the average force over the two pancake load cells for each shoulder, the Encoder angles, and it also displays the vertical forces through the four-bar linkage. All these values are converted to Kg before being displayed. The GUI also offers the function to tare the data by removing any zero offsets from the data. Once the player is ready the start button is pressed, and the software will then count down from 3 then capture data for 10 seconds.

Once the data is captured it will remain on screen to display the graphed forces and can then be saved to a CSV file on the local PC. This file will save both the tared results and the raw data from the serial port in case a different calibration method is wanted in the future.

4.2.5 Revisions

After testing the new prototype, and consulting with professional players and coaching staff, some revisions were made to the design of the machine to improve its usability. These were:

1. Improve stability of the linkages
2. Add shrouds
3. Mounting the unit to the floor

The first change was made after players noted a small amount of instability in the sideways movement of the four-bar linkages. This was due to the small width of the square extrusion used. This issue was fixed by using a larger-width steel tubing and adding steel flanges to some areas, this gave a much stiffer and more durable feel to the machine.

The second change was to add shrouds to cover the springs and increase the safety of use. Due to the handles being fixed to the backplate of the pads the shrouds were able to be fixed to the rams without worrying about mounting anything to them. The unit also moved around a lot in initial testing and flexed in the centre, pivoting around the hinge where the foot ladder meets the machine. This was solved by mounting the whole machine to the ground.

With these revisions completed the design of an instrumented scrum machine to capture specific forces produced by the player was completed.

5 Method Development

Given that in the literature review four methods of postural data collection were named and all had reasonable success in their investigations. This section shows the step gone through to compare and select the postural data collection methods. It also provides a brief explanation of the data collection steps for the initial experiment.

5.1 Overview of Method Development Process

An investigation was conducted to decide which one was most applicable to use in the validation experiment. This initial stage of experimentation will also allow the errors of each method to be evaluated so that a clear error value can be associated with the final experiment results.

Each option for postural data collection will be compared against a list of criteria which will evaluate its ability to resolve the gap between research and industry stated in section 3.6. The option selected for the experiments in this research will need to accurately find the joint angles, hip extension, knee flexion, and ankle flexion shown in Figure 9.

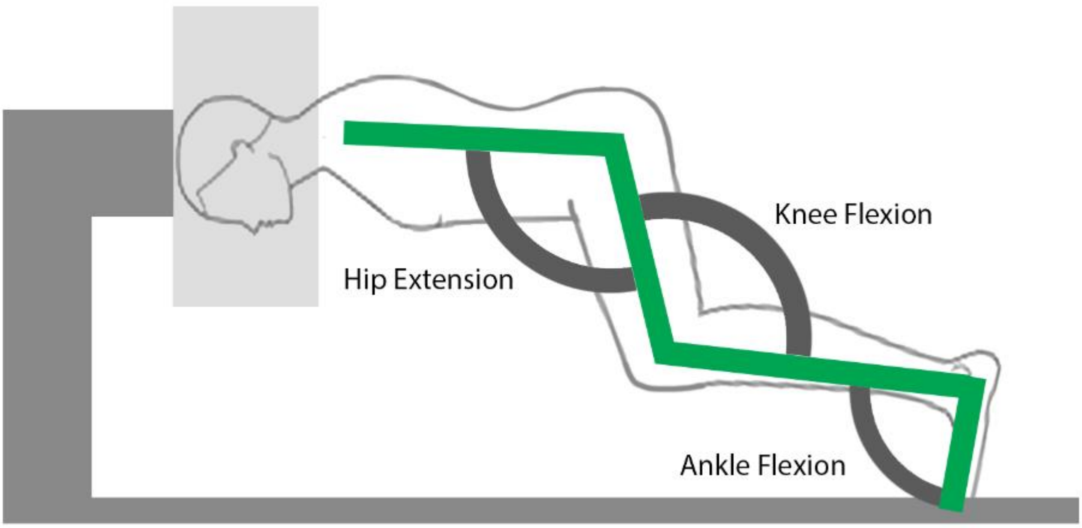

Figure 9: Joint Angles Illustrated

5.2 Criteria for Method Selection

The method was selected based on the criteria listed below, these were created based on the conclusions from the literature review and consultations with leading scrum coaches.

1. Practicality and Reliability
   The methods will be investigated for their ability to bridge the gap between a research tool and a training tool. For this to happen the method must be simple and reliable to use. The simplest method with the least time needed for setup, calibration, and time between players is optimal.

2. System Accuracy and precision

The accuracy of the system is also very important to the reliability of the conclusion about optimal postural positions that will be made at the end of this thesis. The precision will also be suitably low to be able to properly analyse the small difference between similar scrum stances.

3. Cost of the system
   While the cost of motion capture is not often evaluated when deciding upon a method of motion capture technology in research papers. The ability to bridge the gap between research use and everyday training use will be influenced by the price of the system, particularly in lower-tier clubs/teams.

5.3 Methods to Compare

5.3.1 Motion capture

A multi-camera motion capture system has been the gold standard for research into posture-based studies. The systems are very reliable and have very high accuracy and precision giving the best possible results for the research. Unfortunately, systems such as these require markers to be placed on each test subject in very specific places, they have a lengthy calibration stage for both the player and the 3D space calibration, which is used to find the location and direction of all cameras in the system. These drawbacks prevent it from becoming frequently usable by teams as a training tool. The other drawback is the price, these systems cost tens of thousands of dollars (NZD). This makes them unsuitable for most teams below the professional level. For these reasons, this type of motion capture system does not meet the criteria for method selection.

5.3.2 Neural Network

The Neural network approach was used here to evaluate the effectiveness of a postural estimation neural network to determine the body position of the player. Pre-trained neural networks such as Open Pose (Cao et al., 2017), Blazepose (Bazarevsky et al., 2020) and Pose net (Chen, Shen, Wei, Liu, & Yang, 2017) can be found which provide reasonably accurate results when working with images which include the entire body of the subject. The use of one of these networks in this project is sub-optimal as the camera only sees one side of the subject, and the subject's head is obscured by the scrum machine pads when engaging in pushing. A neural network is a practical solution for this project and is low-cost. The only downside is that it will be using a neural network that was not specifically made for scrum scenarios. The head being obscured may pose an issue.

5.3.3 Annotated Images

Annotated images have been used in studies in the past (Bayne & Kat, 2018; P. D. Milburn, 1990; K. L. Quarrie & Wilson, 2000). This option provides relatively accurate results and removes large outliers in positional data that may be observed using other methods. The major downside of this method is the time it takes to annotate each frame, this makes the cost of this method very high. When creating a custom neural network many images must be annotated by hand. Including annotated images not as a final solution, but as a representation of what a custom-trained neural network could achieve, is worthwhile for the initial experiment.

5.4 Selected Method

The initial experiment will utilise all three of the above data collection methods. The motion capture system will be used to collect the major joint angles and provide the “ground truth” for the other two methods. A camera on each side of the player will be used to collect images which will then be passed through a postural estimation neural network and annotated by hand. The error for each system can then be found before use in the validation experiment. To improve the results from a neural network one should be trained specifically for the intended use case. In this case, annotated images from scrum trials should be used to train the network to take images with only one side of the body and an obscured head and output the relevant angles from the joints. Due to the small number of images that were hand-annotated for this initial experiment, this was not possible. So, the performance that a custom-made neural network would provide to find the key points of the player will be represented by the hand-annotated coordinates.

6 Initial Experiment

6.1 Image Postural Acquisition devices

The ground truth for postural data will be collected using a 6-camera Vicon Bonita motion capture system. This will provide accurate and precise results for the initial stage of testing. The positional error for each camera is displayed after calibration. The specifications for this experiment are:

- Frames captured at 240Hz
- 0.3 Megapixel (640x480p)
- precision, down to 0.5mm in a 4m x 4m volume.

The images used for the hand-annotated images and the neural network images were captured on the Kinect V2 sensor. This sensor allows 3 different types of images to be captured. These are infrared (IR), Red Green Blue (RGB), and Depth.

The image acquisition specification for the Kinect V2 was:

- Frames captured at 10Hz
- Infrared and Depth frames captured at 512x424p
- RGB frames captured down-sampled to 800x450p

6.2 Setup

The experiment was conducted by collecting data on two test subjects each conducting 20 test scrums. Of the two test subjects, subject A weighed 84kg and subject B weighed 101kg. The footing position on the ladder was selected by the subject and positioned where they felt it was comfortable. For the experiment, thirty sample scrums were captured, each containing 130 frames to compare the three systems.

