EVENT DETECTION FOR POWERED LIMB PROTHESIS

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May 2024

3rd Year Project Final Report for degree of BEng in Engineering

Abstract

Due to the oversimplification of the mechanics of the human knee joint in powered prosthetics, event detect of walking falls short of the ideal. The kinematics of the knee is a complex system, which translates its position while bending. The motion of the knee has a big impact on gait, and when it is simplified into a pin joint, which it often is, much detail of its behaviour is lost. Which when used to replace the knee, makes a phycological disconnect. The purpose of this report is to identify markers for event detection that correlate to a change in walking speed. The Russell knee joint is a mechanical knee which mimics the movement of the human knee in the sagittal plane. The joint offers the ability to characterise the movement of the knee by the displacement the mechanical equivalent of the anterior and posterior cruciate ligaments. This displacement captures the full movement of the knee, which is dependent on walking speed, thus allowing a potential marker for speed variation to be identified. Using this knee with a healthy human subject in an analogue prosthetic, would allow for muscle activity to be measured simultaneously. Also being dependent on speed, muscle activation is potentially another speed detection marker. Analysing this data in conjunction with traditional motion capture will allow for the markers to be identified against knee angle, a more natural and indicative measure of gait progression. Speed markers then can be found by identifying the speed dependent areas of the cycle for the muscles and ligaments. They can be used to both measure the speed of a prosthesis, and predict a change in it speed, which when implemented in a control algorithm could allow for a more natural mode of walking in powered prothesis.

Acknowledgements

I would like to express my deepest respects and gratitude to Dr Peter Ellison for being a fantastic supervisor, and for always going above and beyond to support me throughout project.

Further thanks extended to Mike Angus for always being available and enthusiastic for his endless assistance with fabricating and altering the mechanical parts throughout this project.

Statement of Ethics

The nature of this project requires the use of myself as “healthy” human subject for collection of psychological data. Ethical approval with university guidelines and informed consent has been approved by the fast-track process, of which a copy of the approval form can be found in the appendix.

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1 - Introduction

1.1 - Human Anatomy vs Prosthetic Design

Walking is a complex subconscious process, one that provides people with untold benefit. This is made painfully aware to amputees, where healthy people might not give thought. The aim of a prosthetic is simply to replace missing functionality. Passive prosthetics, that use only mechanical parts, achieve this, but do not escape any drawbacks. They offer shock absorption on impact, but for above knee amputations, or transfemoral amputations, they cannot apply energy to lift the leg back up again. This causes the user to compensate for the lack of power with their residual limb, which can result in an asymmetric gait [14]. The solution to this then is to add the ability to lift the leg, which is the principle of powered prosthetics. However, they use a mechanical design first approach which forces the control system to match the mechanical joints of the prothesis which are not a biological match for the real joints (Fig 1,2). This stems the biological disconnect of current prosthesis and adds to the picture of cumbersomeness they portray.

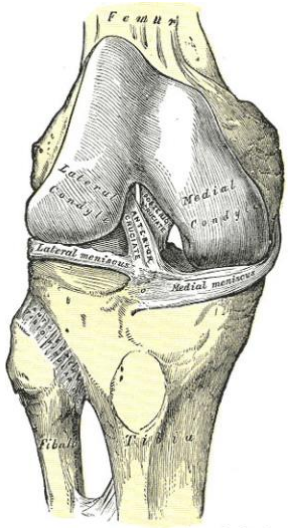

Figure 1 - The anatomy of the knee joint, taken from Greys Anatomy [17]

Figure 2 – The Power Knee, an example of a powered prosthetic knee device, using a pin joint. Taken from [18].

Leaving usability behind is the result of this simplification, it forces the user to walk in a new way, which is a very nonintuitive, lengthy process. The goal is to give seamless and fluidic function, or simply putting back exactly what is missing. Analysis of the progression of walking, specifically isolating details of the gait is known as event detection. By simplifying the human knee to a pin joint, you are altering the system for typical gait analysis, which would give a fundamentally different result to “healthy” gait. Removing this detail, leaves event detection for powered prothesis less than the ideal and has a hard limit on optimisation. Using a mechanical knee that matches the movement of

the human knee, allows a more typical gait, making analysis for event detection more ideal. If implemented into a prosthetic, theoretically the control of the prothesis would be far more fluid and match that of “healthy” walking.

1.2 - Speed Event Detection

Control of prosthetics is split into “tasks”, where isolated systems are designed specifically to handle each task. Walking is considered the most common task for a prosthetic, others include sitting, standing, and climbing steps. Within walking, speed regulation is an incredibly important, and is a massive consideration to the problem semantics. The ability to regulate speed during walking without having to interact with an interface, would be a massive step towards natural walking. Which would subsequently have large quality of life benefits. Where a pin joint is used, an encoder can be used to measure the angle of the knee joint. Using a mechanically accurate knee, the angle cannot be directly measured internally as simply as the pin joint due to the motion’s complexity. However, characterising the angle of the knee by the stretch of the anterior and posterior cruciate ligaments (ACL, PCL) would provide a unique advantage in analysis (Fig 4). The ACL and PCL guide the motion of the knee joint; thus the motion of knee is directly stored in the displacement of both ligaments. This means that the ligaments can be used in place of a pin joint encoder, allowing for speed dependent information to be isolated from the knee. Speed dependant areas of the ligament stretch would mean potential markers for speed detection.

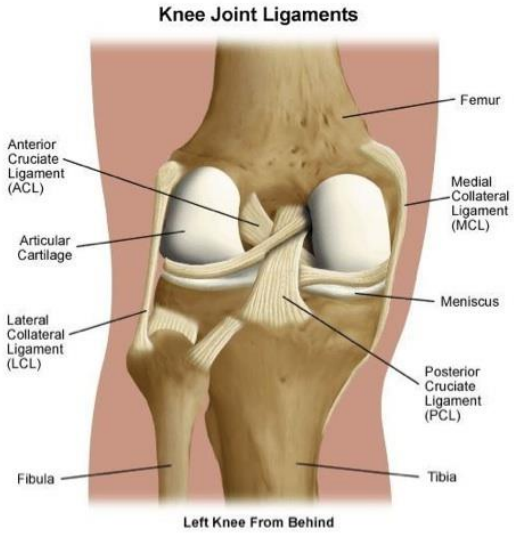

Figure 4 - Anatomy of the knee from behind. Taken from [21].

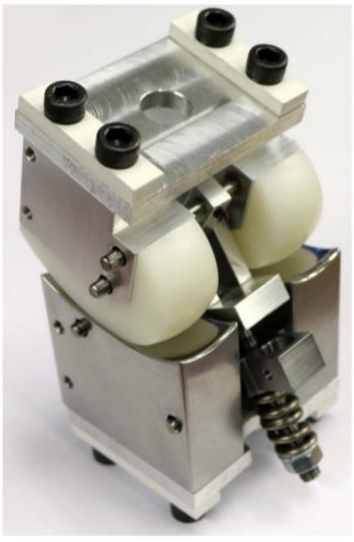

Figure 3- The fabricated design of the Russell knee, showing the anatomical match, with the condyle profiles and ligaments. Taken from [16].

The Russell knee joint (Fig 3) is a design that mimics the motion of the knee in the sagittal plane, using mechanical analogues of the ACL and PCL [12,16]. This makes it an ideal candidate for use in implementing in the project. The sagittal plane restriction is a design choice to capture the behaviour of the joint in a controlled system. More energy is exerted to increase speed, therefore muscle activation must differ with walking speed. Muscle activation then, will be the key to finding more markers of speed. Ligament displacement and muscle activation recorded simultaneously could give an average result of detect speed change. To do this, the healthy knee must be replaced with the mechanical knee while recording muscle activation. In a previous project, a version of the knee had been mounted to a custom-made bent knee crutch [14,16]. The knee design has since been updated and is now more favourable. The knee must be mounted to new a bent knee rig device in order to proceed with data capture.

1.3 - Aims and Objectives

The aim of this project is to understand if events in human movement, such as gait, can be predicted using mechanical and electrophysiological signals. The following objects will be completed to achieve this:

- To update the design and fabricate the knee prothesis rig.
- To measure the kinematics and muscle activity of the lower limb simultaneously during gait.
- To analyse the kinematic and muscle data as a time series to identity markers that are predictive of changes in speed.

2 - Literature and Background Review

2.1 - Limitations of Powered Prosthesis

A control system for a prothesis that does not attempt to interface with the existing limb to find what is missing from what is left. But instead uses muscle activation as a switch, forcing the user to adapt and relearn a different way of walking [15]. Reportedly, for patients with passive prosthetics, they must be consciously aware of each individual step [15]. The lack of proprioceptive feedback could be creating this, a passive prosthesis has no way of indicating the state of the device to the user. Even for powered prosthetics, features like haptic feedback are still limited. Electromyography (EMG) controlled powered prosthetics aim to use the existing musculature to control the prosthesis. However, with muscles at the end of the neuromuscular hierarchy, control of gait does not originate from the activity of muscles. Idealy EMG sensors would be used to measure individual muscles during gait, in order to gain a prediction of the walking state. Confirming an increase of the mental load in relation to prosthetics of any kind has been unsuccessful, as a method of measure cannot be found. However, reports from users support an increase in mental load [15]. If implemented this active approach would be able to control the prosthesis subconsciously.

2.2 - Gait and Locomotion

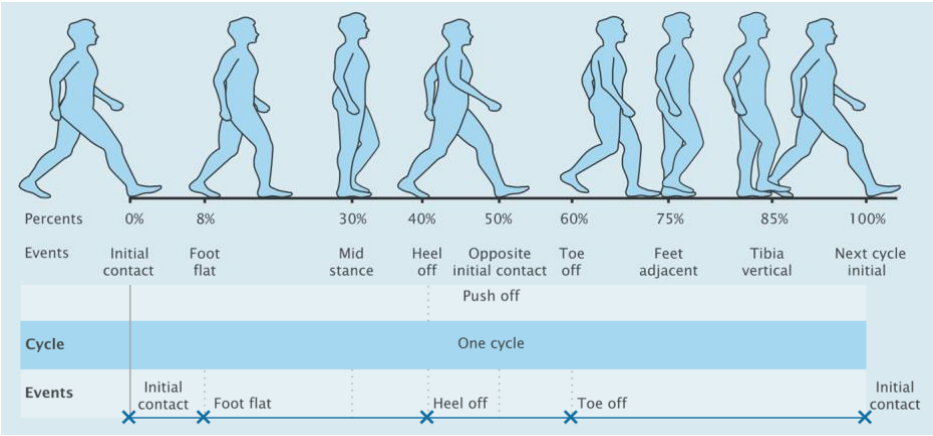

Figure 5 - The gait cycle, shown with landmark events against percentage. Taken from [1].

Gait analysis is the specific method in which walking is analysed. As walking is a cyclical event it can be analysed using a gait cycle (Fig 5). The gait cycle can be defined, starting when an observed foot hits the ground, known as the initial contact (IC) [1]. Then ending with the foot returning to the ground again [1]. Gait cycle analysis is divided into two major phases, the stance phase, and the swing phase. The stance phase constitutes the first 60% of the cycle and starting with the IC and ending

when the foot leaves the ground or toe off [1]. The remaining 40% of the cycle is the swing phase, the muscles of the other leg stabilise the body during the swing of the observed limb, which are also the muscles responsible for generating push off [1,2]. The end of the swing phase is the IC of the next cycle. Gait speed can be estimated by the gait cycle, practically this can be done with motion capture, which analyses the limbs as gross kinematic bodies. The drawback is that a kinematic skeleton assumes the joints as pin joints, which incurs the issues with this simplification discussed in section 1.1 [1].

2.3 - Neuromuscular Hierarchy and Muscle Timing

Physiologically walking can be viewed as the unconscious harmony of the leg muscles firing at differing strengths and times. It is carefully synchronised patterns that are key to walking. The control of neuromuscular events, which have been identified in EMG signals, have shown precise pacing rhythms within the EMG signals [3]. Works in the 1990's confirmed a correlation between the EMG pacing rhythms and the brains motor cortex. Allowing them to be considered activity of the central nervous system (CNS) [3]. However, no correlation between the motor cortices and the activated muscle in regard to the pacing rhythms was found [6]. This indicates the pacing rhythms being added lower in the neuromuscular hierarchy, more specifically by pre-programmed functions for long rhythmical actions like walking [3]. These functions describe the premise of a central pattern generator (CPG), which are a collective of neurons organised into a neural circuit. They respond to non-rhythmic inputs with rhythmic outputs [5]. CPGs might then explain the subconscious nature of the control of walking [5].

