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| “The Development and Comparison of Impedance and Admittance Control Strategies for a 2 Degree of Freedom Planar Rehabilitation Robot” |
|  |
| PhD Transfer Report |
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**Abstract**

**Nomenclature**

* AR – Altered Reality
* CTE – Cognitive Therapeutic Exercise
* DoF – Degrees of Freedom
* FEA – Finite Element Analysis
* FPGA – Field Programmable Gate Array
* OS – Operating System
* PC – Personal Computer
* PNF – Proprioceptive Neuromuscular Facilitation
* RTOS – Real Time Operating System
* sEMG – Surface Electromyography
* VR – Virtual Reality

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# **Chapter 1: Introduction**

## Motivation

The likelihood of having a Stroke increases with age. Statistics show that the population of the UK is aging, due in part to an increase in life expectancy. This means that Stroke is becoming more prevalent in the UK, and this is a trend reflected across much of the Western world. The increase in Stroke prevalence places a large burden on the NHS and rehabilitation services, especially considering that it is understood that effective neural rehabilitation should be intensive and occur early after the onset of Stroke. In order to ease the burden on medical services and provide more access to therapy, research is increasingly focused on the use of robotics.

Rehabilitation robotics for the rehabilitation of neurological injuries such as Stroke are designed to assist the patient with training exercises, and by necessity focus on specific target areas. Gait trainers assist with walking rehabilitation, for example, and upper limb devices assist with reaching exercise training. The benefits of rehabilitation robotics are that repeatable, measurable and consistent training exercises can be provided alongside traditional human-led physiotherapy. This comes at the cost of systems which are expensive and therefore only appropriate to install in community settings such as hospitals, which limits the access to important rehabilitation. Whilst there has been some research into low cost robotic systems, all the commercially available rehabilitation robots cost in excess of $100 000.

## Current MyPAM Rehabilitation Robot

Placeholder - introduction

### Architecture

Placeholder

### Trajectory Generation and Low-Level Control

In the current MyPAM system the game is responsible for generating the trajectory for each reaching movement, running at 30Hz on the host PC. The game creates the final target position according to a high-level control strategy and generates equidistant intermediate positions between the start position and the final position as a linear path, as shown by figure 1.1:

|  |
| --- |
|  |
| **Figure 1.1:** *An example of a linear trajectory generated by the game*. |

These intermediate positions are passed one at a time to the low-level controller. The low-level controller, running at 500Hz on a Real Time Operating System (RTOS), is only aware of the current position and the next intermediate position. Using position PID, the low-level controller generates the motor demands. This can be considered as a highly coupled arrangement, since there is a dependence on reliable and timely communication between the game and the low-level controller to ensure correct and safe operation of the MyPAM.

# **Chapter 2: Literature Review**

## Stroke Mechanisms and Effects

Stroke, also known as Cerebrovascular Accident, is the leading cause of disability in the UK according to the Stroke Association (2018). Stroke is classified by 2 mechanisms: Haemorrhagic Stroke and Ischaemic Stroke. Haemorrhagic Stroke occurs when an artery in the brain ruptures, often as a result of high blood pressure. Ischaemic Stroke occurs due to the blockage of an artery in the brain, usually caused by a blood clot or fatty deposits. Both mechanisms lead to cell damage or cell death in the affected region of the brain because of a lack of oxygen (Moskowitz et al, 2010).

The symptoms of Stroke are wide ranging and dependant on which region of the brain has been affected and the severity of the Stroke. Different regions of the brain control different behaviour, as shown by figure 2.1 (Stroke Association, 2018):

|  |
| --- |
|  |
| **Figure 2.1:** *Different regions of the brain associated with control of different behaviours.* |

Common symptoms include motor impairment along one side of the body (known as hemiparesis), paralysis along one side of the body (hemiplegia), impairment to speech, difficulties swallowing, muscle spasticity (hypertonia) and impairment to memory. It was found in a study by Sommerfeld et al (2004) that up to 80% of Stroke patients initially experience motor difficulties. Lawrence et al (2001) performed a community-based study on first-time Stroke patients in which 77.4% of the Stroke patients suffered from upper limb impairment.