For this initial experiment, three different systems were used to capture all the data. These were the motion capture Vicon Bonita, Kinect V2, and the scrum machine software. The Two Kinect V2 sensors were placed either side of the player to capture the frame in the sagittal plane. The configuration of the 8 cameras is shown below in Figure 10. As mentioned in section 5.4, the Vicon system will be used as the “ground truth” to check the accuracy and precision of the annotation and neural network methods.

The Vicon Nexus software was triggered manually for each trial, whereas the scrum machine GUI controlled all other systems. Figure 11 shows the connections between the systems. The main PC controlled the GUI and the Vicon software, starting a trial on the scrum machine GUI would also trigger the two capture PCs to begin recording the player with the two Kinect cameras. The Kinect images were stored locally and named by timestamp. The images were captured at 10Hz and were captured for 13 seconds, this starts one second before the player is given the “set” call and lasts until two seconds after the player should have stopped the push.

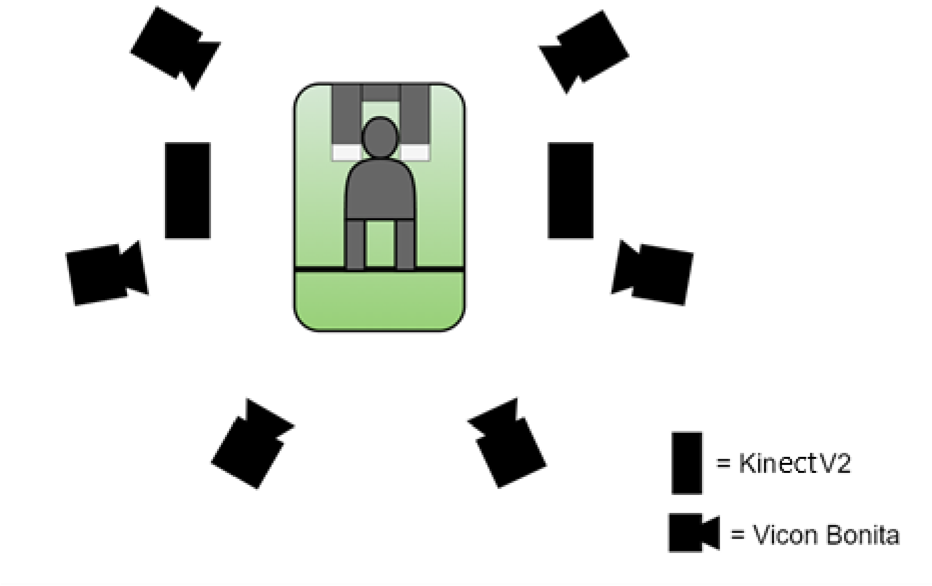

Figure 10: Camera Layout for Experiment

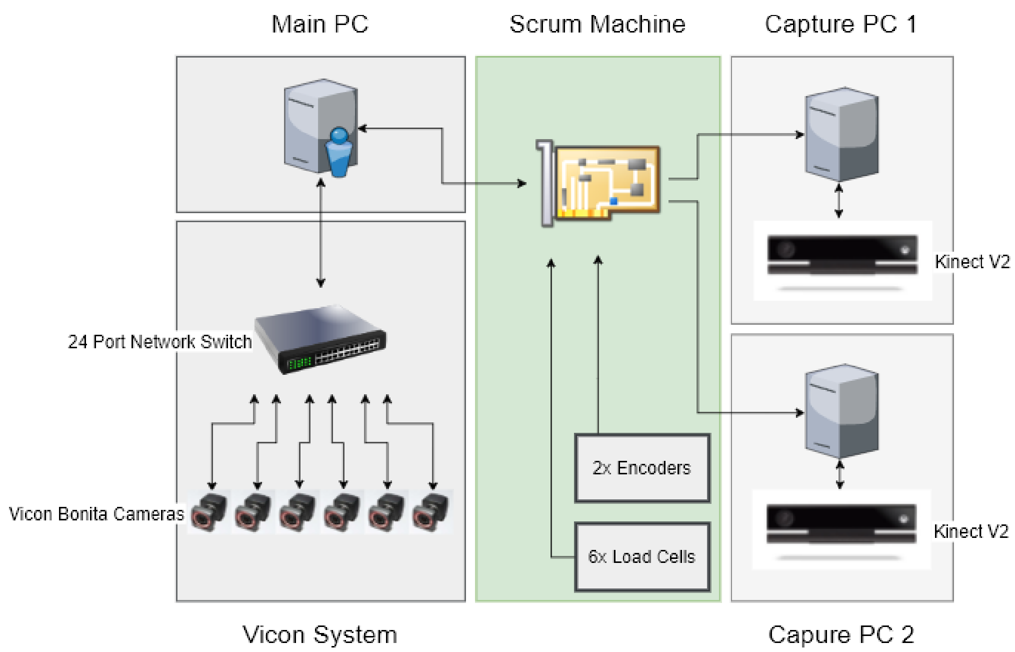

Figure 11: System Design

The full list of equipment used in the initial experiment:

- 6-camera Vicon Bonita motion capture system
- Vicon calibration wand
- Reflective markers for motion capture
- 2 Kinect V2 (each connected to a PC running the capture software)
- Scrum Machine
- Central PC (to run Vicon Nexus 2.0 software and capture scrum machine data)

6.2.1 Vicon Bonita System

The software used to calibrate, capture, and store is Vicon Nexus 2.0. The data will then be analysed and have joint positions and angles extracted using Vicon PROCALC. The initial setup of the Vicon system is done by setting the cameras uniformly around the target volume. The cameras were calibrated using the LED calibration wand. This stage involved waving the wand around in view of the cameras for the system to calculate the camera's position and orientation. This stage also gives an error for each camera. The configuration of the cameras is shown in Figure 12, these 6 Vicon Bonita cameras were placed uniformly around the scrum machine at varying heights and angles to always ensure good coverage of the player.

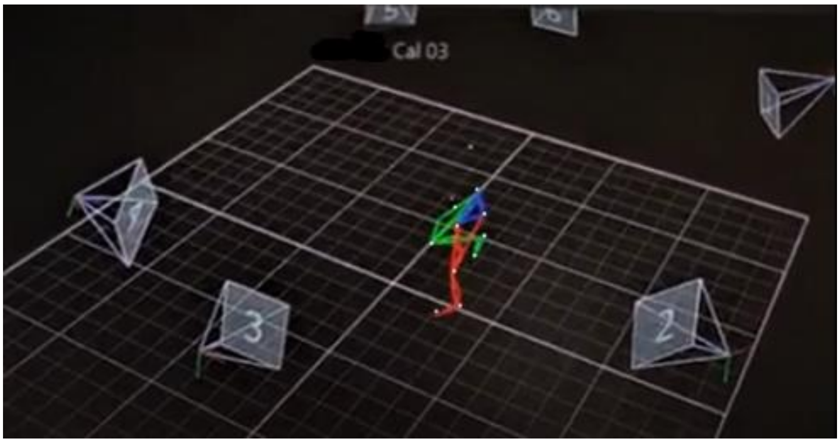

Figure 12: Camera Position

The test subjects were dressed in form-fitting black sports clothing with reflected markers attached in the configuration shown in Figure 13. The markers were placed in a way to maximize the amount of information about the key limbs (rotation and position), while not being placed in positions that would be obscured by the scrum machine during the trial. The marker template closely follows the Vicon plug-in-gait marker placement, for the bottom half of the body, while the top half is adapted to account for the scrum machine obscuring some cameras (Figure 14).