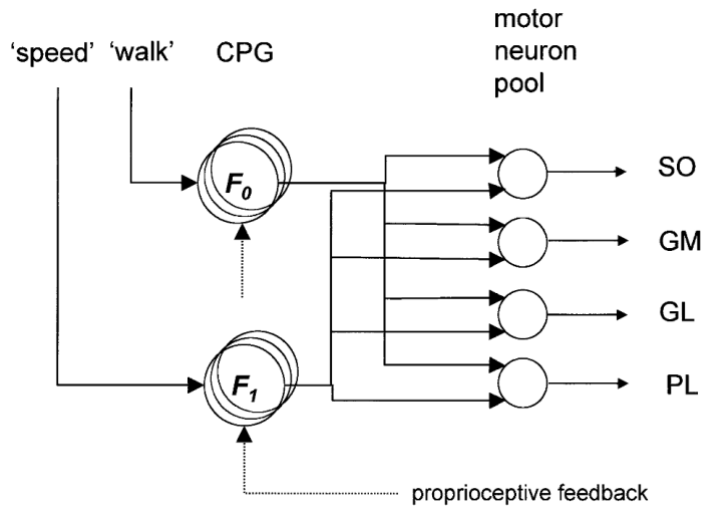

Figure 6 - The mathematically decomposed neurological circuit from Hof et al, showing the implementation of CPGs to drive the muscle activation. Taken from [4].

A picture of the neurological control of walking can then conceptualised as a neural circuit consisting of CPGs [4]. The output of a CPG is consistent and cyclical, allowing it to be modelled mathematically [5]. Hof et al, follows the distilling of EMG signals of a human in gait into the neuromuscular model (Fig 6) [4]. It breaks down the control of walking into two main functions, firstly F_0 which generates the base speed independent pattern of walking. This can be seen as the base pattern at which the muscles of the leg follow, with a binary activation from the CNS. It also has a secondary proprioceptive input, forming a control loop with environmental factors [4]. Secondly the F_1 function takes a gradient input from the CNS, as this is the function that deals with speed control. Responding to the level of the gradient, it varies the amplitude of the speed dependent areas of the muscle activation, also with proprioceptive feedback. The existence of this model shows that components of the speed dependence areas of gait can be readily isolated, and due to the repeated behaviour, predicted. Even if the muscles are missing, the CPG processing still occurs, and it is this repeatability that could allow for a prothesis to replace the gaps in the system.

2.4 - Surface Electromyography

The definition of EMG is the study of the electrical activity in a muscle that results in its contraction [7]. The presence of this electrical activity allows its measure as the potential difference between two electrodes [7]. Placing them on the skin is known as surface-electromyography (sEMG) [7]. Neurological signals are transmitted to the muscles via motor neurons. When a neuron fires, it changes the electric potential, with a positive spike followed by a smaller negative spike [7,8]. This is known as an action potential, and is present in EMG signals [7,8]. Neurons cannot fire continuously, as they have a refractory period, a long period of activity will exbibit a repetition of action potentials [7,8]. The envelope of an EMG signal can be considered to be equivalent fixed amplitude of the muscle's activation [7,8]. One neuron is responsible for a handful of individual muscle fibres, known as a motor unit. Each will have a unique action potential, or the motor unit action potential [7,8]. The EMG signal of muscle will be the summation of all the motor units within it. With slightly different timing for each, the average action potential may be inconsistent or seemingly random, but the signal envelope will have a consistent correlation to muscle activation [7,8].

SEMG is not alone in methods of measuring muscles, but it's the least invasive and commonly used. It is currently being used less in studies in gait analysis, favouring other sensors do to complex requirements [2,1]. SEMG can be extremely sensitive to a build of sweat and moisture, also having

an issue with crosstalk from neighbouring muscles [1]. Crosstalk comes from the skin shifting the sensor over to another muscle, causing a consistent issue when focusing specificity on a muscle [1]. Despite known issues, few alternatives are available, making sEMG practically unavoidable if muscle activation is required. Precautions can be taken to mitigate the effects of errors, like placing sensors in the centre of the muscle belly [1]. Reduce the chance of cross talk by shifting, this also gives the strongest possible signal as it is the largest point of muscle [1].

2.5 - Effect of Speed Increases in EMG and Kinematics

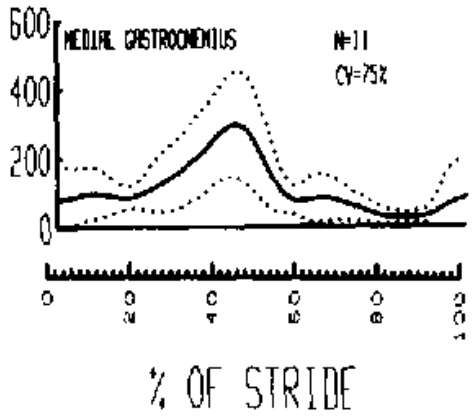

Figure 8- The Winter profile for the gastrocnemius medialis muscle, showing only one unknown speed. Adapted from [22].

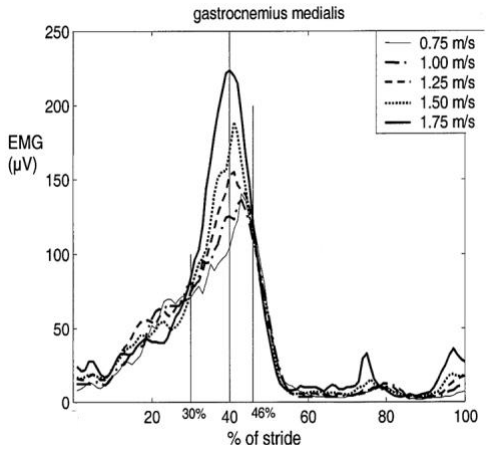

Figure 7 - The equivalent EMG profile from Hof et al, taking speed variation into account for the gastrocnemius medialis muscle. Taken from [4].

The Winter profile (Fig 8) is considered to be a respected averaged EMG profile for muscles in a gait cycle. It can be used as a reliable source to check if EMG data fits the norm [4]. It was derived from a number of trials at an unknown speed [4]. Hof et al, identified that no averaged EMG profiles existed like the Winter profile that took speed into consideration [4]. EMG signals have a very strong correlation with walking speed, leading Hof et al produce a mathematical distillation discussed in section 2.3 [4]. Speed selectively changes EMG, making the effect nonuniform, also being visible around landmark events within the gait cycle [4]. Shown in the gastrocnemius medialis muscle (Fig 7), where speed dependence has an effect at 40% of the cycle or push off [4]. This could allow for speed to be detected and predicted, by measuring the amplitudes of landmark events in the cycle.

With a positive correlation of speed with electrophysical signals, we must then gain a picture of the relationship between the kinematics of the leg and speed, specifically in reference to the ligaments of the knee. When walking speed increases so does the force of the muscles, and stride length, which naturally makes the angle of flexion increase. A significant correlation between the peak of flexion and walking speed has been identified [9]. If flexion increases, the overall displacement will increase

for the ACL and PCL, meaning that there must be a correlation between speed and the ligaments displacement. Specifically at the peak point of flexion, another landmark with a speed dependent component. Since speed dependence in the cycle lines up with landmark events in both the EMG and kinematics, there is a potential for markers of detection of increase of speed to identified.

2.6 - Variations in Factors for Non “Healthy” Limbs

Data collection will be performed using the knee prothesis, using a healthy subject. There is an importance to understand what effect this will have on typical data from a “healthy limb”. As movement is restricted, this will likely change the pattern of muscle activation. While unavoidable, taking this into consideration will help explain results. Variation in EMG data have been shown in similar situations, covering different aspects [10,11]. Knee replacement surgery replaces the knees contact surfaces with metal and plastic parts to mimic the smooth movement of cartilage, similar to the construction of the knee rig. Patients who have undergone the surgery have differing EMG patterns from a “healthy” knee (Fig 9), even at 24 months post-op [11]. The patterns hold the general shape but have periods in the cycle where the muscles are providing more force [11].

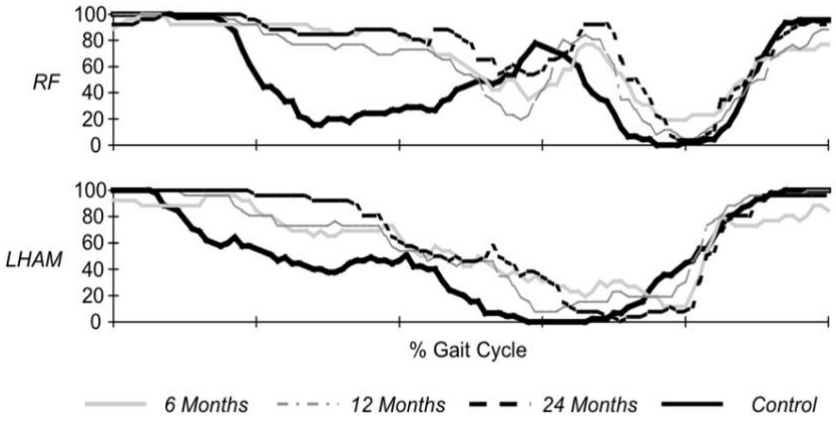

Figure 9 - The EMG activation of TKR patients over 24 months. Examples the of RF (rectus femoris) and LHAM (lateral hamstrings) against a control group. Adapted from [11].

For a transtibial amputation, or below the knee, EMG variance is also present while more subtle (Fig 10). Taking different speeds into consideration, Fey et al, shows a similar principle of the EMG during the cycle holding the same pattern, but having decreased amplitude in key landmark peaks [10]. Regardless of this decrease, the speed dependence in these regions is still distinct and could be identified [10].

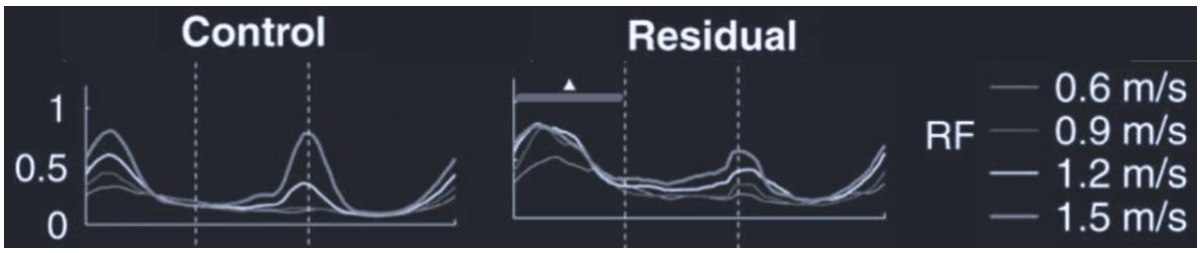

Figure 10 - The speed variable EMG activation of the rectus femoris muscle for a control group as well as a group of transtibial amputees, showing the activation of the residual muscle. Adapted from [10].

2.7 - Summary

Speed dependence has been shown within the EMG of a gait cycle, and in key landmarks of the cycle. The landmark amptlitudes, due to their dependence on walking speed, have positive correlation with walking speed. With this information it is theoretically possible to measure walking speed, and predict a change in real time. It is logical then, to use this information in a potential control system. However, EMG is an exteremly abitary measure, it has a high variablity, despite a consistent average. If used alone the data would not be reliable enough to determine an accurate prediction. It is simply a abritary indicator of an event. Comparatively, the correlation of the ligament displacement and walking speed, allows for the maximum displacement to be considered as another marker of speed detection. Ligament stretch is direct physological measure, and is not subject to the abritary nature of EMG. Using the ligament stretch and EMG together means system is no longer dependent on only the EMG. The EMG can serve as a indicator a speed increase, while the ligement data, being a direct measure, can make the predtiction of speed far more reliable, as it no longer an abritary indirect measure.