Stroke has a significant negative impact on a patient’s quality of life. Regular activities such as walking, eating, and manipulating objects become difficult or impossible. This often leads to dependency on care and assistance from others. Aside from the personal impact on the patient, Stroke has financial implications for society. Xu et al (2018) estimated the mean cost of health and social care per Stroke patient to be £46039. This figure is in close agreement with the Stroke Association (2017), who estimated that in 2015 the mean cost of health and social care per Stroke patient was £45409.

## Stroke Prevalence

A study by O’Mahony et al (1999) found that 1.75% of a sample population of 2000 had suffered from Stroke. Stroke can occur in people of any age, but it has been shown by the Stroke Association (2018) that the likelihood of an individual having a Stroke increases with age. According to the Office of National Statistics (2018) the population of the UK is aging, with 26.5% of the population projected to be aged 65 or older by 2041. This ‘greying’ of the population is common across most Western societies due to falling birth-rates and an increased life expectancy, a trend which is projected to become an issue globally. Figure 2.2 shows an age group distribution of the population using data gathered from 195 United Nations countries from 1950 onwards and projected to 2050 alongside a projection of the population aged 65 or older in the UK:

|  |  |
| --- | --- |
|  |  |
| **Figure 2.2:** *Left:* *Aging population in the UK (Office of National Statistics, 2018), and Right: the world (Lee and Mason, 2011).* | |

Observing the projected trend, it is reasonable to expect that the total number of Strokes will increase. This will increase the demand and financial costs upon the NHS and rehabilitation services, especially when considering that the research shows that early and intensive physical rehabilitation is an important factor in recovery.

## Stroke Recovery

### Neurological Recovery

Since Stroke is a neurological issue, it follows that Stroke recovery must exploit neurological mechanisms. Cerebral plasticity (otherwise known as neurofunctional plasticity) is the ability of the brain to “reorganise during ontogeny, learning or following damage” (Duffau, 2006). It is this ability of the brain to reorganise that provides the mechanism for Stroke recovery, though this mechanism is not yet fully understood according to Kreisel et al (2007).

Without the intervention of rehabilitation, there does remain some natural motor recovery after Stroke, though this varies considerably from patient to patient. The timeline for natural motor recovery after Stroke is summarised in the table 2.1:

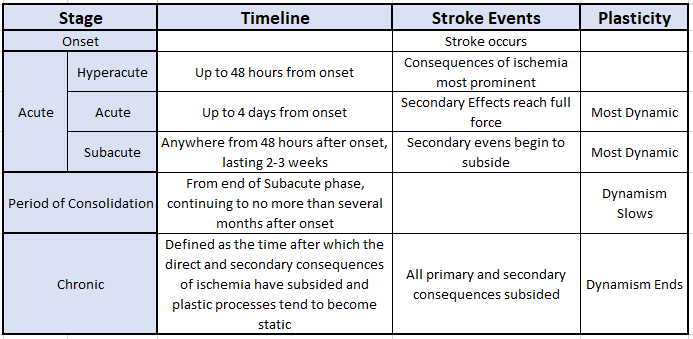


Table 2.1

It can be seen from table 2.1 that the neurofunctional plasticity of the brain is most dynamic after the Hyperacute phase, but then the dynamism slows. Once the patient has reached the Chronic stage, the plastic processes become static and motor deficits remain unchanged after this point without the intervention of therapy (Kreisel et al, 2007).

### Physiotherapy

The use of physiotherapy is an accepted element for the rehabilitation of Stroke patients. Physiotherapy is applied by trained physiotherapists, though there has been a rise in the use of robots for post-Stroke physiotherapy in recent years. There is little agreement on the effectiveness of different rehabilitation strategies. 2 main rehabilitation strategies are in widespread use according to Morreale et al (2016) and Coleman et al (2017). Proprioceptive Neuromuscular Facilitation (PNF) involves stretching and contracting a targeted muscle group, as shown by figure 2.3:

|  |
| --- |
|  |
| **Figure 2.3:** *Proprioceptive Neuromuscular Facilitation (PNF) (Marek et al, 2005)* |

More advanced PNF involves resisting the movement of the patient, although this relies on the patient having enough motor control to move the exercised limb.

Cognitive Therapeutic Exercise (CTE) involves high level cognitive training through task-based activity (Lee et al, 2015). Robotic rehabilitation devices use the CTE strategy due to the ease of the gamification of tasks using computer game or virtual reality technologies.