Figure 13: Player with Reflective Markers

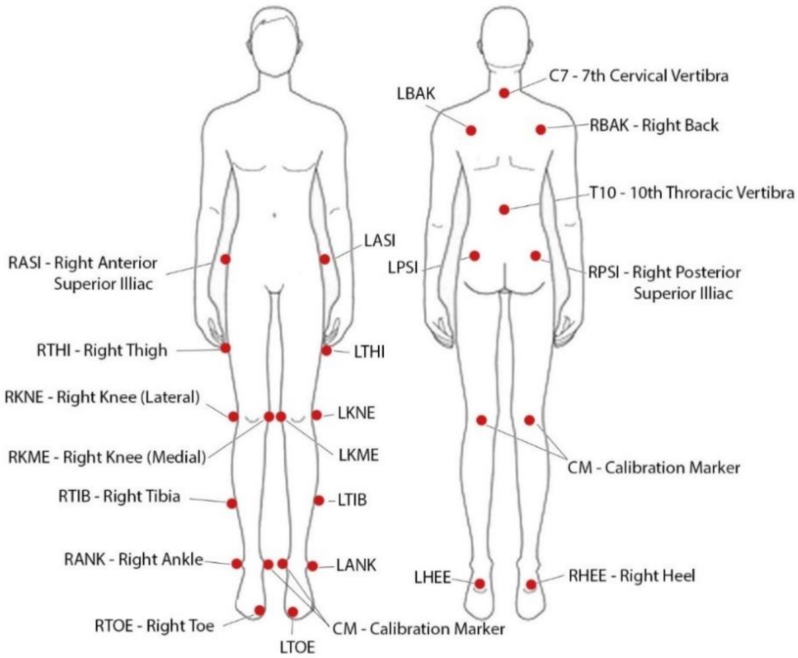

Figure 14: Custom Marker Template

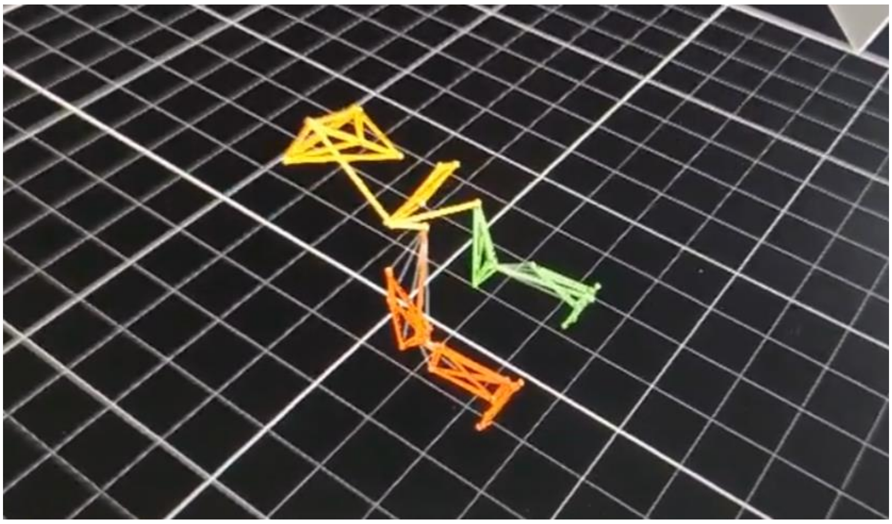

Figure 15: Vicon Nexus Skeleton

The player skeleton model generated by the Vicon system is shown in figure 15 above. Using the Vicon Procalc software, coordinates of each key point and the angles between limbs were able to be found for each trial.

6.2.2 Neural Network System

The neural network system utilised the RGB images from the Kinect V2 sensor. The network chosen for this test was Blazepose (Bazarevsky et al., 2020). Blazepose (Bazarevsky et al., 2020) was developed to compute the coordinates of 33 skeletal key points and is noted to be effective at real-time fitness tracking. This network is designed to give all skeletal points, however, the code for these trails was adapted so that the Kinect RGB image from each side would search for five points. This gave ten points on the player overall. The network would often find the strongest weighted key points on a target in the background of the image if there happened to be someone else in the frame. To fix this issue the background corner where the coaches sat during trials was masked out of the image.

6.2.3 Annotation System

The second method that was tested for the collection of postural angles was annotated images. The images used for this method were captured on the Kinect V2 sensor. This sensor allows 3 different types of images to be captured. These are infrared (IR), Red Green Blue (RGB), and Depth.

To test this method an annotation software was created in Python which provided a tool for the user to load an image and place 5 markers on the image to show the location of the main joints. From these joints, the angles of each joint could then be calculated. After review, the contrast on the infrared images was better for distinguishing the player from the background, the option remained to switch between the 3 channels if the user was having trouble placing the marker-based purely on IR.

Figure 16: Annotation Tool Examples

The same five-point annotation was performed by the same person on all images to reduce variation in marker placement.

6.3 Results and Discussion

This section compares the results from the two methods to the data captured using the Vicon Bonita system. All the data used in this section are from either the engagement or sustained phase of the testing.

Figure 17 shows the results of the annotated method being compared to the ground truth for the experiment found by the Vicon mocap.

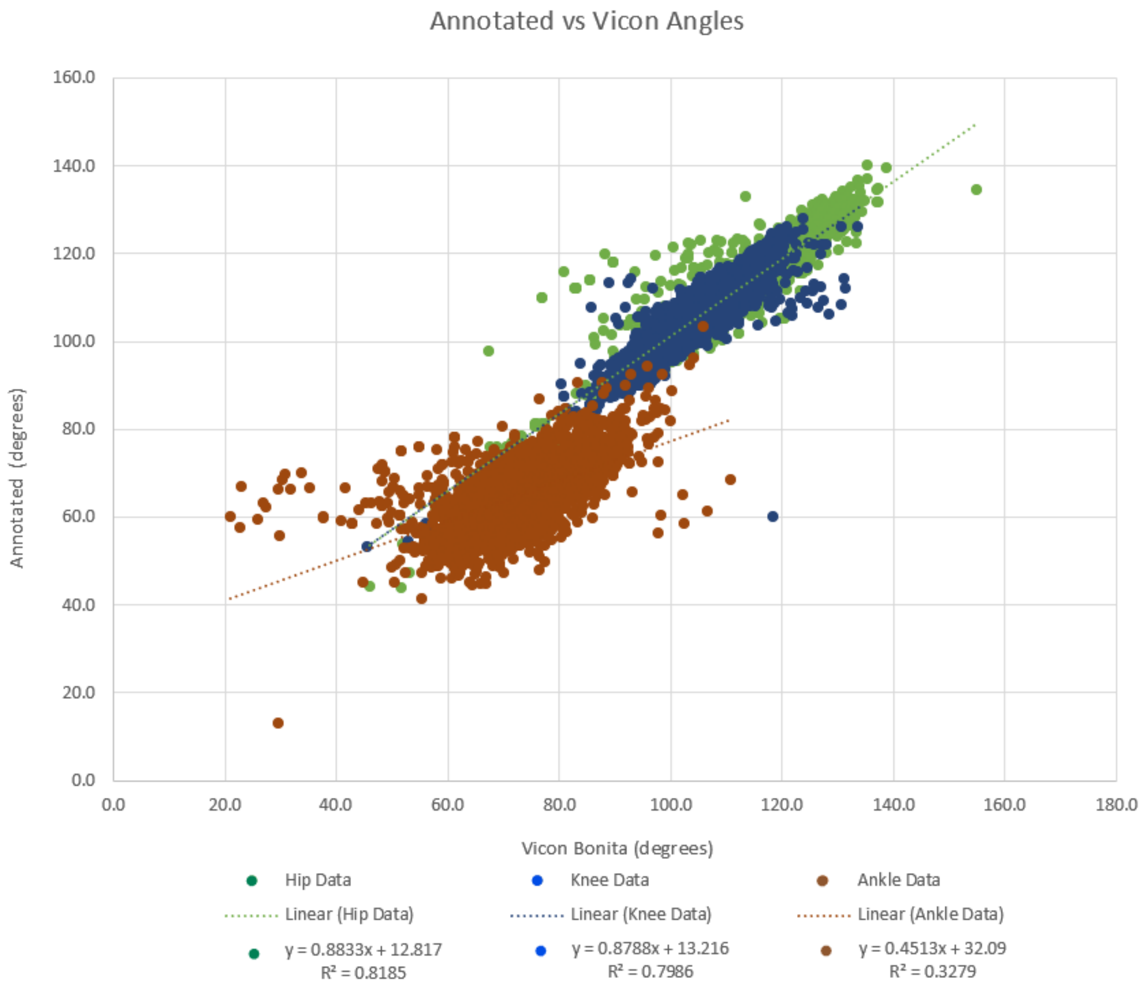

Figure 17: Annotated vs Vicon Results

The overall R^2 value for the annotated data compared to the Vicon was 0.9148 this shows that the overall fit of the model was very close to the Vicon results. The results in figure 17 show that the Hip and Knee joints are very accurate to the Vicon results, this is due to the cluster of points being uniform and roughly following a gradient of one. The graph also shows that the data for the ankle angles is far less accurate. These conclusions are confirmed by the R^2 values shown at the bottom of the graph.