3 - Testing and Experimentation

3.1 - Materials

3.1.1 - Updating the Knee

Before the project, a prototype was made to attach a newly manufactured knee, onto the I-Walk 3.0 knee crutch [12,16]. Originally majority 3D printed, this prototype version of this was quick to fail, and was unstable. It had aluminium extrusion for the tibia alongside motion tracking markers in the extrusion. These had both come from a prior version of the project and lacked the ability to have height adjustment. It was clear that the rig needed to be updated before use in testing. First of which was updating the femoral condyle holders, as the printed parts failed. Alongside this was the issue of tortional forces at the joint, which could have further damaged the device. A decision was made that

replacing as many parts as possible with mild steel would be the best approach for coping with compressional forces. This led to the redesign of the tibia and femoral mounting plates to best satisfy manufacturing constraints (Figs 13,14). As for the issue of height adjustment, the tibia mounting plate redesign was an opportunity to reuse the tibia of the I-Walk 3.0. Which had the benefit of height adjustment, as well as a robust foot which the device lacked. The tibia mount was designed to accept the spring button fastening of the current tibia (Figs 11,12).

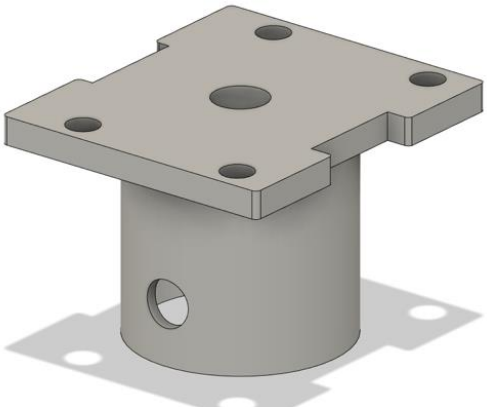

Figure 11 - CAD design of updated tibia mounting plate.

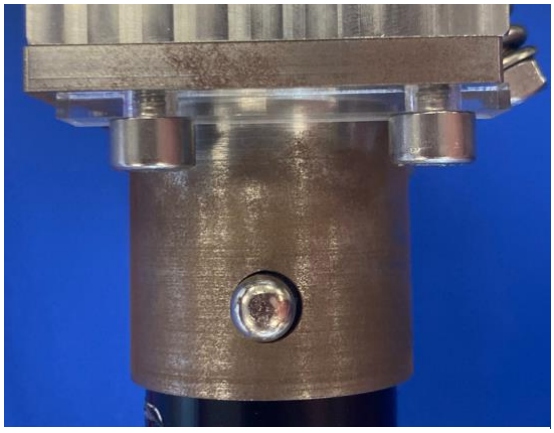

Figure 12 - Manufactured design of the tibia mounting plate, machined from mild steel.

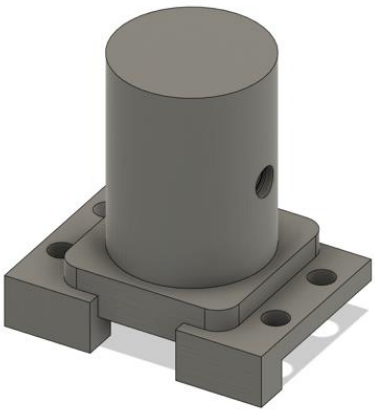

Figure 13 - CAD redesign of the femoral mounting plate.

Figure 14 - Example of 3D printed test part used to validate the fitting and tolerances of the design before committing to manufacture.

As the tibia was now a tube, a new method of attaching the motion tracking dots would have to be designed (Fig 15). A jubilee clip inspired design was made, that could be used for both the femur and the tibia. 3D printed, brass inserts would be press fit into the parts, and the motion tracking dots threaded on.

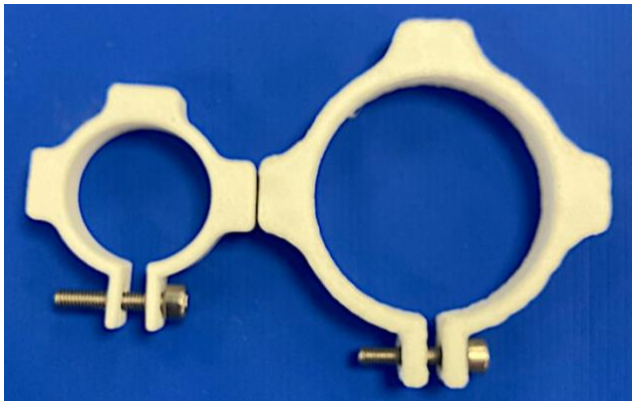

Figure 15 - Show on the left the femoral motion tracking mount design and the tibial on the right, both 3D printed

The human knee joint is already supported from torsion by the collateral ligament either side of the joint (Fig 4). The analogue ligaments can be two plates either side of the knee to restrict rotational movement. The existing femoral condyle holders had to accept two lengths of aluminium which had been used to replace cross bars to reduce torsional forces of the crutch. Constraints of manufacture would mean the femoral condyle holder would now have to remain printed. Adding the collateral ligament analogues onto the design would increase conventional manufacturing complexity (Fig 16). To increase compressional rigidity, the parts were printed in a stronger plastic, PETG. Unfortunately, during initial testing the rig suffered damage, and the part had to be redesigned to have thicker collateral plates, then parts were printed in solid plastic (Fig 17). A pinhole had been added in the first design to align with a pre-existing pin hole on the condyles, but was originally considered as futureproofing. As part of the stronger redesign two steel pins were then fabricated to lock the condyles horizontally with the pinhole. After strengthening the femoral condyle holders, they behaved as intended in testing and were able to deal with both compressional and torsional forces (Fig 18).

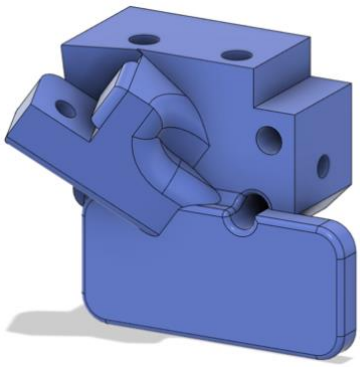

Figure 16 - Original redesign of the femoral condyle mounts, introducing the collateral ligaments.

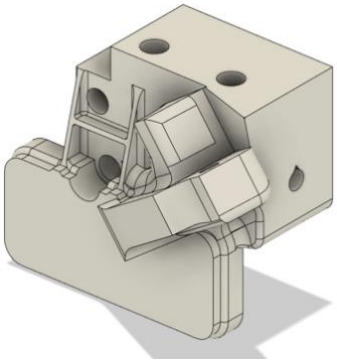

Figure 17 - Strengthened redesign of the femoral condyle mount, with thicker plates and ribbing supporting the weak points.

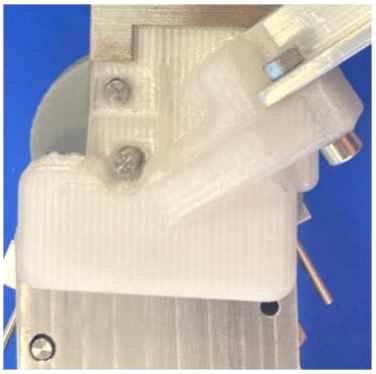

Figure 18 - Final 3D printed condyle holder installed into the knee, shown here covering the tibial condyle for torsional. support

During the failure of the existing prototype, a large issue was the holders for the LVDTs sheering in half, causing further instability. The identical pair were modified slightly for ease of manufacture and were machined in aluminium. During the aforementioned failure of the updated design, the pins that held the ligament springs had been deformed (Fig 20) . Brass pins from the previous project were reused instead with a steel thread, which had to be resized (Fig 19).

Figure 19 - The brass ligament pin installed with the spring tension at the minimum. Also Showing the LVDT holder.

Figure 20 - Original aluminium pin, with deformation on the top thicker thread.

When using the device, the weight of the subject's leg forced the knee to bend unintentionally, making walking awkward. A bungee cord on the front of the leg was employed to counteract the weight (Fig 22). This implementation worked as expected and made walking on the device more natural. Lastly adding a force sensitive resistor (FSR) to the bottom of the foot would allow for the recording of IC. Used in data analysis, the signal can split up the other data streams into gait cycles. A potential divider circuit was used, having the FSR as one of the resistors. This was manufactured onto a small prototype board and mounted to a 3D printed foot cover. The FSR had adhesive backing and was stuck onto the head and taped for security (Fig 21).

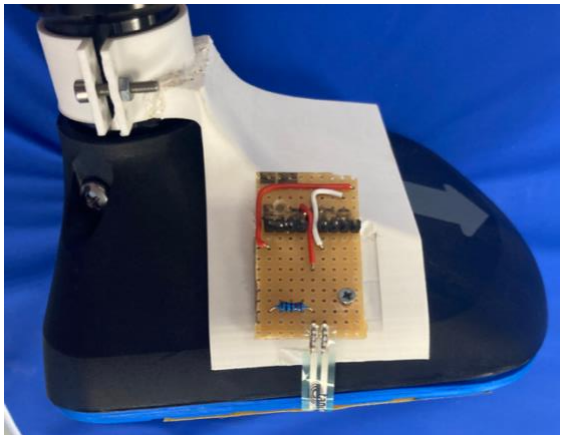

Figure 21 - Manufactured FSR circuit mounted to the foot of the rig.

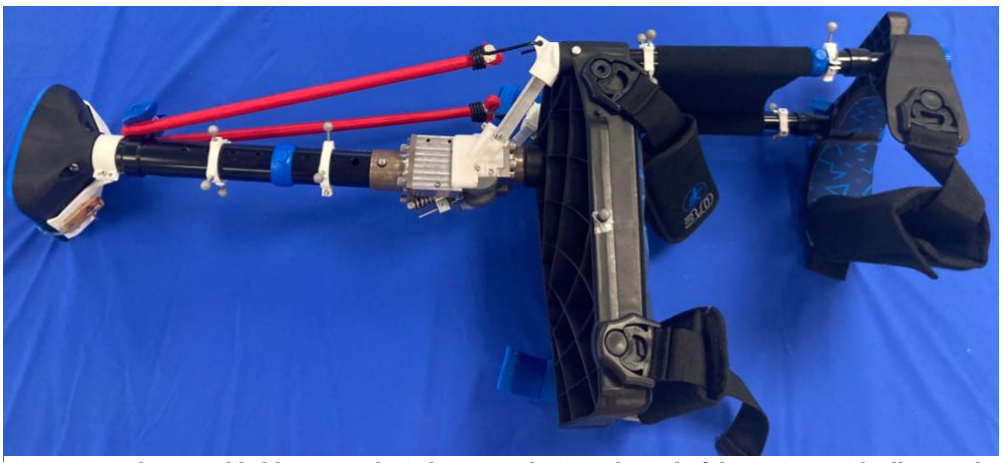

Figure 22 - The assembled knee prosthetic knee crutch rig at the end of the project, with all upgrades installed.

3.1.2 – Data Capture Setup

The data collection box for the previous project, contained two amplifiers and a national instruments DAC card (Fig 23). The amplifiers were for original linear variable differential transformers (LDVT). They would be used to measure the displacement of the ligaments as a voltage change, which could be scaled to find the displacement. The DAC card collected the data at the output of the amplifiers. New LVDTs had been acquired since and the amplifiers were first setup to match. They were then verified to send the expected change in amplitude when placed into the knee using an oscilloscope.

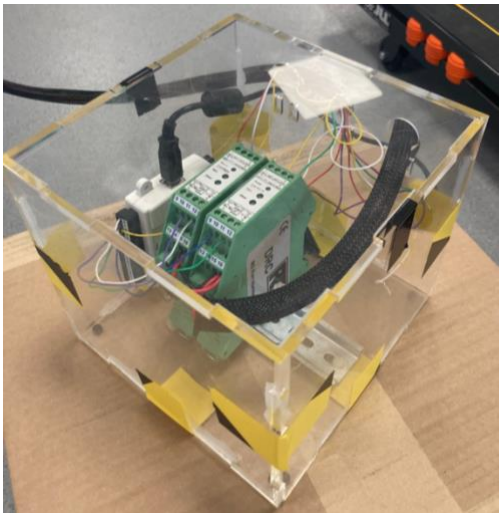

Figure 23 - Data collection box, with the national instruments DAC card in white, and the two green LVDT amplifiers.