Van Peppen et al (2004) performed a systematic review which showed that physical rehabilitation is more effective when performed intensively and early after Stroke. This is corroborated by Morreale et al (2016), who observed that early intervention was a factor on the effectiveness of rehabilitation. Indeed, these findings make sense when considering the neurofunctional plasticity of the brain is most dynamic early after onset, as shown in table 2.1. Morreale et al (2016) also stated, however, that “the optimal schedule and content of rehabilitation in the acute phase of care is still undefined”. It is generally agreed that early intervention of physical rehabilitation is important for recovery, but there is little evidence to support the existence of an optimal rehabilitation strategy. Kreisel et al (2007) agree, stating that “mechanisms that support or modulate recovery are not yet fully understood”.

## Using Robots for Rehabilitation of Stroke Patients

In recent years there has been an increase in interest and research into the use of robots for rehabilitation of Stroke patients. According to Maciejasz et el (2014) and Culmer (2007), rehabilitation robots are categorised by their mechanical structure as either an end-effector based device or an exo-skeleton based device. These can be further categorised as Class 1 or Class 2 devices, as stated by Sulzer et al (2007) and Sivan et al (2014). Class 1 devices are of high cost and intended for lab or hospital use, whereas Class 2 devices are low cost and intended for home use. Most of the research in robotic rehabilitation devices has focused on Class 1 devices, since it was necessary to produce evidence that robotic rehabilitation was a valid rehabilitation strategy. However, Johnson et al (2007) identified a “need to improve the cost-to-benefit ratio of robot-assisted therapy strategies and their effectiveness for stroke therapy in home environments characterized by the low supervision by clinical experts, low extrinsic motivation as well as low cost requirement”, which justifies further work in the area of Class 2 devices.

### Control Hierarchy

An established control hierarchy exists for rehabilitation robotics, which is necessary since a high-level rehabilitation strategy must be encoded as low-level strategies according to Marchal-Crespo and Reinkensmeyer (2009). The high-level control strategy is responsible for generating tasks which fulfil rehabilitation aims. A trajectory must be generated from these tasks, and finally the low-level controller must use these trajectories to generate actuator demands. The low-level control strategies usually run in real time, since these control specific implementations of force, position or other types of interaction control. This hierarchy is shown by figure 2.4:

|  |
| --- |
|  |
| **Figure 2.4:** *Rehabilitation Robotics Control Hierarchy* |

### High Level Control Strategies

All rehabilitation robotic devices must consider and implement both high-level control strategies and low-level control algorithms according to both Maciejasz et al (2014), who performed a systematic review of rehabilitation robotic devices, and Marchal-Crespo and Reinkensmeyer (2009), who performed a systematic review of control strategies for rehabilitation robotic devices. The high-level control strategy describes the movement strategy of the robot designed to promote neurofunctional plasticity of the damaged motor control areas of the brain, whereas the low-level control algorithms describe the specific implementation of position, force, impedance or admittance control. Erol and Sarkar (2007) suggest that the role of the high-level controller is equivalent to the role of the physiotherapist, in that it monitors the status of the task, monitors the safety of the patient and “informs the low-level controller about the task updates”.

High-level control strategies can be broadly split into four categories: 1. Assistive control, 2. Challenge based control, 3. Haptic stimulation, and 4. Non-contacting coaching (Maciejasz et al, 2014) and (Marchal-Crespo and Reinkensmeyer, 2009).

Assistive control is a strategy whereby the patient is aided to complete the task. Usually, measures are put into place to allow the patient to move unrestricted as long as the correct trajectory is being followed. If there is deviation from the desired trajectory a restoring force proportional to the level of deviation is applied, as seen with the MIT-MANUS (Krebs et al, 2004). An Assistive control strategy is commonly implemented with Impedance or Admittance control as the low-level control algorithm. Another type of Assistive control uses a counterbalance to make a task easier for the patient, the Wilmington Robotic Exoskeleton (WREX) (Sanchez et al, 2005) being a good example. A further method of implementing Assistive control is to use Surface Electromyography (sEMG) sensors to measure signals in the nerves, which is used to trigger assistance according to the patient’s movement intention. This is difficult, however, since the noise to signal ratio is very high.