This difference in the accuracy of the ankle is to be expected due to the angles being derived from coordinates in the images. With each point annotated having roughly the same positional error, the distance between the points that make up each angle has the greatest effect on accuracy. With the hip having the longest limbs from the shoulders to hips and hips to knees, the large positional displacement between the points should give the angle a higher accuracy. Likewise, the ankle points are grouped closely together, so it follows a small error in the coordinates of each point would have a higher effect on the angle.

Figure 18 shows the results of the Blazepose method being compared to the Vicon mocap system.

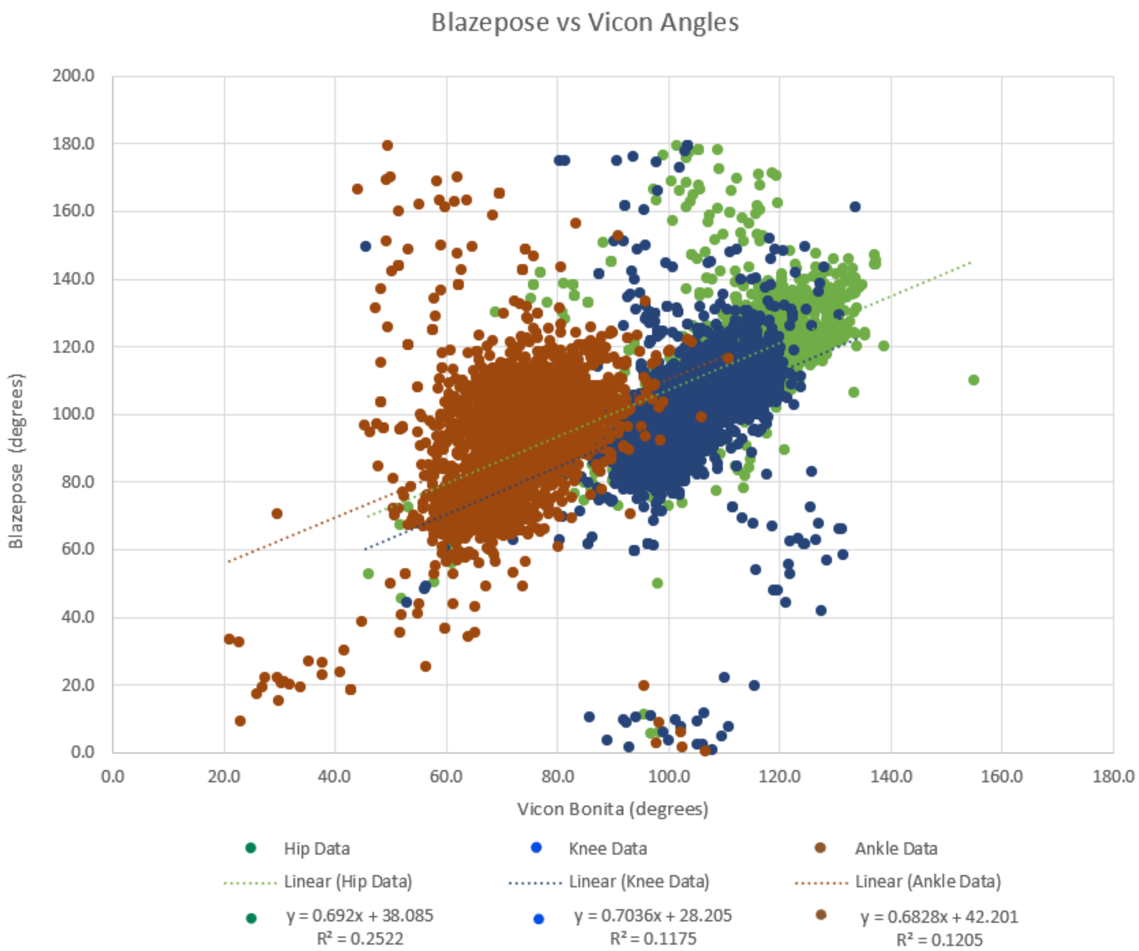

Figure 18: Blazepose vs Vicon Results

The overall R^2 value for the Blazepose data compared to the Vicon was 0.3175 this shows that the overall fit of the model was not very close to the Vicon results. However, the gradient of the joint trendlines shows that the data did follow very similar gradients and intercepts to each other. The gradients for each line are too low at 0.7x, but the intercepts are around 40 which will offset the low gradient. This indicates that the data is roughly following the Vicon data, but the number of outliers shown in Figure 18 explains the low R^2 values and offset trendlines.

The high quantity of outliers compared to the annotated method is to be expected. The neural network was not designed to handle a side view of a subject or to have obstructed view of body parts. To compare the precision of the methods the standard deviation (SD) for each key joint was found. To do this the following equation was used:

$$\text{Standard Deviation} = \sqrt{\frac{\sum(xi - \mu)^2}{N}}$$

Where:
xi = each value from the population
μ = population mean
N = number of samples in the population

Table 3: Standard Deviation Results

Joints SD	**Annotated (Engagement Phase)**	**Blazepose (Engagement Phase)**	**Annotated (Sustained Phase)**	**Blazepose (Sustained Phase)**
Left Hip Extension	13.08˚	13.43˚	7.25˚	12.66˚
Right Hip Extension	7.60˚	10.57˚	8.03˚	14.02˚
Left Knee Flexion	7.27˚	18.90˚	7.46˚	13.96˚
Right Knee Flexion	7.45˚	12.20˚	7.53˚	17.31˚
Left Ankle Flexion	7.39˚	17.02˚	6.38˚	14.70˚
Right Ankle Flexion	7.15˚	20.52˚	6.97˚	20.36˚

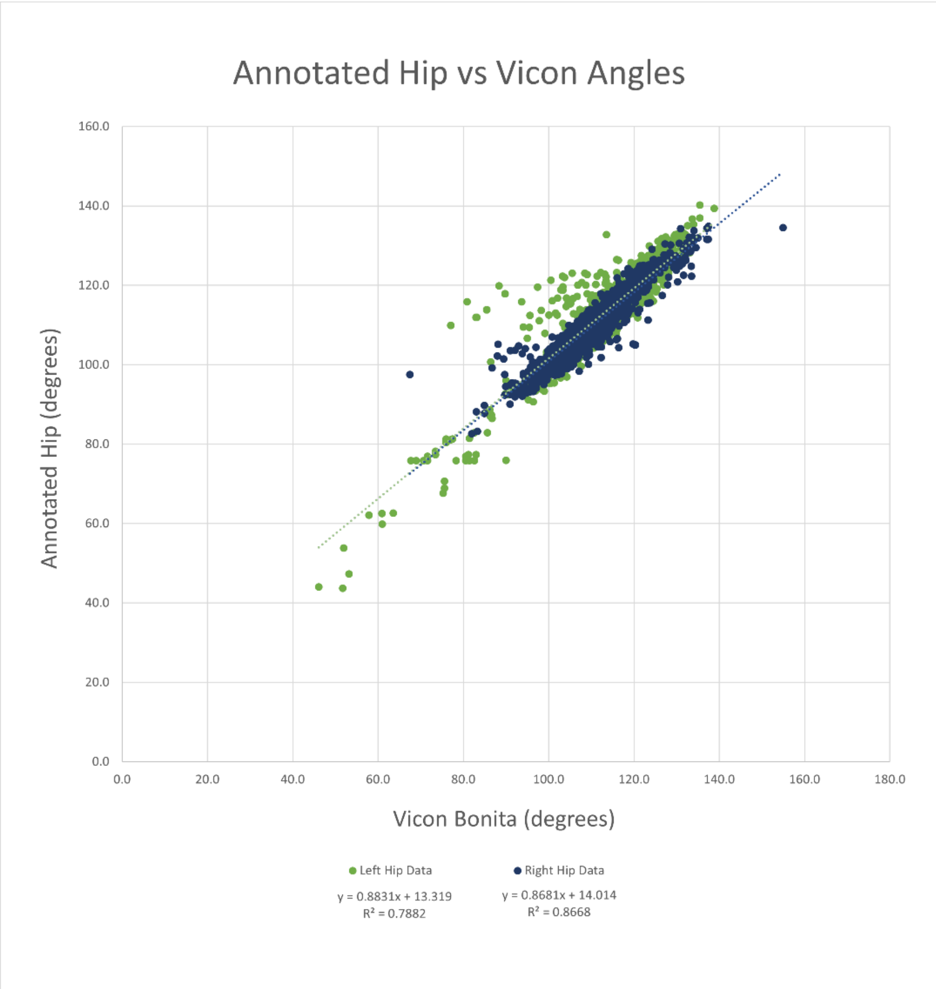

Figure 19: Annotated Hip Angles vs Vicon

Table 3 shows that the annotated data always has a lower standard deviation compared to the Blazepose. Interestingly the left hip appears to have a higher deviation than expected at 13.08˚ during the engagement phase when compared to the other joints, which all have values of around 7.5˚. Figure 19 above, shows that the left hip data contained more points trailing down toward the 40-45° region indicating that for at least one trial the subject had a smaller hip extension. This does not mean that the results are inaccurate, to find the accuracy of the angles found the RMSE values for each of the methods were found.

$$RMSE = \sqrt{\frac{\sum(xi - vi)^2}{N}}$$

Where:
xi = each value from the population
vi = each value from Vicon
N = number of samples in the population

To compare the accuracy of the two tested methods the RMSE for each joint was found and displayed in Table 4 below.