It was here that it was discovered they clipped outside the maximum voltage range of the amplifiers in operation, even after the maximum tension of the ligament strings was applied. The brass pins that were used after the failure of the updated design were much shorter than the original pins. A shorter

pin increased the tension, and therefore reducing movement, keeping the travel within the voltage range for the majority of the cycle. For the FSR, the DAC card had a 5-volt output that was used to power the potential divider, and the dividers output was collected by an input to the DAC.

The device would have to be used inside a fixed motion capture volume, which would mean using a treadmill (Fig 24). The lengths of the wire for the LVDTs were too short to have the box at a safe distance, therefore they were extended to have some slack for walking while maintaining a safe distance. A power supply was placed next to the treadmill to power the amplifiers. The USB cable from the DAC card terminated at the computer which drove the motion capture system, outside the volume. The cameras had to be recalibrated several times due to consistent issues tracking the femur.

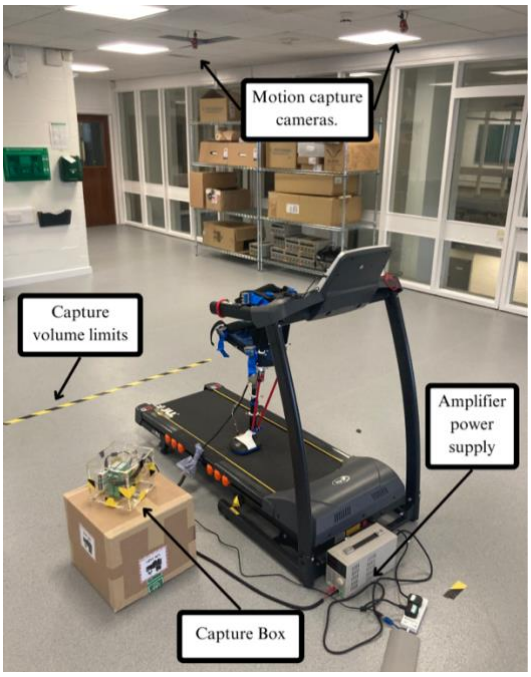

Figure 24 - The final test capture space, excluding the computer which is behind the frame outside the volume.

3.2 – Procedure

The first round of data capture introduced the FSR, LVDTs, and motion capture. Once fitted, the placement of the LVDT sensors were validated to be in range, and close to the null point of 0 volts. Then the FSR was validated by applying a force, then checking if the signal reacted. The subject then stood on the treadmill, after calibration and prothesis fitting. The motion tracking markers placed on the prosthesis, were assigned as two rigid bodies in the software, the tibia and femur. The second round of data capture was to be the same, bar the introduction of Delsys EMG sensors. With five being placed on the major muscles of the thigh and confirmed to send an adequate signal to the computer. The data capture procedure was as follow:

- The subject will walk three time for 1 minute to allow for 10 good strides to be collected at three speeds:
    - 1.0 ms^{-1}, 1.5 ms^{-1}, and 2.0 ms^{-1} [4].
- For the first, all data will be simultaneously collected organised by speed and subject.
- This will repeat until all three are complete for the subject.

3.3 – Analysis

3.3.1 – Data Pipeline

During recording, all the data streams are directly read by Opti-Track's Motive software, the principal software for the motion capture. The national instruments DAC card has native software support where there is direct synchronisation to the motion capture. The Delsys EMG system does not have native synchronisation to Motive. This would then have to be matched up manually during analysis with an event such as a stamp. Motive exports the DAC and motion capture data as separate csv files, and Delsys system likewise exports a CSV file. These files were then be imported directly into MATLAB for analysis.

3.3.2 – MATLAB Implementation

Once imported, for the processing of the LVDT data is used to make two tables containing the time series data for both the ACL and PCL. Processing is a relatively simple step, each LVDT quotes a sensitivity value, which has units mV/mm/V. During operation the LVDT core is energised to a core voltage of 3 volts, which when substituted into the voltage term of the sensitivity gives the scalar value between voltage and displacement:

$$Displacement\ Scalar\ \left(\frac{V}{mm}\right) = Sensitivity * \frac{Core\ Voltage}{mV}$$

Each LVDT has its own sensitivity. Therefore, to process ACL and PCL data, two displacement scalars are assigned to the ligament dependent on the LVDT used. A loop steps through each voltage value in the table and divides the voltage to give the displacement. The result is a time-displacement table for both the ACL and PCL.

The data for the motion capture is exported as quaternions for both rigid bodies in the motion capture file. Both bodies are imported to MATLAB, represented as two time series quaternion tables. It is typical for some frames of data to be missing, where markers have been obscured. Therefore, an interpolation is run, and then it proceeds to joint angle calculation. For two quaternions, the rotation between them can be calculated as:

$$\theta\ (degrees) = \frac{180}{\pi} * cos^{-1}(real(\ tibia * \overline{femur}\ ))$$

Processing the EMG starts with importing a voltage time-series for every muscle into MATLAB. First, a mean of the signal is taken, the DC offset, and is used to centre the signal on zero volts. The signal is run through a 5-pole Butterworth band-pass filter with a range of 10-500Hz [19]. It is then rectified and synchronised to the FSR using the stamp recorded during the capture [19]. Following this, it is interpolated to match the time scale of the FSR, as they record at different sampling frequencies. A low-pass filter of 2Hz is then applied to the resulting EMG signal, which provides the envelope of the signal. This filtered EMG envelope can be considered to be the activation of the signal and is the final result.

The FSR data is made into a voltage time series. The IC is represented in the raw data as the first time the voltage is less than the input of 5V, in practice the signal at rest is 4.83V. To limit false triggering in the code a threshold of 0.5V is applied to remove noise and the signal is inverted to rest at 0 volts. A loop runs through the modified FSR data and creates a binary table of every point it exceeds 0V. However, extraneous triggers could be caused by a fluctuation of the voltage during the IC. To solve this, a time threshold is applied, to remove any triggers that are less than a specified time and is inspected manually.

To separate the data into individual cycles, a function splits up and stores cycles in a cell array using the time between the ICs. The average cycle of a trial is now calculated, by first assigning a common time grid. It is chosen to be the longest cycle in the trial. Each cycle is then interpolated to match the common time grid. With the trials now the same length, each interpolated data point can then be averaged to give the average cycle of the trial. As it is now a common time grid, the average cycle is now plotted against percentage progression for easy comparison to other trials.

3.3.3 – Testing

Initial testing began by taking data from individual systems separately. Firstly, the motion capture system, of which early data was taken by bending the knee by hand (Fig 25). It verified that sensible knee angle values were being collected from the data, and the knee angle processing was working correctly.

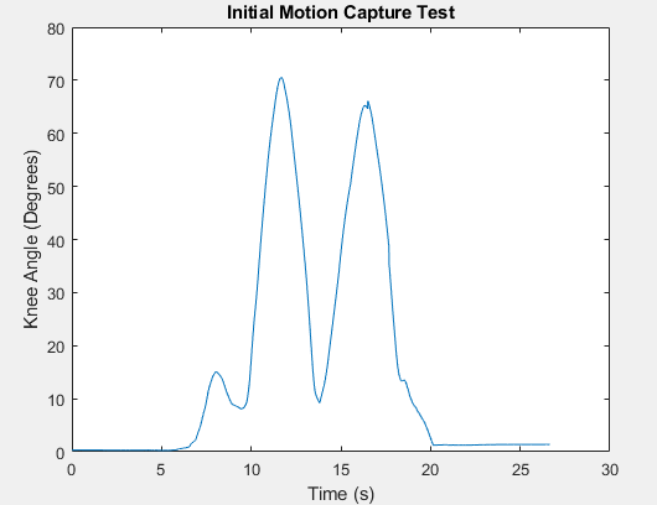

Figure 25 - Initial motion capture trial, bending the knee in the volume to roughly 90 degrees.

Early EMG testing began with using two sensors on the quadriceps and hamstrings, when walking for an arbitrary amount of time and speed. It was used to determine if processing the activation was achievable with the implemented code. The hamstrings are a good example of a weaker signal, but the processing is able to extract the amplitude envelope regardless.

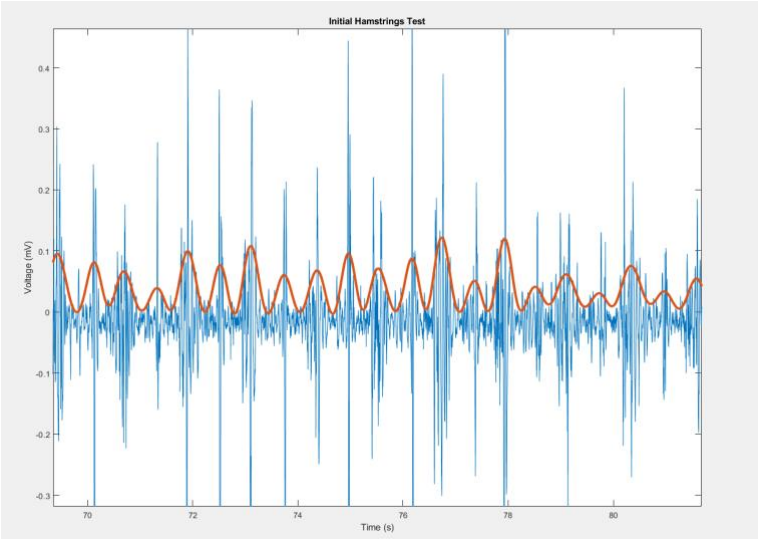

Figure 26 - Initial hamstring EMG trial showing the signal envelop successfully isolated from the raw data.

The quadriceps, a bigger muscle group, had clear distinct periods of activation and it can be shown that the processing is able to correctly isolate the amplitude envelope of the EMG signal (Fig 27).

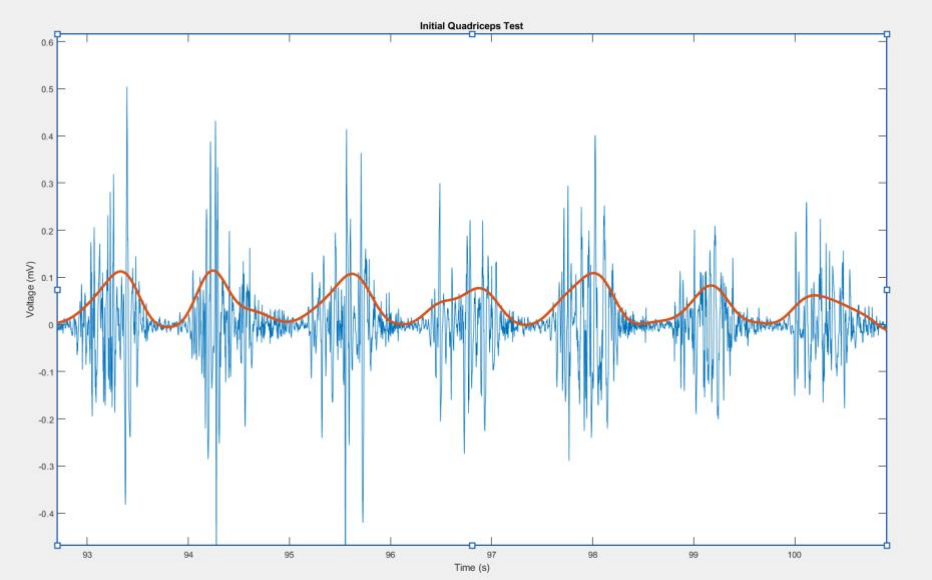

Figure 27 - The initial test for the quadriceps muscle group, with the signal envelope isolated from the data.

For the FSR, initial testing was done in a fabrication space, away from the DAC collection box. Instead, the onboard DAC on the Arduino Mega was used. This initial test was the first indication of the false triggering (Fig 28), which prompted the addition of the time thresholding. After which, the resulting signal was an approximate indicator of the IC.