Challenge based control methods are designed to make the task more difficult for the patient, and are categorised as resistive, error amplifying or constraint induced. Resistive strategies resist the movement of the patient, simulating the more advanced techniques of Proprioceptive Neuromuscular Facilitation (PNF). Error amplifying strategies amplify movement errors rather than decrease them, according to (Marchal-Crespo and Reinkensmeyer, 2009). Error amplification strategies have been shown to increase motor learning compared with assistive strategies according to Patton et al (2006), who tested 18 hemiparetic Stroke patients.

Constraint induced strategies involve constraining the unimpaired limb, so that the impaired limb must perform the task. This particular strategy is particularly suited to exercises involving 2 limbs, for example reaching for a sizable object. Constraint induced strategies are not relevant, however, for end effector type devices such as the MIT-MANUS or MyPAM. In general, challenge-based control methods are not useful for severely impaired patients with little or no motor control, since the patient does not have sufficient control to begin the required movement.

Haptic strategies involve the use of Virtual Reality (VR) or Altered Reality (AR), where the user must where a headpiece which provides visual feedback in a 3-Dimensional environment. This was implemented by Montagne et el (2007), who found that the use of an engaging VR environment for visual feedback coupled with an exoskeleton robotic rehabilitation device significantly increased patient motivation. A clinical trial of this device showed increased motor control after 6 weeks of use, though only 3 chronic patients were tested and there is no evidence to show that the implementation of VR provides a greater clinical benefit than simply displaying visual feedback via a computer screen, as implemented by many other robotic rehabilitation devices.  
 Non-contact coaching devices do not interact with the patient, and simply provide instructions to the patient, according to both Maciejasz et al (2014) and Marchal-Crespo and Reinkensmeyer (2009). This may be useful for patients with high amounts of motor control but is not useful for patients with higher levels of disability who require assistance to complete exercises.

### Trajectory Generation

As with any robot designed to move an end-effector from a starting position to a desired position, a trajectory must be generated. A number of approaches exist, the selection of which depends on what the trajectory is required to optimise. The simplest solution is to generate a simple linear trajectory which covers the shortest distance between the current position and the desired position, which is the current trajectory generation method for the MyPAM. This method, however, potentially means that unacceptable changes in acceleration may be planned.

A better solution, implemented by the MIT-MANUS (Hogan et el, 1998), produces a minimum jerk trajectory. A minimum jerk trajectory minimises jerk, which is the third time derivative of position (), thus a minimum jerk trajectory ensures that there should be no unacceptable changes in acceleration. Minimum jerk trajectories are an example of trajectories based on normative mathematics, which cover the most common trajectories used for rehabilitation robotics according to Marchal-Crespo and Reinkensmeyer (2009), though there is no evidence that normative trajectories maximise motor plasticity. Another common approach is to pre-record a trajectory, whilst a further, less common, method is to generate the trajectory based off of the movement of the non-affected limb

### Low-Level Control

It is the responsibility of the low-level controller to use the trajectory to generate actuator demands. This may be achieved simply by position control, as with the MyPAM, or Force control. More complex low-level controllers employ interaction control schemes. Maciejasz et al (2014) argue that the case of a robotic physiotherapy device interacting with a human patient should be considered as a coupled mechanical system. This means that the use of a force control strategy or a position control strategy alone is insufficient, since interaction forces with the patient are not accounted for and are thus inherently unsafe. Further to this, failure to account for interaction forces raises the possibility of controller instability. Hogan and Buerger (2004) demonstrated this instability by showing that the Rough-Hurwitz stability criterion were met when considering an example system in isolation but were not met when considering the same system in a coupled mechanism.

In order to account for interaction forces, the majority of rehabilitation robotic devices employ Impedance Control or Admittance Control as the low-level control strategy. Impedance Control and Admittance Control involve modulating the dynamic behaviour of the robot alongside position or force control, according to Hogan (1984), by specifying the robot’s position and force relationship using virtual mass, spring and damping characteristics. Essentially, the desired position changes due to the application of an external force in a predictable manner defined by the mass, spring and damping characteristics, which are heuristically determined (Richardson, 2001). This is shown by explains this using figure 2.5:

|  |
| --- |
|  |
| **Figure 2.5:** *The external force changing the desired position (Richardson, 2001)* |

A physical system which accepts force inputs and produces position outputs is defined as an admittance. A physical system which accepts position inputs and produces force outputs is defined as an impedance (Ott et al, 2010) (Hogan,1984). The end effector of a mechanically coupled robot is subject to physical constraints, so it may act as either an admittance or an impedance. If the environment acts as an admittance, the end effector must act as an impedance according to Hogan (1984). Conversely, if the environment acts as an impedance, the end effector must act as an admittance. The practicalities of what this means will be discussed in the next 3 sections.