Table 4: RMSE Results

Joints RMSE	**Annotated (Engagement Phase)**	**Blazepose (Engagement Phase)**	**Annotated (Sustained Phase)**	**Blazepose (Sustained Phase)**
Left Hip Extension	4.22°	12.92°	5.67°	16.55°
Right Hip Extension	3.21°	7.39°	3.26°	10.86°
Left Knee Flexion	4.24°	19.42°	4.25°	16.86°
Right Knee Flexion	3.74°	8.90°	2.76°	15.67°
Left Ankle Flexion	11.83°	26.33°	10.94°	25.50°
Right Ankle Flexion	10.59°	26.24°	11.06°	25.89°

K. L. Quarrie and Wilson (2000) stated that their annotated joint angles had an error of ±4°, they found this using repeated annotation of results. This agrees with the annotated results in this study which were about 4° for the hip and knee joints, the ankles had a higher RMSE of around 11°. This difference could be explained by the annotation coordinate placement being slightly offset from the joint placement of the Vicon system. Or that they had better image resolution of the smaller joints (i.e., ankles) which led to the more consistent placement of the markers. To improve the accuracy and precision of the ankle joint estimations it may be better to annotate using a second camera view of the feet or use a blown-up version of the image focused on the feet region.

Improvement to the ankle joint using a blown-up section of the image when annotating is the easiest method to achieve for the next stage of testing, without the need to change the scrum machine or camera layout. Not changing the camera layout will mean that the only angle affected by the new ankle annotation method is the annotated ankle value.

The angle being within ±4° shows that a custom-made neural network designed for scrummaging would have very usable results and would be acceptable as a coaching tool. The Blazepose angle was within 7.39°-19.42° for the hips and knee joints, while the ankle was around 26° of error. This shows that the neural network roughly followed the correct angles. Although we observe low R^2 values for the Blazepose method, indicating a high variation in the residuals, the overall results from the network show a trend of correctly estimating the angle. The observed error margins would not be acceptable for coaching purposes.

The initial experiment results do show that the neural network runs into similar issues as the annotated method around the resolution of the ankle and that improving the size of the ankle region for the network may be able to bring the angular error down toward the 20° region like the hips and knee joints.

To improve upon the accuracy of the ankle angles in this study, an adaption of the annotation tool was created which provided the user with an enlarged image of the foot region. All the frames used in this initial experiment were then reannotated for the lower three points, to reduce the RMSE values. The adaption to the annotation tool is shown in Figure 20, for the reannotation the yellow markers were shrunk to allow the annotator a more precise placement of the markers. The markers for the toes were placed on top of the player's foot above the Metatarsals.

Figure 20: Reannotated Foot Section

The results for this are shown in Figure 21 below, where they are compared to the previous annotation results.

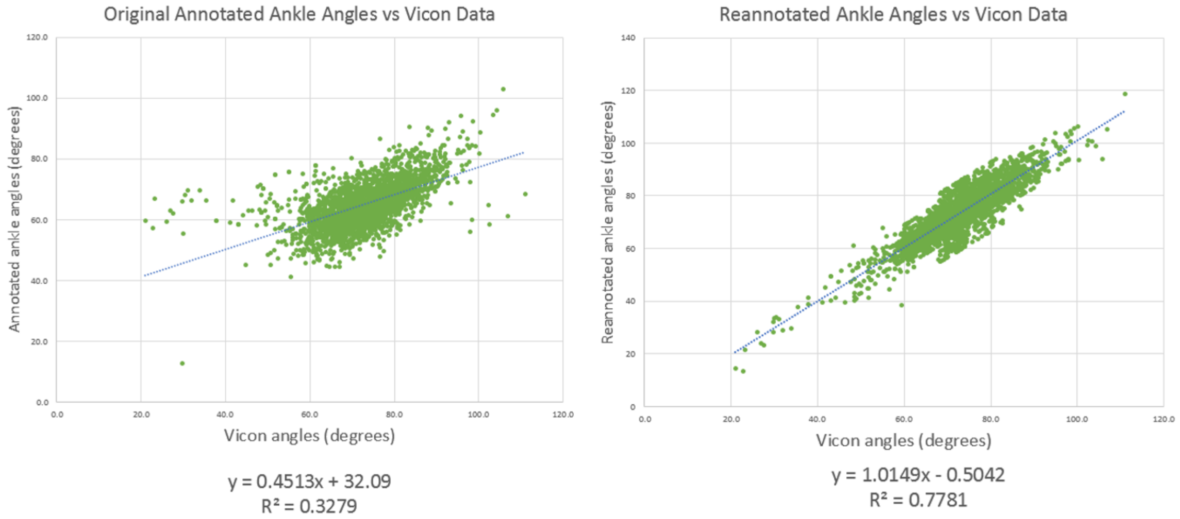

Figure 21: Original Annotation vs Reannotation Ankle Values

Figure 21 shows that the new annotation method greatly improves the accuracy of the ankle angle values. By removing the error due to the image in the annotation tool being smaller than the other sections, the ankle angles follow the Vicon angles very closely, with an R^2 value of 0.78 instead of the original 0.33 R^2 value. We can also see that the number of outliers is decreased, and the magnitude of the outliers is very small. This should reduce the error of the method down to a usable value.

Table 5: Reannotated RMSE values

Joints RMSE	**Engagement Phase**	**Sustained Phase**
Left Ankle Flexion	4.47°	6.27°
Right Ankle Flexion	6.53°	3.40°

Table 5 shows the new RMSE values from the reannotated data. The new values are between 3.4° and 6.53° showing a large drop from the previous 10-11° error. This new method for annotating the ankles has an average RMSE of 5.12° making it a lot closer to the ±4° of the other joints in the system. It is still expected to have a slightly higher error than the hips and knees due to the smaller physical distance between the annotated points.

The ankle angle error from the Vicon will not be as accurate as the other large angles due to the distance between points, however, for this experiment, it is fine to use as a standard for the other two methods. The ankle error observed in the annotated results is largely due to the very small number of pixels in the ankle region and the small distance between two given points. The Vicon finds each marker in a 3D space with up to 4mm accuracy, these markers are still roughly 200mm from ankle to toe marker, and 450mm from ankle to knee. This means that the Vicon still has reliable results to use for this experiment.

Overall, the initial experiment has succeeded in proving that a neural network can be an effective solution to the project's aim. It shows that this very low-cost system can provide joint angles using images fed via the Kinect sensors. The annotated images show the kind of performance that could be expected from a custom-trained network if a large enough set of data were annotated and trained. This network would provide feedback to the player/coach with around ±4° accuracy with little-to-no setup time or calibration. To ensure that the postural data produced in this experiment is consistent with the other data in past literature, a validation experiment will be completed to compare the data to other scrum machines and postural capture methods.

This section successfully designed a method to capture the postural data of the player. Then during post-processing, the key joint angles were extracted, and the accuracy and precision of the system were evaluated. The final design is made affordable due to the removal of the expensive motion capture system previously used in this area of research. It is also user-friendly, due to not requiring dot markers to be placed on the player, and not requiring calibration. This completes two of the project aims to set out in section 1.5.

7 Validation Experiment

To test the validity of the results concluded in section 5.4, a validation experiment was created to evaluate whether the results found using the hand annotation and neural network would agree with the results found by other researchers. This section will test the maximum compressive force of players, find their key limb angles, and compare them to the optimal joint angles found in section 3.4.2.

7.1 Overview of Experiment Process

The validation experiment follows the same data capture steps as the initial experiment without the use of the Vicon motion capture system. This experiment also focuses more on the force output side of the data collection. The 2 professional rugby players performed their usual pre-scrum training warm-up routine and 3 non-recorded practice scrums on the machine before trials commenced. Both players play in the front row of the scrum. Prior research has found that players are unaffected by fatigue when given 30 seconds to recover between scrums (Morel & Hautier, 2017). Each player was given at least one minute between trials to remove the effect of fatigue. The players then recorded 10 scrums each, collecting the postural and scrum machine force data giving a total of 20 sample scrums to compare.