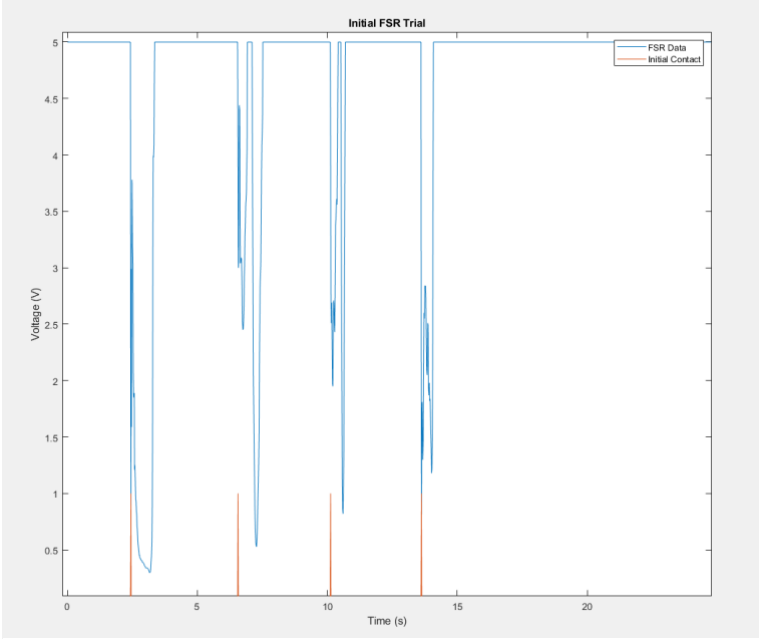

Figure 28 - The initial FSR data showing four steps, and the derived ICs. Shown in steps 2 and 3 are the false trigger events when the signal goes back to the quiescent voltage.

The first phase of final testing excluded the EMG and had three runs following the procedure. The first capture run, with the initial rebuild of the knee rig, caused the aforementioned part failure when the weight of the subject was applied to it. After the strengthening redesign, the second trial, with the original ligament pins took place. In this trial the rig was far more stable. However it took place with the healthy leg standing still on the edge of the treadmill, for support, to limit parts failures. Initial data looked promising, but it was clear that the LVDTs were clipping (Fig 29).

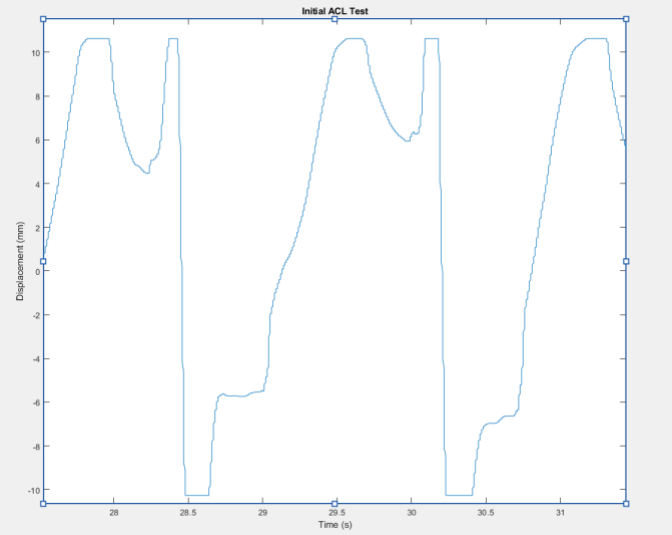

Figure 29 – The initial ligament stretch analysis showing considerable clipping on both upper and lower peaks.

Unfortunately, alongside this, the motion capture system had significant issue tracking the femoral ridged body and was unable to be interpolated. For trial three, the shorter ligament pins were used. The motion capture system had also been extensively recalibrated, in order to better track the femur. The LVDT data from this trial was significantly better than before, but still had a small portion of clipping. The motion capture, while improved slightly, was still very difficult to process, this again was to significant data loss on the femurs tracking.

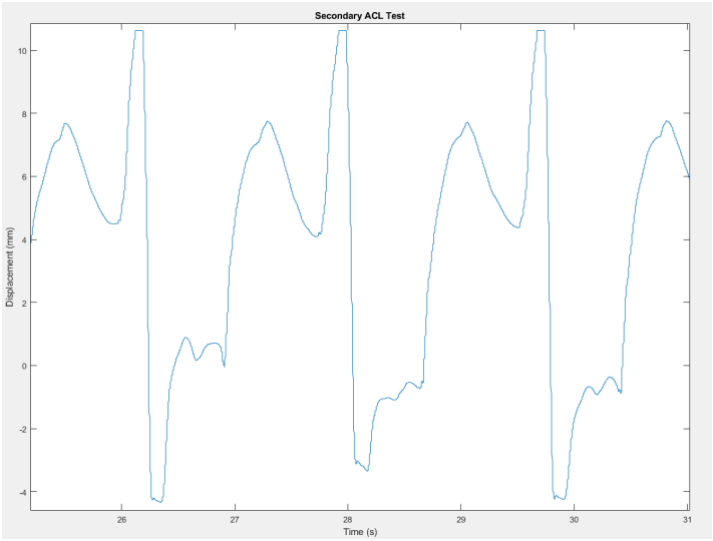

Figure 30 - The secondary ligament trial, showing the reduced clipping on the lower peaks, but with a small portion of clipping on the highest peak.

Due to time constraints, the EMG testing was altered. Separate from the knee rig, the gross muscle bodies of the quadriceps and hamstrings were captured. The FSR was also attached to the shoe of the subjects to measure the IC. This data would differ from the potential results within the rig, but it is still important to understand the behaviour of EMG in the scope of his project. Due to the inability to synchronise the DAC and the Delsys system, a stamp was used in-between two periods of quiescence to manual align the data. While not as accurate as a syncing pulse, the time of misalignment would be negligible, and out of the scope of this project.

3.3.4 – Results

The results of the final test of the first phase are shown as ligament stretch against percentage progression of the gait cycle. We can see that for the ACL (Fig 31) there is a peak at roughly 20% of the cycle, the peak of the 1.0kph cycle is at 7.9mm, the 1.5kph is 6.8mm, and the 2.0kph is 6.4mm. Likewise at roughly 55% of the cycle, or push off, there is another landmark peak present. The peak of the 1.0kph cycle is at 10mm, the 1.5kph is 9.63mm, and the 2.0kph is 9.98mm.

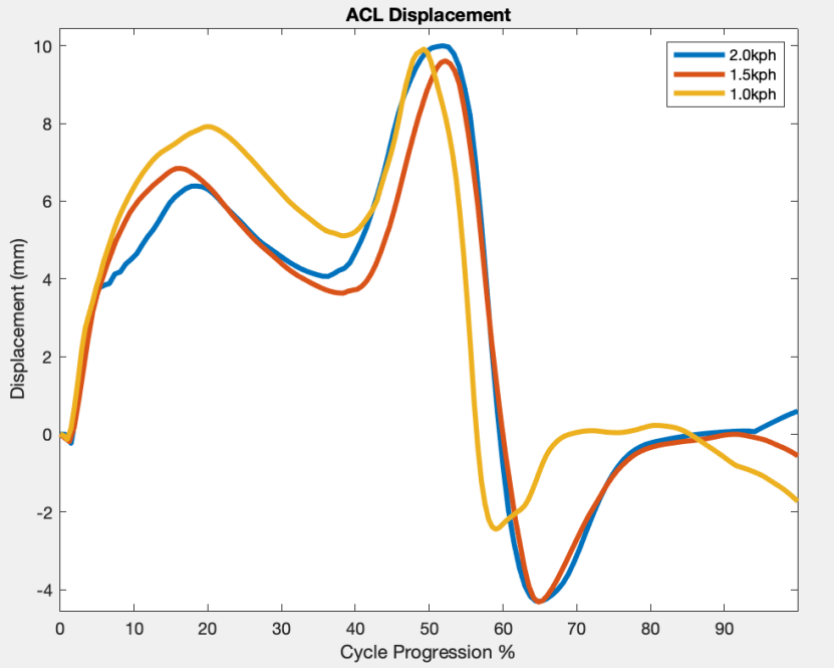

Figure 31 - Final result for the averaged ACL displacement plotted against the gait cycle, for 1.0kph, 1.5kph, and 2.0kph.

For the PCL (Fig 32), there is a peak at roughly 10%, which is roughly the loading response of the cycle. The peak of the 1.0kph cycle is at 6.9mm, the 1.5kph is 7.6mm, and the 2.0kph is 10mm. There is also a peak present at roughly 50%, also at push off. The peak of the 1.0kph cycle is at -0.9mm, the 1.5kph is -1.1mm, and the 2.0kph is -0.2mm.

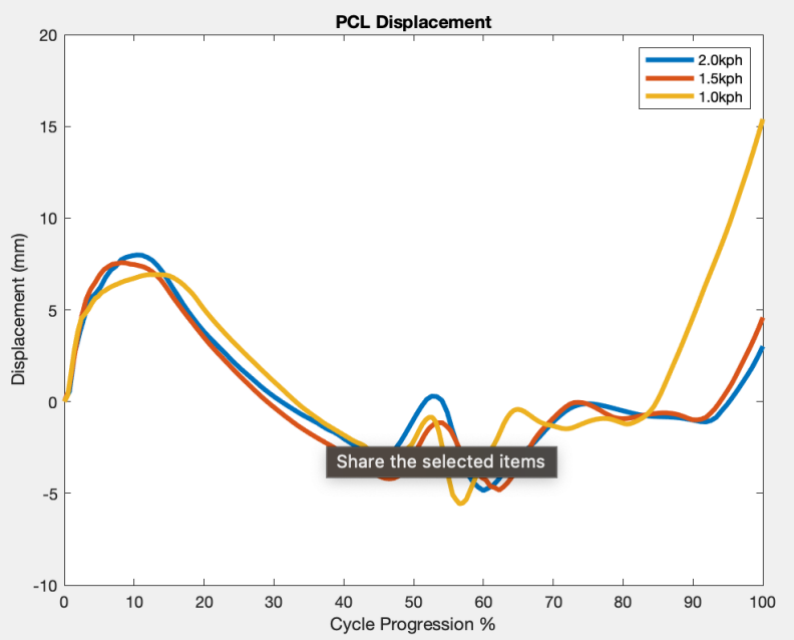

Figure 32 - Final result for the averaged PCL displacement plotted against the gait cycle, for 1.0kph, 1.5kph, and 2.0kph.

The EMG results are similar those of the ligaments, with a peak at around 10% of the cycle. For the quadriceps (Fig 33), there is a clear peak at 10% of the cycle with the peaks for 1.0kph cycle is at 0.0171mV, the 1.5kph is 0.0208mV, and the 2.0kph is 0.0218mV. Again, the hamstrings peak (Fig 34) at around 10%, With the peaks for 1.0kph cycle is at 0.004mV, the 1.5kph is 0.005mV, and the 2.0kph is 0.003mV.

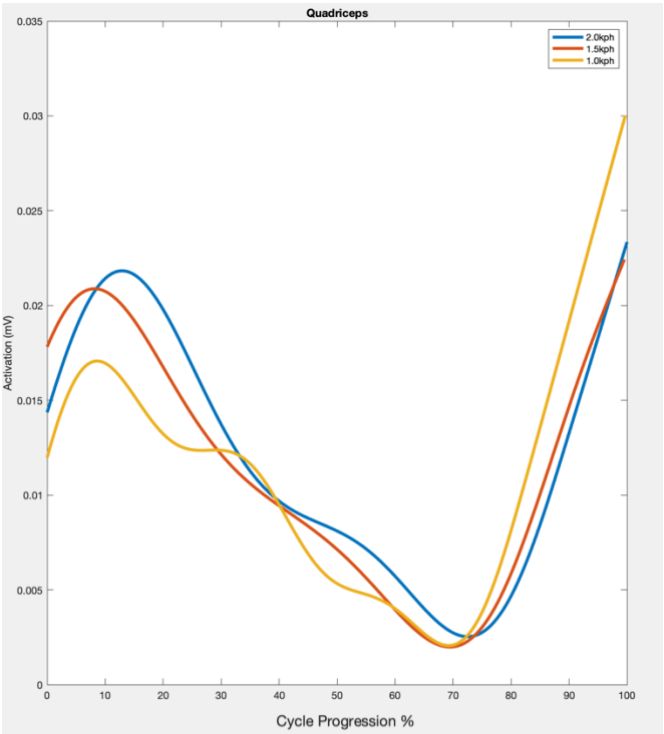

Figure 33 - Final result for average amplitude of the quadriceps plotted against the gait cycle, for 1.0kph, 1.5kph, and 2.0kph.