### Admittance Control

Admittance control is a strategy whereby the force exerted on the end effector is measured, and the robot provides the corresponding displacement (Maciejasz et el, 2014). This means that the controller is acting as an admittance and the environment is acting as an impedance. As such, an Admittance control strategy is based around an inner loop position controller, as shown by the block diagram in figure 1.5.4.1:

|  |
| --- |
|  |
| Figure 1.5.4.1: A block diagram for a generic Admittance Controller (Richardson, 2001) |

According to Culmer et al (2010), the control signal can be simply defined as shown by equation 1.5.4.1:

|  |  |
| --- | --- |
|  | Eqn 1.5.4.1 |

Where:

### Impedance Control

Impedance control is a strategy whereby the motion of the end effector is measured, and the robot provides the corresponding force-feedback (Maciejasz et el, 2014). This means that the controller is acting as an impedance and the environment is acting as an admittance. An Impedance control strategy is based around an inner loop force controller, as shown by the block diagram in figure 1.5.5.1:

|  |
| --- |
|  |
| Figure 1.5.5.1: A block diagram for a generic Impedance Controller (Richardson, 2001) |

According to Culmer et al (2010), the control signal can be simply defined as shown by equation 1.5.5.1:

|  |  |
| --- | --- |
|  | Eqn 1.5.5.1 |

Where:

# **Chapter 3: Current Work**

## Trajectory Generation

As described in section 1.2.2, in the current version of the MyPAM the game generates equidistant intermediate positions between the start position and the final position of each reaching movement and passes these one at a time to the low-level controller. This leads to a number of issues:

1. A linear trajectory of this nature is not reflective of natural human motion.
2. The game does not operate at 30 Hz reliably as a result of being dependant of the non-deterministic Operating System (OS) on Windows. There may be instances where the game rate will drop, resulting in incorrect intermediate position data being sent to the controller.
3. There are occasions where no intermediate points are generated and the final target position is sent to the controller as the next target, for example during some game types and during transitions between different games. This leads to a large difference between the current position and the target position, and large motor demands are generated. This leads to aggressive accelerations and potentially dangerous interaction forces between the patient and the robot.

### Generating a Smooth Trajectory

A smooth trajectory is desirable in order to mimic natural human motion when assisting the user to reach a target. Mathematically, a smooth trajectory translates to minimising the rate of change of an input, where the input corresponds to the order of the system. For example, a 1st order system corresponds to a kinematic model where velocities may be arbitrarily specified. This is summarised in the table 3.1 below:

|  |  |
| --- | --- |
| **Order of the system** | **Input to the system** |
| 1st | Velocity, |
| 2nd | Acceleration, |
| 3rd | Jerk, |
| 4th | Snap, |
| 5th | Crackle, |
| 6th | Pop, |

Table 3.1

The function for the trajectory may be found using Calculus of Variations, using the general equation shown by Equation 3.1:

|  |  |
| --- | --- |
|  | *(3.1)* |

Where .

Alternatively, the trajectory may be found by satisfying the Euler-Lagrange equation shown by Equation 3.2:

|  |  |
| --- | --- |
|  | *(3.2)* |

### Minimum Jerk Trajectories

For a Minimum Jerk Trajectory, , since a minimum jerk trajectory is based on minimising the sum of squared jerk across the trajectory (Flash and Hogan,1985).