7.2 Automated Data Collection program

The automated data collection process will be the same as the initial experiment, in this experiment the data collection is fully automated, as there is no longer a need to manually start the Vicon software as it is not used. The camera placement and GUI control are the same as in section 6.2. The players were given the “crouch”, “bind”, and “set” commands verbally as the GUI counted down. The images were again captured at 10Hz for 13 seconds, starting one second before the player was given the “set” call and lasting until two seconds after the player should have stopped the push. Players were instructed to push through the ten seconds of force measurements to ensure a large region of the sustained push for processing.

The force data and camera data are both timestamped when save so that frames can be matched to the corresponding force measurement for post-processing. Players were instructed to have their shoulders roughly in the centre of the shoulder pads for better distribution and analysis of the pancake load-cell results.

7.3 Measurement Process

Two key measurement methods are present in this experiment, are the postural and force measurements. This section explains the measurement processes used in the validation experiment and justifies changes made after the initial experiment process.

7.3.1 Force Measurement Process

The force data for this was collected using the sensor fixed to the scrum machine. This includes 2 s-type load cells, 4 pancake load cells, and 2 magnetic precision encoders. Each of the load cells was calibrated individually using an Instron mechanical tester. The main forces used in this validation experiment were from the four pancake load cells. These are used to capture the total forward compressive force generated by the player.

Once the trigger is sent to the scrum machine to begin recording data, the main PCB begin to send all the force data to the GUI using serial. This data is still in the raw format and has the calibration equation applied in the software after it is received by the PC. This allows both the raw data and the calibrated data to be saved to a CSV file, in case a better calibration equation is found in the future. The data is all stored in Kilograms, except for the angular encoder data which is stored in degrees.

The force data used in this comparison is the sustained phase, or active phase (P. D. Milburn, 1990). The measurement of this force is the mean forward force produced by the individual during the sustained phase. Peter D Milburn (1993) stated that the mean over the sustained phase is an effective measurement of scrum performance. It also allows the results of this trial to be directly compared to other publications that use maximal sustained force. Figure 22 shows the section of the force data that is used in the validation experiment.

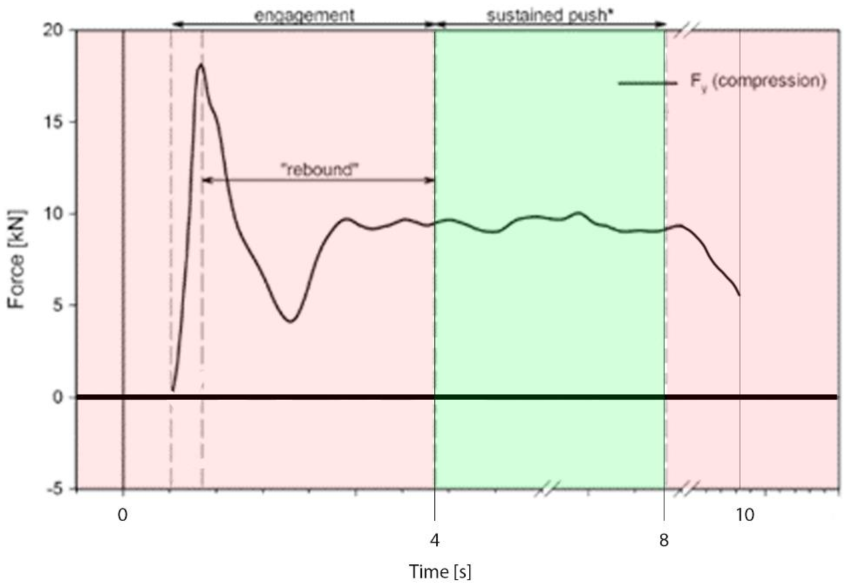

Figure 22: Sustained Push Explained

The green region in Figure 22 shows the sustained push region used for this experiment highlighted in green. After reviewing some test data from the machine starting the sustained push at four seconds was decided to account for any late engages and ensure that the sustained push data did not include any of the engagement phases. Although the sustained push phase continues until 10 seconds in the experiment testing, it was decided to not use the final 2 seconds as in some trials players would begin to ease up towards the end, which would distort the data. A flow diagram of the force measurement process is shown in Figure 23.

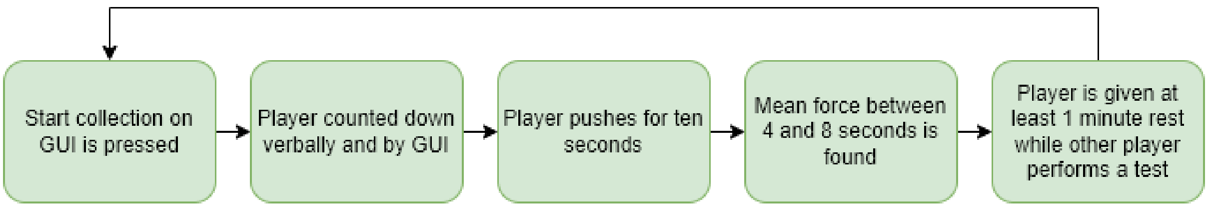

Figure 23: Process Flow Diagram of Force Measurement Procedure

As stated above the mean ± SD over the sustained push will be taken as the primary force measurement for this experiment, this experiment will be based on total forward compression force. This will allow the results of the validation experiment to be directly compared to similar experiments from past literature.

7.3.2 Postural Measurement Process

The data for the angles will be expressed as mean ± SD to follow the template of the other authors in literature and make comparisons easier to draw. Due to the foot ladder configuration of the scrum machine the feet will be in a parallel position for all trials. All the angles in the validation trial are measures of the extension in each joint, with the full extension being 180°.

The data will be processed using both the Blazepose neural network (Bazarevsky et al., 2020) and the annotation tool, including the enlarged ankle annotation process from section 6.3. The angles will be averaged across the sustained push period to get the mean joint angles. The standard deviation of the angles will also be found across this time. Figure 24 shows the main steps in the postural measurement process.

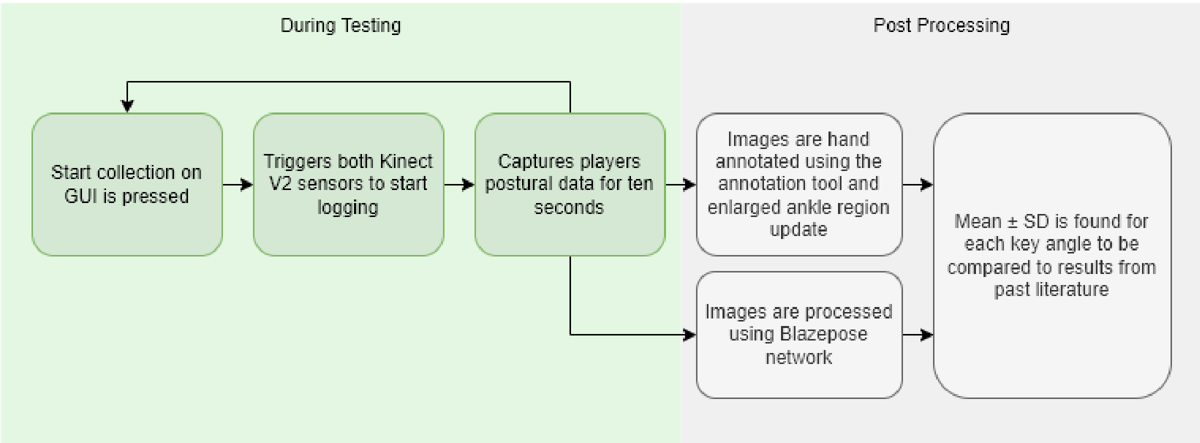

Figure 24: Process Flow Diagram of Postural Measurement Process

The back extension angle was included in the validation experiment, requiring no added information to compute, as it could be found using the should and hip locations. This was included due to Dan Cron's comments about the back angle being parallel to the ground having an impact on force output (Cron, 2021).