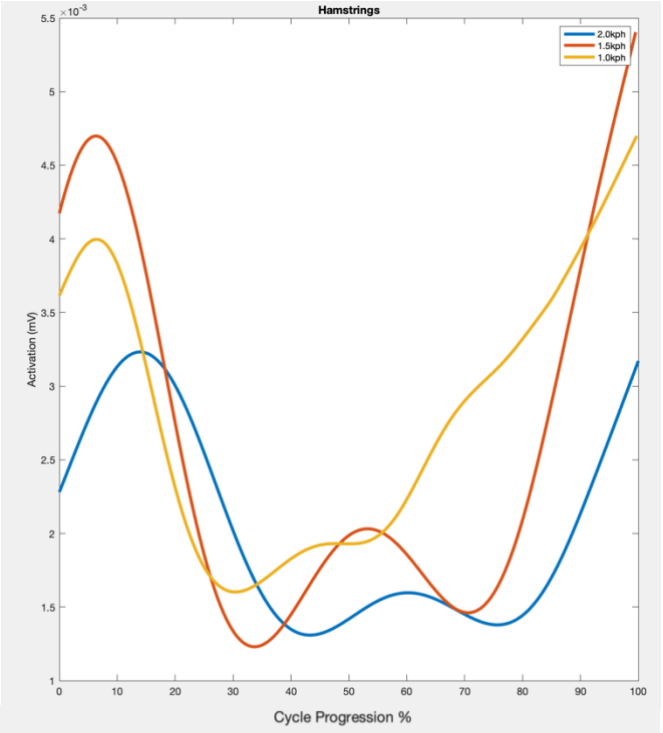

Figure 34 - Final result for the average amplitude of the hamstrings plotted against the gait cycle, for 1.0kph, 1.5kph, and 2.0kph.

3.4 – Discussion

An orignal intention was to plot the data from the trials against knee angle. Unforuntaley due to the issues tracking the femoral ridgid body, enough data was not recorded to be recovered correctly by interpolation. Numerous factors could have contributed to this such as, day light, old dirty tracking dots, and other eronious noise. Regardless of this, analysis against percentage gait cycle is still a commonly used measure and gives a informative picture. For the ACL, the 20% midstance peak shows signs of speed dependence, with an inverse proportionality. This can be directly compared to the similar peak of the PCL cycle, which has a non-inverse proportionality. As the ligaments are in a cross in the knee, they will have oppositing displacements to eachother. This is confirmed here in the 20% peaks for both ligaments. This is also could be confimred in the 50% push off peak, although voltage clipping during recording for both LVDTs is present here. Average values for the cycles would have been interpolate out of the known data set and have been skewed. However dispite this fact, a speed dependence is clearly present in the 50% peak. The literature review, and the previous data indicates that for the 50% peaks the ACL might have been non-inversely proportional, and the PCL inversely proportional.

For the quadriceps and the hamstrings, there is a clear non-inversely proportional speed dependence present in the 10% peak. This is shown clearly by the quadriceps, but it must be noted that the value of the peak on the 2.0kph trial, is closer to the peak of the 1.5kph trial than expected. This can be explained in part by the hamstrings, where the 2.0kph considerably lower than the 1.0kph peak. But the remaining peaks still show a non-inverse proportionally. The 2.0kph trial was the last of several trials in the run, stickers that are used to attach the Delsys sensors to the skin may have become loose. Introducing more noise, and reducing the amplitude and changing the charateristic of the signal [20]. Despite this, the remaining peaks show clear evidence of speed dependence, which allows for the 10% peaks of both EMG sources to be potential markers in speed detection. Alongside them, there are two possible markers identified in the 20% peaks of both ligaments, and potentially the 50% peaks.

Using the CPG concept from the neurological by Hof et al, a similar logic diagram (Fig 36) for a control system can be made ([4]. Two functions, one speed dependent, A_1 , and one not, A_0 , are used to drive the actuators of the prosthesis. The peak values for the ACL and PCL are isolated and fed into A_1, alongside the peak amplitudes for the muscles of the thigh. Within A_1, an average speed is calculated, and used to drive the speed dependence specific to the detected speed. A_0 does not need

an input, as it simply provides the base pattern of actuation, if the speed is 0, the inputs will cancel and there will be no signal sent to the actuators.

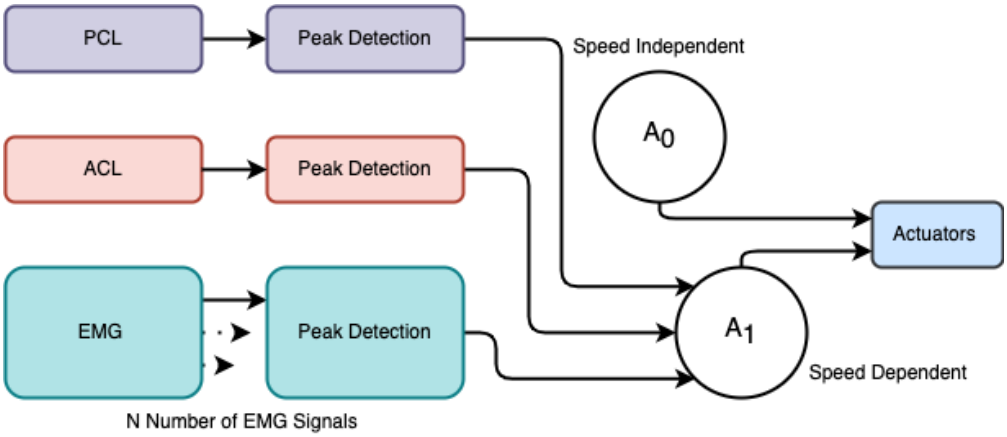

Figure 36 - The proposed logical circuit inspired by the works of Hof et al [4]. Using equivalent functions to drive the actuators of a powered prosthesis with the kinematic and electrophysical data acquired from the muscles and artificial ligaments.

4 - Planning and Time Management

The time management plan outlined in the initial report was followed (Fig 35). Due to trouble shooting issues with the LVDTs, data collection was not able to take to take place during week six. To recover from this the data processing section, chiefly the MATLAB implementation was started instead. This meant that data capture started in week 7, with no delay. The data capture also stretch alongside the analysis, having a complementary effect on each other. Retrospectively this should have been considered in the planning but did not incur delay. A majority of delay in the project was caused by the troubleshooting of the LVDTs, to which significant time and effort was involved. This pushed final data capture further than expected, and due to lengthy data analysis, questioned the opportunity to record the EMG in the second phase of data capture. The issues with the motion capture recording for the femur rigid body could not be resolved in the time of the project.

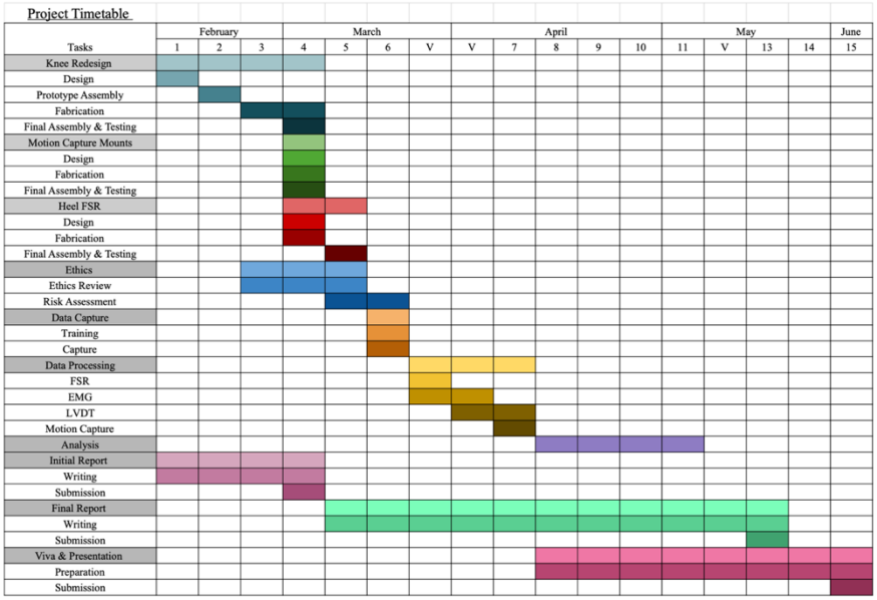

Figure 35 - Time management Gannt chart from the initial report of the project.

Unforeseen delays, errors and challenges within a project are inevitable. It is the way they are approached that makes the difference. For the most part, these challenges were able to be solved quickly, but instances of back-to-back issues made for a noticeable delay. It was extremely important to the project to have a form of EMG implementation, which unfortunately meant reducing the complexly of the EMG trial. As the data analysis for the original trial would have been incomplete within the time frame. Despite this, referring back to the original aims and objectives of the project, a majority of them were satisfactorily met. A full, robust design and update of the prosthetic knee rig was completed to a high standard. While not simultaneously, muscle activity and kinematic data was successfully recorded to a high enough quality for satisfactory analysis. Analysis of the collected data took place and was successfully able to identify speed dependent markers within the kinematic data.

5 – Conclusion

In summary, speed dependent markers in the ligament stretch, and EMG data have been identified. Confirming the validity of implementing such a control system for a powered prosthetic device. With the identified markers, the control system can be realised as a state diagram. Ultimately, two of the three main objectives were met in their entirety. The completion of a robust redesign of the knee rig was successful, which allowed for the collection of quality data. While the electrophysical and kinematic data was not recorded simultaneously, it was recorded in a format for easy comparison, of which both trials followed the same procedure. Finally, the data was able to be comparably analysed, identifying correlating speed dependent markers, despite the methods of data capture and analysis varying from the original intention. With this, a feasible control system has been proposed, which is the ultimate aim of the project, to suggest improvement on speed detection in powered prosthetic devices.

6 - Future Considerations

Firstly, finding a solution to the tracking of the femur would be the immediate next step for this project. While percentage gait cycle is acceptable for analysis, it is an arbitrary measure that loses the dimension of time. To compare the cycle data to a direct measure of the system, like the knee angle, would give a more informative picture, and provides more information to design a control system.

This would be an opportunity to take repeat results to further solidify the conclusion. And an opertunity to recollect the sEMG simultaneously with the ligament data. This would help gain insight into the correlation of markers. However, the best source of data would be from the user itself. Adapting the rig for a transfemoral amputee would be a far more indicative data source of the practical use case, rather than the approximation of a “healthy” subject the project has operated under.

More ambitiously the next step would be to add more complexity to the system. Having the knee restricted to one plane reduces the potential data. Unrestricting it, having a 3-dimensional movement, would allow for further insight into the ligament stretch. Subsequently, replacing the rigid ankle joint with an ankle joint similar to the bioinspired design of the Russell knee joint, would allow for another level of data capture and understanding of the kinematics [12,16].

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8 - Appendices

8.1 – MATLAB Implementation.