Forming the Euler-Lagrange formulation as shown by Equation 3.3:

|  |  |
| --- | --- |
|  | *(3.3)* |
|  | *(3.4)* |
|  | *(3.5)* |
|  | *(3.6)* |
|  | *(3.7)* |
|  | *(3.8)* |
|  | *(3.9)* |
|  | *(3.10)* |
|  | *(3.11)* |
|  | *(3.12)* |

The boundary conditions are shown by table 3.2:

|  |  |  |  |
| --- | --- | --- | --- |
|  | Position, | Velocity, | Acceleration, |
| t = 0 | a | 0 | 0 |
| t = tf | b | 0 | 0 |

Table 3.2

The function x(t) shown by Equation 3.12 must be differentiated twice to give the function for velocity and acceleration.

|  |  |
| --- | --- |
|  | *(3.12)* |

Thus:

|  |  |
| --- | --- |
|  | *(3.13)* |
|  | *(3.14)* |

Substituting boundary conditions:

|  |  |
| --- | --- |
|  | *(3.15)* |
|  | *(3.16)* |
|  | *(3.17)* |
|  | *(3.18)* |
|  | *(3.19)* |
|  | *(3.20)* |

Solving for the coefficients:

|  |  |
| --- | --- |
|  | *(3.21)* |
|  | *(3.22)* |

Substituting the coefficients into equation 3.12 produces equation 3.23:

|  |  |
| --- | --- |
|  | *(3.23)* |

Finally producing the minimum jerk trajectory shown by equation 3.24:

|  |  |
| --- | --- |
|  | *(3.24)* |

Where:

This matches the function for a Minimum Jerk Trajectory found by Flash and Hogan (1985). A similar proof by Calculus of Variations may be found in Appendix A.

### Justifying the use of a Minimum Jerk Trajectory

A Minimum Jerk Trajectory produces a smooth trajectory, but so too do other trajectories based on minimising the squared sum of derivatives of position. Figure 3.x shows position and velocity graphs for the Minimum Acceleration, Minimum Jerk, Minimum Snap, Minimum Crackle and Minimum Pop trajectories to displace x from 0-100mm in 2 seconds. It may be observed that as the order of the system increases the position curve approaches a step function and the peak acceleration increases.

|  |
| --- |
|  |
| **Figure 3.x:** *Position and Velocity Graphs showing a displacement of 100mm in 2 seconds using Minimum Acceleration, Jerk, Snap, Crackle and Pop trajectories.* |

For assistive rehabilitation technology, it would be advantageous to generate a trajectory which mimics human movement. According to Richardson and Flash (2002), one measure of human reaching motion is the ratio of peak velocity to average velocity across the movement. Flash and Hogan (1985) found that the ratio of peak velocity to average velocity, R, across a reaching movement is around 1.8. The ratio for Minimum Acceleration, Minimum Jerk, Minimum Snap, Minimum Crackle and Minimum Pop trajectories is shown by table x:

|  |  |
| --- | --- |
| **Trajectory Type** | **R = Peak Velocity/Average Velocity** |
| Minimum Acceleration | 1.50 |
| Minimum Jerk | 1.88 |
| Minimum Snap | 2.19 |
| Minimum Crackle | 2.46 |
| Minimum Pop | 2.71 |

Table 2

Thus, it is clear that by this measure the Minimum Jerk trajectory most closely resembles natural human motion and is therefore the most appropriate trajectory for the MyPAM.

## End-Effector Force Sensor

A necessary component for the Admittance or Impedance control schemes planned for comparison on the MyPAM is the ability to measure the interaction force between the patient and the end effector. Since the MyPAM is planar, it is only necessary to measure the x-y components of force (2 DoF). The majority of rehabilitation robots which require a force sensor use off the shelf force sensors. For example, the iPAM used a 6-axis ATI Mini40 (Culmer, 2007), with a cost of around $5500. Since the MyPAM is designed to be a low-cost device it is necessary to develop an economically viable force sensor.

The majority of industrial force sensors operate by measuring strain and converting this into a force reading. Other force sensing methodologies include piezoelectric transducers. Both of these methodologies have downsides for the MyPAM, which are xxxxx. In recent years there has been much development in tactile sensors blah blah blah Petes stuff. This is promising because it allows a low-cost force sensor to be designed for the MyPAM.