7.4 Results & Discussion

The results from the 20 validation samples were analysed to find the mean ± SD for each joint. These results are shown in Table 6. We can see that the Blazepose means are very similar to the results from annotation, this shows that overall, the Blazepose method does perform to a reasonable standard. However, we know from the findings in section 6 that the RMSE of the Blazepose method is higher than the annotated method. The Blazepose method in this experiment showed a slightly higher SD than the annotated one. This shows that the Blazepose method is noisier from frame to frame giving it a high error, but on average has good results. The average sustained push force for the trails was 2100 ± 555 N.

Table 6: Sustain Phase Mean ± SD Results

Kinematic Parameters	Annotated	Blazepose
Right Hip Extension (°)	119 ± 18	123 ± 19
Left Hip Extension (°)	120 ± 19	120 ± 18
Right Knee Flexion (°)	118 ± 12	113 ± 14
Left Knee Flexion (°)	116 ± 14	114 ± 18
Right Ankle Flexion (°)	74 ± 6	88 ± 7
Left Ankle Flexion (°)	73 ± 10	87 ± 11
Back Extension (°)	173 ± 8	175 ± 9

Table 6 shows the results for all relevant angles during the sustain phase of the validation experiment. The results show that the subject's limb angles were very close to even across both sides of their body, with each angle being within 2° of the opposite side. The results also show that the back extension angle is close to 180° needed to be parallel to the ground.

Table 6 also shows a larger SD for the annotation stage, the validation values are closer to the Blazepose SD. The Blazepose SD values are similar for both the initial and validation experiment stages. This change in annotation SD could be due to the change from two amateur rugby players to two professional players. After reviewing footage of the scrums, the professional players had more body movement throughout the sustain section of the scrum. The validation subjects would often regrip, push harder, or adjust their feet during the sustain portion of the scrum. Whereas the two amateur players did not move very much at all during the sustained portion, this resulted in less overall force output over this period.

Table 7: Comparative Postural Results from Past Research

Author	Sample size	Hip (°)	Knee (°)	Ankle (°)
K. L. Quarrie and Wilson (2000)	56	123 ± 24	107 ± 13	78 ± 11
Wu et al. (2007)	10	121 ± 7	101 ± 18	62 ± 16
Andrew Green, Samantha Kerr, et al. (2017)	25	114 ± 17	144 ± 16	73 ± 16
A Green et al. (2017)	12	103 ± 33	124 ± 16	89 ± 18
Bayne and Kat (2018)	29	126 ± 17	129 ± 14	89 ± 7
This study	*20*	*120 ± 19*	*117 ± 15*	*73 ± 11*

**The back extension angle is not included as it is not present in most of the past studies present in Table 7, all angles from this study use the annotated results due to the lower RMSE of that system*

Table 7 shows that the results found in the validation experiment are like those found in past studies. Each angle from this study is middle of the pack when compared to the other 5 studies above. This shows that the system is outputting believable results. The standard deviation in the results observed have similar values.

To evaluate whether the key joint angles correlated to higher compressive force output the correlation coefficients were found and shown in Table 8 below.

Table 8: Correlation coefficients between the kinematic parameters and the force output

Kinematic Parameters	**Annotated**	**Blazepose**
Right Hip Extension (°)	0.334	0.197
Left Hip Extension (°)	0.165	0.057
Right Knee Flexion (°)	-0.473	-0.124
Left Knee Flexion (°)	-0.531	-0.115
Right Ankle Flexion (°)	0.051	-0.198
Left Ankle Flexion (°)	0.070	-0.146
Back Extension (°)	0.478	0.357

After the correlation coefficients were calculated, each was then tested for statistical significance. The annotated left and right knees both had a value of $p = 0.016$ and $p = 0.035$, showing that they had a mild correlation in this experiment. The annotated back extension angle had a p-value of 0.032 that it had a relationship with the force produced. The rest of the joints all had values of $p > 0.05$ and therefore were statistically insignificant. This differs from literature in that others tended to not find relationships between joint angles and force output. Andrew Green, Samantha Kerr, et al. (2017) did observe a small relationship between the straightness of the back and the force generated. This agrees with the findings above. This also agrees with the advice given to players by scrum coach Dan Cron (Cron, 2021), and the observational findings he has had over his career about the player's back angle influencing scrum force output. None of the correlations for Blazepose angles was found to be significant, this could be due to the slight increase in the error of the positional system reducing the strength of the correlations.

K. L. Quarrie and Wilson (2000) and Andrew Green, Samantha Kerr, et al. (2017) also found zero correlations between joint angles and the output force (excluding back extension). Although Andrew Green, Samantha Kerr, et al. (2017) did observe a relationship between player bodyweight and force generated in both the engagement and sustain phases of the scrum. In this study weight was not accounted for so we cannot compare this correlation, however, the other correlations in this study agree with this experiment. Wu et al. (2007) did find negative correlations between the hips, knees, and ankle joint angles and the force output.

One limitation of this experiment is the small number of players and samples gathered for analysis. It is well known that not all players in the scrum produce even amounts of force. Du Toit et al. (2005) reported that the front row generates the most force, followed by the locks, and then the loose forwards. This experiment is currently limited to players from the front row, so expanding the player positions in the samples would give a better indication of how the system would perform with people of different heights, builds, and scrum tactics. Another limitation is that the body weight of the players at the time of trials was not recorded. Andrew Green, Samantha Kerr, et al. (2017) found a correlation between weight and force output in the scrum, so including this in the validation experiment would have been useful to see if that statistic would also agree with past literature. This experiment was focused on postural data collection accuracy and reliability, so not collecting body weight does not subtract from the experiment results.

Using the annotated data, we were able to find the optimal body position for the two test subjects across the 20 samples. This was found to be a hip angle of 120°, a knee angle of 117°, an ankle angle of 73°, and a back angle of 173° relative to the ground (Table 7). This optimal position was compared to, and agreed with, others found in the literature which gave further validity to the results of the system. Completing these two tasks completed the final two project aims from section 1.5.

7.5 Future Research Opportunities

The clear next step in developing the system is to create and test the annotated neural network. This would involve high volumes of annotated images to train a network. Doing so and then testing the network would give a better indication, of the annotated results, of the error margins that players and coaches could expect. A neural network was trained using the annotated images created in this research project. However, due to the posture of the player being similar in most frames, the network trained itself to output the average player stance for all inputs. If the proposed network were to be created properly in the future, then it would need to be trained on a dataset with a higher variation in limb position.

The Kinect V2 camera has also collected depth and infrared data on all the scrums. This data, when combined with the joint position data from the annotation, could give a 3-dimensional skeleton of the player. This would give the user information about the 3-dimensional joint angles and leg separation. On the other hand, if the 3-dimensional data is deemed not worth it, then the Kinect V2 sensor could be replaced with a standard camera or webcam to reduce the cost further and improve resolution and frame rate.

The final area to research is whether the proposed neural network solution would have better accuracy if it were created to find the angles of the limbs in the frame, rather than the coordination of the joints. A lot of neural networks take a greyscale image as input, and these are usually down-sampled to be a fraction of the original size. Perhaps a neural network would have a better chance of detecting the gradients of straight lines in the image and thus have a higher accuracy of finding the angles of these gradients instead.

9 Conclusion

This project achieved the aims set out in section 1.5 of designing a user-friendly system to capture relevant force data generated by a player during scrummaging and collect the player's postural data. The data was then validated by finding the optimal body position to maximise forwards compressive force, which was then compared to literature. The measurement accuracy of the postural system using inexpensive cameras, and neural network that require little-to-no calibration, is promising, but with plenty of room for improvement. It also provides very usable results when using the annotated results.

The results of this project can be used to develop a tool for coaching and player development to bridge the gap between the state-of-the-art equipment used in literature and the basic scrum machines that are currently used for training, even at the international level. The main drawback of this project was the use of annotated data to replace the use of a purpose-built neural network. Unfortunately, the lack of annotated data, budget, and time, made creating a large enough dataset for a reliable custom network unachievable. However, the use of hand-annotated frame data was a suitable replacement in this project to show how accurate this theoretical network could be. It introduces the user error that would be present if the network were created based on annotated images, and so provides data comparative to the best-case scenario of a purpose-built neural network. The inclusion of the Blazepose results shows that a neural network, even ones not designed for side view or the head to be obstructed, can generate joint positions and angles.

The primary area for future improvement would be to create and test the annotated neural network. As the depth and infrared frames were not utilised apart from during annotation, the Kinect V2 cameras could also be substituted for webcams to keep the same resolution but improve the frame rate. If the depth sensors in the Kinect sensor were to be utilised, then research into the 3-dimensional joint angles would provide information on the straightness of the back and leg separation in the final coaching tool. Another area to research would be whether a neural network to produce the joint angles of the images would be more effective than identifying the joint positions.