8.1.1 – EMG Functions.

```
function filteredEMG = procEMG(EMG,en)
   % Bandpass filter EMG from 10Hz to 500Hz
   % 5 plot butterworth filtering.
   bpEMG = bpassEMG(EMG.v);
   % Rectifying EMG signal.
   recEMG = abs(bpEMG);
   % Calculating the signal envelope en.
   env = envEMG(recEMG,en);

   plot(EMG.t, EMG.v);
   hold
   plot(EMG.t, env, 'LineWidth',3);
   filteredEMG = array2table( [EMG.t, env] );
end
```

```
function bpEMG = bpassEMG(EMG)

   Freq = 2000;
   NyqFreq = Freq/2;
   % 500Hz lowpass 5 pole butterworth filter.
   Lowpass = 500;
   Wn = Lowpass/NyqFreq;
   [B,A] = butter (5,Wn,'low');
   lowEMG = filtfilt(B,A,EMG);
   % 10Hz highpass 5 pole butterworth filter.
   Highpass = 10;
   Wo = Highpass/NyqFreq;
   [D,C] = butter (5,Wo,'high');
   bpEMG = filtfilt(D,C,lowEMG);
```

```
end



function env = envEMG(EMG,co)

   % 5 plole lowpass butterworth filter with custom input.
   Freq = 2000;
   NyqFreq = Freq/2;
   Lowpass = co;
   Wn = Lowpass/NyqFreq;
   [B,A] = butter (5,Wn,'low');
   env = filtfilt(B,A,EMG);
end
```

8.1.2 – FSR Functions.

```
function ic = icFSR(fsr,dis)
   % Remove DC offest and inverse signal (Pull-up to Pull-down).
   invfsr = fsr - 5 ;
   invfsr = abs(invfsr);
   con = invfsr.v;
   % Remove anthing bellow 0.5 volts (Found to be insignifcant).
   for i = 1:size(con)
       if  con(i,:) < 0.5
           con(i, :) = 0;
       end
   end
   % Initalise binary array of points of contact.
   on = con > 0;
   ic = zeros(size(on));
   conflag = 0;
   previc = 0;
   % Detect initial contact peaks, if the next detected peak is within
   % minimium distance it is constsidered a blip and rejected, if not its
   % is then considered the next inital contact.
   for i = 1:length(on)
```

```
        if on(i) == 1 & conflag == 0
            if (i - previc) > dis
                ic(i) = 1;
                conflag = 1;
                previc = i;
            end
        elseif on(i) == 0 & conflag == 1
            conflag = 0;
        end
    end
    % Plot for visual verification, adjust min distance if needed.
    plot(fsr.t, fsr.v);
    hold
    plot(fsr.t, ic);
    ic = array2table([fsr.t, ic]);
end
```

8.1.3 – Motion Capture Functions.

```
function angle = kneeAng(tibia,femur)
    % Interpolation of rigid body data
    tibinter = fillmissing(tibia, "previous");
    feminter = fillmissing(femur, "previous");
    % Initialsing array
    [col,row] = size(tibinter);
    jtheta = zeros(col,1);
    rows = col;
    % Calcuting the angle from both quaterions, for the array.
    for rows = 1:rows
        pretib = tibinter(rows,2:5);
        prefem = feminter(rows,2:5);
        tib = quaternion(pretib.w, pretib.x, pretib.y, pretib.z);
        fem = quaternion(prefem.w, prefem.x, prefem.y, prefem.z);
        rot = tib * conj(fem);
        [a,b,c,d] = parts(rot);
        theta = 2*acos(a);
```

```
        jtheta(rows) = rad2deg(theta);
    end
```

8.1.4 – Plotting Functions.

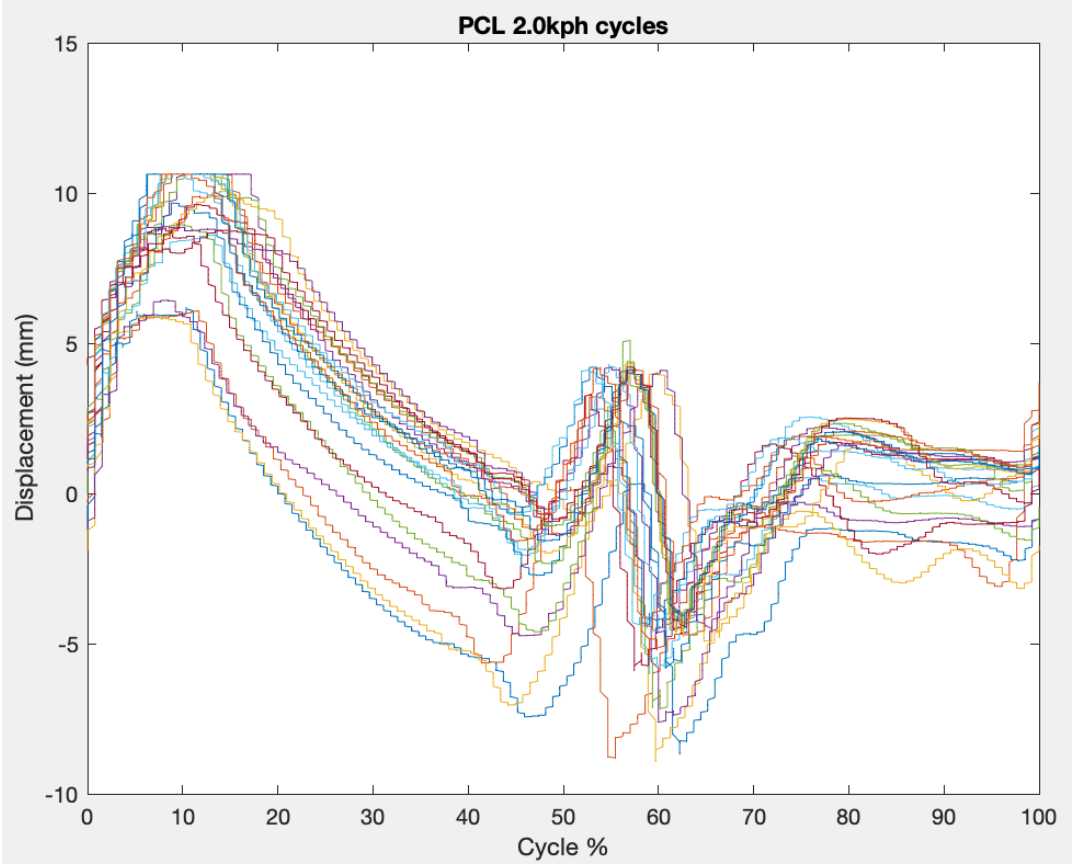
```
function cycles = cycleSep(data, ic)
    % Initialise varibles.
    first = 0;
    cycles = {};
    cycleNum = 0;
    primus = 0; % cycle start.
    ultimus = 0;  % cycle end.
    for i = 1:height(ic)
        if ic.c(i) == 1
            if first == 0
                %For the first initial contact, set start value and
                % increment cycle index.
                primus = i;
                first = 1;
                cycleNum = 1;
            elseif first == 1
                % For any other cycles, mark the end value.
                ultimus = i;
                % Isolate the cycle data from the trial.
                cycle = data(primus:ultimus, :);
                % Append cell array and increment cycle count.
                cycles{cycleNum} = cycle;
                cycleNum = cycleNum + 1;
                % End of current cycle becomes the next's start.
                primus = i;

            end
        end

    end
end
```

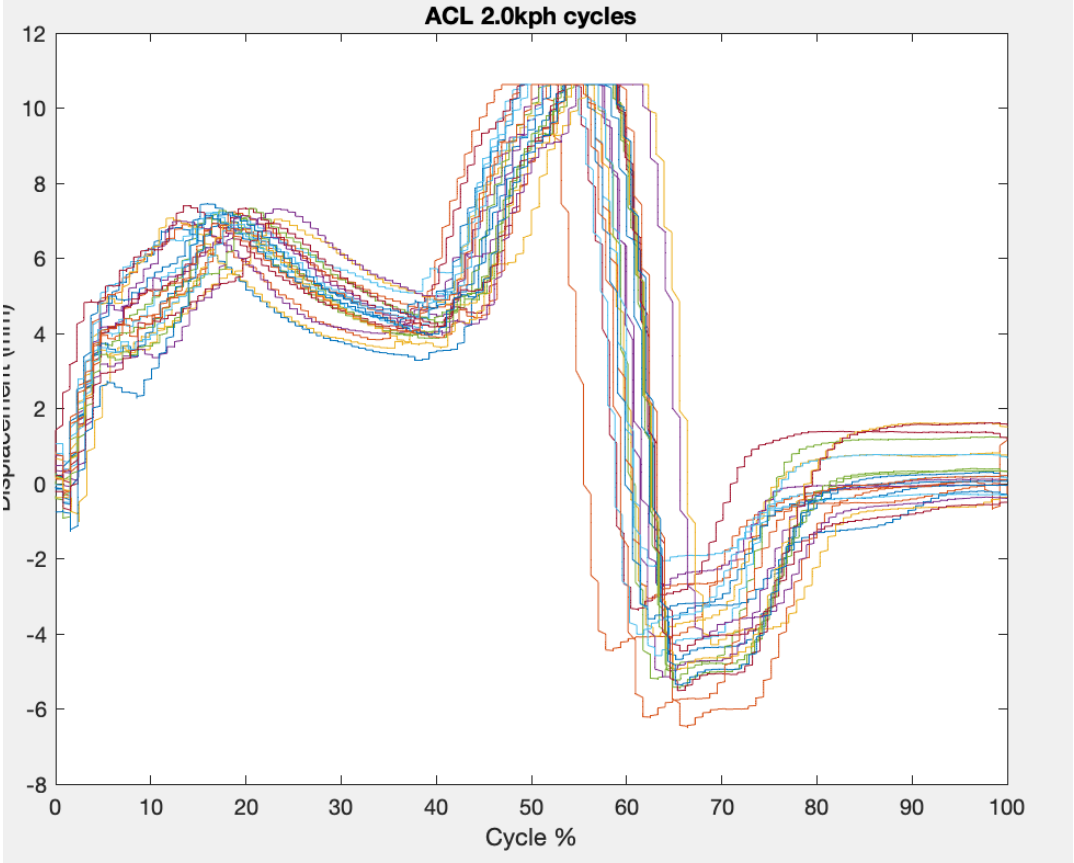
```
function cycAve = plotCycles(cycles,x,y)
   % New figure for plot.
   % For each cycle in cell array.
   for i = 1:numel(cycles)
       % For current cycle, find the time of the first value.
       currentCycle = cycles{i};
       currentTime = currentCycle.(1);
       primus = currentTime(1);
       % Remove the first time value from all values to start cycle at 0
       % seconds.
       for j = 1:height(currentTime)
           currentTime(j) = currentTime(j) - primus;
       end
       %Initialise array to calculate percentage progression.
       p = zeros(height(currentTime), 1);
       final = currentTime(height(currentTime));
       % Calcuate the cycles as a percentage progression.
       for k = 1:height(currentTime)
           p(k) = ( currentTime(k) / final ) * 100;
       end
       % Create time and percentage progession tables.
       tCycles{i} = table(currentTime, currentCycle.(2), 'VariableNames',
{'t', 'd'});
       pCycles{i} = table(p, currentCycle.(2), 'VariableNames', {'t',
'd'});

       % Plot current cycle as percentage progression.
       plot(p, currentCycle.(2));
       hold on;
   end
   % Average all the cycles.
   cycAve = cycleAve(tCycles);
   % Finalise plot.
   hold off;
   xlabel('Cycle %');
   ylabel(y);
```

```
    title(x);
end



function finalAve = cycleAve(cycles)
    % Finding the largest cycle within the cell array.
    largestLen = 0;
    for i = 1:width(cycles)
        % Length of cycle.
        len = height(cycles{1,i});
        % If cycle longer than previous longest.
        if len > largestLen
            % Cycle becomes new longest.
            largestCycle = i;
            largestLen = len;
        end
    end
    % Length of the cycle in time.
    maxTime = cycles{1, largestCycle}.(1)(largestLen);
    % Creating commond time grid using the longest cycle
    cycleTime = transpose(0:0.01:maxTime);
    cycleAmplitude = zeros(size(cycleTime));
    % Sum of every cycle, converted to the common time grid.
    for j = 1:width(cycles)
        % Making points unique.
        [uniqueTime, unPoin] = unique(cycles{1,j}.(1));
        amplitude = cycles{1,j}.(2)(unPoin);
        % Normalising time to a percentage.
        normalizedTime = uniqueTime / maxTime;
         % Summing the interpolate cyle amplitude in the common time grid.
        cycleAmplitude = cycleAmplitude + interp1(normalizedTime,
amplitude, (cycleTime/maxTime), 'linear', 'extrap');
    end

    % Calculating the average cycle.
    cycleAverage  =  cycleAmplitude / width(cycles);
    cycleProg = cycleTime/maxTime * 100;
```