### Sensor Design

The handle for the end effector and 2 DoF force sensor were designed as an integrated unit. A rigid aluminium core connects to the end effector housing and was embedded with hall effects sensors. A rigid outer core embedded with neodymium magnets was placed round the inner core, and a hyperelastic silicone material separation layer was placed between the 2 cores, such that an applied force allows the outer core to displace relative to the inner core. This arrangement is shown by figure 3.x:

|  |
| --- |
|  |
| **Figure 3.x:** *The integrated end-effector and force sensor design.* |

Finite Element Analysis (FEA) was performed to determine a good configuration for the hyperelastic silicone separation layer. EcoFlex™ 0010 and EcoFlex™ 0050 were selected as the hyperelastic silicone material because materials from EcoFlex™ have successfully been used in the manufacture of low-cost force sensors previously by Wang et al (2016). There were some difficulties in modelling the hyperplastic silicone, since the EcoFlex™ products are not traditional engineering materials and as such do not have published material properties. Further to this, whilst EcoFlex™ products have been used in a similar manner in some published scientific work, either the necessary material properties have either been left unpublished or there is disagreement in the published data, which may have arisen due to differences in mixing ratios and testing environments. To this end the FEA results were not considered reliable and 4 physical prototypes were built to find the most appropriate composition. Describe Composition. This can be seen in figure 3.x below:

|  |
| --- |
|  |
| **Figure 3.x:** *The composition of the 4 physical test pieces* |

### Data Acquisition and processing

Data acquisition is performed using an Arduino. The Arduino reads the voltage at the 4 Hall Effects sensors and runs the raw voltage values (which may range between 0 and 1023 since the Arduino is a 10-bit device) through a moving average filter to smooth any measurement noise. The Arduino then builds a transmission frame consisting of 6 bits to begin the message frame followed by 40 bits consisting of the filtered data. This message frame is shown by figure 3.x:

|  |
| --- |
|  |
| **Figure 3.x:** *The message frame* |

The message frame is transmitted via serial to the myRIO when a ‘send’ command is received.

The myRIO sends a request to the Arduino via serial when a frame desired. Upon receipt, the first 6 bits and the length of the frame are checked to see if the frame is valid, where any invalid message frames are discarded. The message frame is then spilt into individual data for each sensor, and run through a neural network which has been trained to obtain Fx and Fy from the raw voltage values. This architecture is shown by figure 3.x:

|  |
| --- |
|  |
| **Figure 3.x:** *The system architecture for the force sensor* |

## Admittance Filter

Placeholder

# **Chapter 4: Future Work**

## Trajectory Validation

Placeholder

## Force Sensor

Placeholder

## Admittance Control

Placeholder

## Impedance Control

Placeholder

## Re-architecture

Placeholder

## Testing and Interdependencies

Placeholder

## Work Plan

Placeholder

# **Chapter 5: References**

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**Appendices**

Appendix A: Calculating the Minimum Jerk Trajectory using Calculus of Variations

For a Minimum Jerk Trajectory, (Flash and Hogan,1985). Using Equation 3.1:

|  |  |
| --- | --- |
|  | *(A.1)* |
|  | *(A.2)* |

Multiplying through by ½ simplifies the maths later on.

Introducing a small variation, , which has the following properties:

|  |  |
| --- | --- |
|  | *(A.3)* |

To minimise , add as a variation:

|  |  |
| --- | --- |
|  | *(A.4)* |
|  | *(A.5)* |

Differentiating with respect to :

|  |  |
| --- | --- |
|  | *(A.6)* |
|  | *(A.7)* |

Integrating by parts:

|  |  |
| --- | --- |
|  | *(A.8)* |

Where:

|  |  |
| --- | --- |
|  | *(A.9)* |

Thus:

|  |  |
| --- | --- |
|  | *(A.10)* |

Integrating by parts again:

|  |  |
| --- | --- |
|  | *(A.11)* |

Where:

|  |  |
| --- | --- |
|  | *(A.12)* |

Thus:

|  |  |
| --- | --- |
|  | *(A.13)* |

Integrating by parts a final time:

|  |  |
| --- | --- |
|  | *(A.14)* |

Where:

|  |  |
| --- | --- |
|  | *(A.15)* |

Thus:

|  |  |
| --- | --- |
|  | *(A.16)* |

Finally producing:

|  |  |
| --- | --- |
|  | *(A.17)* |

Since this must hold true for any function of which has the properties specified above, this means that Equation A.18 must be true:

|  |  |
| --- | --- |
|  | *(A.18)* |

Which may then be solved for as shown in section 3.12 of this report to provide the Minimum Jerk Trajectory.