10 References

Accident Compensation Corporation. Retrieved from www.acc.co.nz

Bayne, H., & Kat, C. J. (2016). *Effect of foot position on the compression and lateral force production of a player in a rugby scrum.* Paper presented at the ISBS-Conference Proceedings Archive.

Bayne, H., & Kat, C. J. (2018). The influence of foot position on scrum kinetics during machine scrummaging. *Journal of Sports Sciences, 36*(24), 2836-2842.

Bazarevsky, V., Grishchenko, I., Raveendran, K., Zhu, T., Zhang, F., & Grundmann, M. (2020). Blazepose: On-device real-time body pose tracking. *arXiv preprint arXiv:2006.10204*.

Cao, Z., Simon, T., Wei, S.-E., & Sheikh, Y. (2017). *Realtime multi-person 2d pose estimation using part affinity fields.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.

Cazzola, D., Preatoni, E., Stokes, K., England, M., & Trewartha, G. (2014). A modified prebind engagement process reduces biomechanical loading on front row players during scrummaging: A cross-sectional study of 11 elite teams. *British Journal of Sports Medicine*. doi:10.1136/bjsports-2013-092904

Cazzola, D., Stone, B., Holsgrove, T., Trewartha, G., & Preatoni, E. (2016). Spinal muscle activity in simulated rugby union scrummaging is affected by different engagement conditions. *Scandinavian journal of medicine & science in sports, 26*(4), 432-440.

Chen, Y., Shen, C., Wei, X.-S., Liu, L., & Yang, J. (2017). *Adversarial posenet: A structure-aware convolutional network for human pose estimation.* Paper presented at the Proceedings of the IEEE International Conference on Computer Vision.

Cohen, I., & Siff, M. C. (1979). Increased safety in the rugby scrum. *South African medical journal SAMJ, 56*(16), 625-625. Retrieved from http://dx.doi.org/

Cron, D. (2021) */Interviewer: H. Simmonds*.

Du Toit, D. E., Olivier, P. E., & Buys, F. J. (2005). Kinetics of full scrum and staggered scrum engagement in under 19 schoolboy rugby union players. *South African Journal for Research in Sport, Physical Education and Recreation, 27*(2), 15-28.

Feek, G. (2021) */Interviewer: H. Simmonds*.

Flavell, C. A., Sayers, M. G., Gordon, S. J., & Lee, J. B. (2013). Mechanisms for triceps surae injury in high performance front row rugby union players: a kinematic analysis of scrummaging drills. *Journal of Sports Science & Medicine, 12*(1), 159.

Green, A., Dafkin, C., Kerr, S., & McKinon, W. (2017). Combined individual scrummaging kinetics and muscular power predict competitive team scrum success. *European Journal of Sport Science, 17*(8), 994-1003.

Green, A., Kerr, S., Dafkin, C., & McKinon, W. (2015). The calibration and application of an individual scrummaging ergometer. *Sports Engineering, 19*(1), 59-69. doi:10.1007/s12283-015-0188-0

Green, A., Kerr, S., Dafkin, C., Olivier, B., & McKinon, W. (2017). A lower body height and wider foot stance are positively associated with the generation of individual scrummaging forces in rugby. *International Journal of Performance Analysis in Sport, 17*(1-2), 177-189. doi:10.1080/24748668.2017.1309094

Green, A., Kerr, S., Olivier, B., Meiring, R., Dafkin, C., & McKinon, W. (2017). A simulated rugby match protocol induces physiological fatigue without decreased individual scrummaging performance. *South African Journal of Sports Medicine, 29*(1).

Lallemand, B., Clanet, C., Blanchard, S., Noriega, P., Piscione, J., Chaplain, O., . . . Cohen, C. (2020). Peak Compression Force Physics in Rugby Union Scrum. *Proceedings, 49*(1). doi:10.3390/proceedings2020049151

Mensaert, S., Sharp, T., & Vanwanseele, B. (2015). *Influence of playing level on the kinematics and kinetics of the rugby scrum.* Paper presented at the ISBS-Conference Proceedings Archive.

Milburn, P. D. (1990). The kinetics of rugby union scrummaging. *J Sports Sci, 8*(1), 47-60. doi:10.1080/02640419008732130

Milburn, P. D. (1993). Biomechanics of rugby union scrummaging. *Sports Medicine, 16*(3), 168-179.

Mills, B. S., McMaster, D. T., & Smith, B. (2019). Strength training recommendations to improve scrum force and impulse in rugby union forwards. *Strength & Conditioning Journal, 41*(1), 64-74.

Morel, B., & Hautier, C. (2017). The neuromuscular fatigue induced by repeated scrums generates instability that can be limited by appropriate recovery. *Scandinavian journal of medicine & science in sports, 27*(2), 209-216.

Preatoni, E., Stokes, K. A., England, M. E., & Trewartha, G. (2013). The influence of playing level on the biomechanical demands experienced by rugby union forwards during machine scrummaging. *Scandinavian journal of medicine & science in sports, 23*(3), e178-e184.

Preatoni, E., Stokes, K. A., England, M. E., & Trewartha, G. (2015). Engagement techniques and playing level impact the biomechanical demands on rugby forwards during machine-based scrummaging. *Br J Sports Med, 49*(8), 520-528. doi:10.1136/bjsports-2013-092938

Preatoni, E., Wallbaum, A., Gathercole, N., Coombes, S., Stokes, K. A., & Trewartha, G. (2012). An integrated measurement system for analysing impact biomechanics in the rugby scrum. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology, 226*(3-4), 266-273. doi:10.1177/1754337111435200

Quarrie, K. L., Cantu, R. C., & Chalmers, D. J. (2002). Rugby union injuries to the cervical spine and spinal cord. *Sports Medicine, 32*(10), 633-653.

Quarrie, K. L., Gianotti, S. M., Hopkins, W. G., & Hume, P. A. (2007). Effect of nationwide injury prevention programme on serious spinal injuries in New Zealand rugby union: ecological study. *bmj, 334*(7604), 1150.

Quarrie, K. L., & Wilson, B. D. (2000). Force production in the rugby union scrum. *J Sports Sci, 18*(4), 237-246. doi:10.1080/026404100364974

Reboursiere, E., Bohu, Y., Retière, D., Sesboüé, B., Pineau, V., Colonna, J., . . . Piscione, J. (2018). Impact of the national prevention policy and scrum law changes on the incidence of rugby-related catastrophic cervical spine injuries in French Rugby Union. *British Journal of Sports Medicine, 52*(10), 674-677.

Rodano, R., & Bulgheroni, M. (1992). *Evaluation of the lower limbs motor strategies during vertical jumping.* Paper presented at the ISBS-Conference Proceedings Archive.

Rugby, W. (2019). World Rugby Year In Review. 116. Retrieved from http://publications.worldrugby.org/yearinreview2019/en/1-1/

Laws of the game, (2022).

Sankey, R. A., Brooks, J. H., Kemp, S. P., & Haddad, F. S. (2008). The epidemiology of ankle injuries in professional rugby union players. *Am J Sports Med, 36*(12), 2415-2424. doi:10.1177/0363546508322889

Sayers, M. (2008). 10 Kinematic analysis of high-performance rugby props during scrum training. *Science and Football VI*, 57.

Sharp, T., Halaki, M., Greene, A., & Vanwanseele, B. (2014). An EMG assessment of front row rugby union scrummaging. *International Journal of Performance Analysis in Sport, 14*(1), 225-237.

Swaminathan, R., Williams, J. M., Jones, M. D., & Theobald, P. S. (2016). A kinematic analysis of the spine during rugby scrummaging on natural and synthetic turfs. *J Sports Sci, 34*(11), 1058-1066. doi:10.1080/02640414.2015.1088165

Taylor, A. E., Kemp, S., Trewartha, G., & Stokes, K. A. (2014). Scrum injury risk in English professional rugby union. *Br J Sports Med, 48*(13), 1066-1068. doi:10.1136/bjsports-2013-092873

Wetzler, M. J., Akpata, T., Laughlin, W., & Levy, A. S. (1998). Occurrence of cervical spine injuries during the rugby scrum. *The American journal of sports medicine, 26*(2), 177-180.

Wu, W.-L., Chang, J.-J., Wu, J.-H., & Guo, L.-Y. (2007). An investigation of rugby scrummaging posture and individual maximum pushing force. *The Journal of Strength & Conditioning Research, 21*(1), 251-258.

11 Appendix

Appendix A – Initial Experiment plots