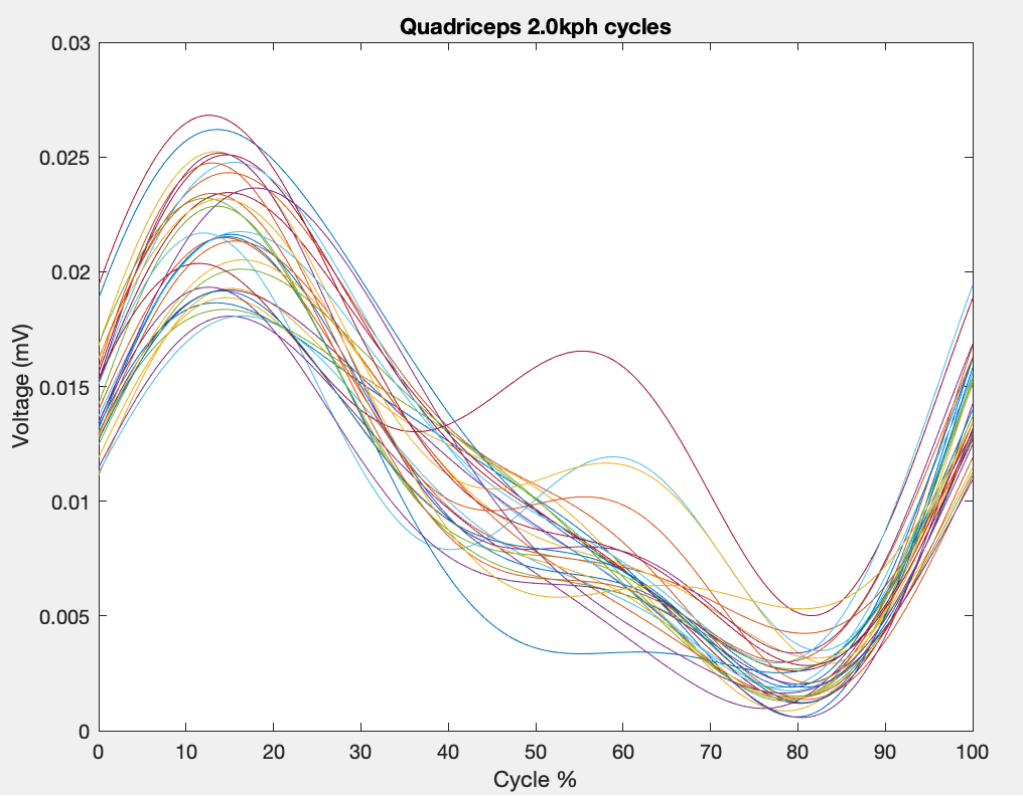
```
    plot(cycleProg, cycleAverage, 'LineWidth',3);
    finalAve = array2table([cycleProg,cycleAverage]);
end
```

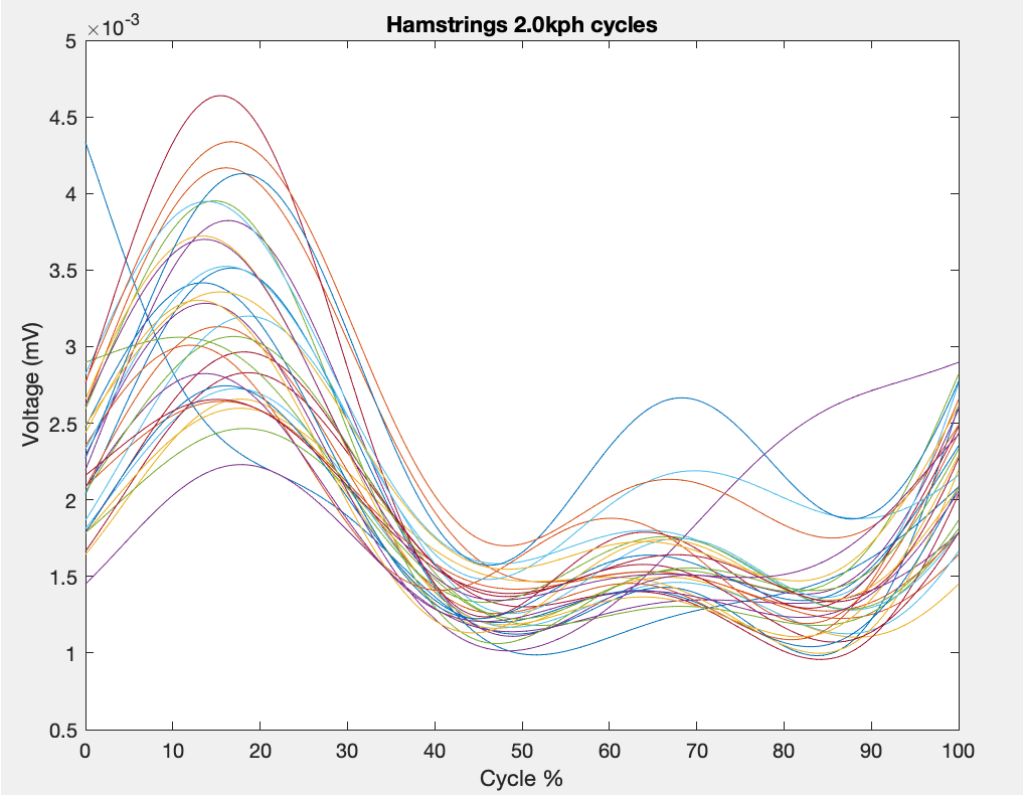
8.2 – Pre-Averaged Final Ligament Example





8.3 – Pre-Averaged Final EMG Example.





8.4 – Ethical Approval Form.

FAST-TRACK ETHICAL APPROVAL FORM (STUDENTS)

This fast-track system for is for taught students only. Research students and staff must complete the full Ethical Approval Form.

If you answer **YES** to any of the following you must complete either this Fast-track ethical approval form, to be signed off by your supervisor, or a full Ethical approval application, to be approved by the Physical Science Ethics Committee (allow at least two weeks for this process).

Note that the outcome of the Fast-track system may result in you needing to complete a full ethical approval application.

Does your project involve any of the following?

	YES	NO
Human participants (adults or children)	X	
Human material (e.g. tissue or fluid samples)		X
Human data (e.g. surveys and questionnaires on issues such as lifestyle, housing and working environments, attitudes and preferences)	X	
Vertebrates, especially mammals and birds		X
Any other organisms not previously mentioned		X
Military or defence context		X
Funding sources with potential to adversely affect existing relationships or bring the University or Department into disrepute.		X
Restrictions on dissemination		X
Overseas countries under regimes with poor human rights record or identified as dangerous by the Foreign & Commonwealth Office		X
Applications that could potentially involve unethical practice, including potential dual-use applications which could be unethical		X

Students: you should discuss the ethical considerations of your project with your project supervisor and, if necessary, fill in a full ethics form to be submitted to the Physical Sciences Ethics Committee.

Supervisors: Please ensure you are familiar with the University's 'Code of practice and principles for good ethical governance' in order to guide your student effectively. Please seek guidance from the Departmental Ethics Officer if you are uncertain about any ethical issue arising from this application.

FAST-TRACK ETHICAL APPROVAL FORM (STUDENTS)

Project Information:
Looking specifically at speed changes, the project aims to improve event detection in the context of a transfemoral powered prosthetics device. The project aims to find correlating events between the displacement of the knee's cruciate ligaments and the activation of the muscles of the surrounding muscles during gait.

Student Name: James Derek Clark

Course Title: Electronic Engineering

***Tick one box**:*

Undergraduate project □X Postgraduate project □

Undergraduate module assignment □ Postgraduate module assignment □

Other (Please state……) □

Title of project: Event Detection for Powered Limb Prothesis
Project supervisor / module leader name: Peter Ellison

Protocol:

a): *If you answer **NO** to any of the following you must submit a full ethical approval form*

X	*If you answer yes to any of the following, this must be explicit in any supporting literature (e.g. consent forms, information sheets and questionnaires)*	YES	NO	N/A
1	Will you describe the procedures to participants in advance, so that they are informed about what to expect?	X		
2	Will you tell participants that their participation is voluntary?	X		
3	Will you inform the participants of the purpose / background of the study?	X		
4	Will you obtain written consent for participation?	X		
5	If the research is observational, will you ask participants for their consent to being observed?	X		
6	Will you tell participants that they may withdraw from the research at any time and for any reason?	X		
7	With questionnaires and interviews will you give participants the option of omitting questions they do not want to answer?			X
8	Will you tell participants that their data will be treated with full confidentiality and that, if published, it will not be identifiable as theirs?	X		

Protocol:

b): *If you answer **YES** to any of the following you must submit a full ethical approval form.*

x		YES	NO	N/A
9	Is your study designed to be challenging/disturbing (physically or psychologically)?		X	
10	Will you deliberately mislead your participants?		x	
11	Does your study involve taking bodily samples?		x	
12	Is your study physically invasive?		x	
13	Is there any obvious or inevitable adaptation of your research findings to ethically questionable aims?		x	
14	Could the methodologies or findings of your study damage the reputation of the University of York?		x	

Health and Safety:
Please identify any risks to the participants and state any precautions you will take to ensure their health and safety:

No health and safety implications for anyone not listed in this document and any nearby researchers and all health and safety guidelines will be followed as set by the school of PET.

Participants: *If you answer **YES** to any of the following you must submit a full ethical approval form. If you have ticked **YES** to 15 and your participants are **patients**, in addition to the full ethical application you must follow the Guidelines for Ethical Approval of NHS Projects.*

			YES	NO	N/A
15	Does your project involve work with animals			x	
16	Will any of the participants be from one of the following vulnerable groups? **Note that you may also need to obtain satisfactory DBS clearance (or equivalent for overseas students)**	Children under 18		x	
		People with learning difficulties			
		People who are unconscious or severely ill			
		NHS patients			
		Other vulnerable groups (specify)			

Data Protection: *If you answer **NO** to any of the following you must submit a full ethical approval form*

		YES	NO	N/A
17	Any personal / sensitive data will be stored in password protected folders on computers.	x		
18	Any hard copies of personal data (including consent forms) will be stored in a secure place.	x		
19	Only the student and supervisors will have access to the data generated from the study. (The supervisor may share the anonymised data with other researchers at the University of York)	x		
20	The data will be preserved beyond the study in line with University policy and will be placed in the custody of the supervisor at the end of the project.	x		
21	All data will be anonymised prior to analysis. Please state your method of anonymisation: Data will be anonymised at the point of capture. No reference to the participant will be contained in the file names when saved.	X		

FOR THE STUDENT TO COMPLETE:

Please complete and sign the following section and submit to your supervisor alongside any supporting documentation (this includes consent forms, information sheets and questionnaires where necessary).

Provide a brief summary of the participants and procedures of your project (max 100 words)

The participant demographic will be healthy males, ages 18-25. Gait patterns vary significantly by gender; thus, the group will have to be all the same gender. Exclusion criteria will be participants with a history of knee injury/conditions. A sample size a 1 has been picked in acknowledgement of time constraints. It will involve having participants fitting their leg into a bent knee prothesis, with a mechanical knee. They will walk on a treadmill, in a motion capture volume, at various speeds. Surface electromyography will be used on multiple muscles of the thigh to obtain muscle activation data.

I have considered the ethical implications of this project and have identified no significant ethical implications requiring a full ethics submission to the Physical Sciences Ethics Committee ☐

I have included all relevant paperwork (e.g. consent form, information sheet, questionnaire/interview schedules) with this application ☐

Signed……  …… Print name: James Clark Date: 9/05/24
(Student)

FOR THE SUPERVISOR TO COMPLETE:
By signing this form you are taking responsibility for the ethical conduct of this project

The student has taken all reasonable steps to ensure ethical practice in this study and I can identify no significant ethical implications requiring a full ethics submission to the Physical Sciences Ethics Committee ☐

I have checked and approved all relevant paperwork required for this proposal ☐

STATEMENT OF ETHICAL APPROVAL

This project has been considered using the Physical Sciences Ethics Committee Fast-track ethical approval procedure, agreed by the Physical Sciences Ethics Committee of the University of York, and is now approved.

Signed…….. Print name Peter Ellison 
(Supervisor)

OR

The details on this form indicate a need for a full application to PSEC. The practical aspects of this project will not proceed until this has application has been approved.

Signed…….. Print name…….. Date……
(Supervisor/Module leader)