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Abstract : The state-of-the-art in distal upper-extremity prostheses is an underactuated hand with few degrees of control. Consequently, physiological acceptance and hand dexterity are compromised. We hypothesise that a fundamentally limiting aspect of the amputee's learning process is the lack of sensory feedback. In this technical report we present an idealised experimental setup in which we will address this hypothesis under a variety of hand control and artificial sensory feedback methods, regarding the healthy human hand as a gold standard. Treating the resulting prosthesis as a model of the healthy hand, we we will attempt to answer some interesting open questions in human sensorimotor control. We will use the closed-loop device as a novel manipulandum which, unlike in healthy individuals, can be independently deprived of proprioception, exteroception and control at a fine temporal granularity.

Keywords : Prosthetic hand, Sensory feedback, Proprioception, Force feedback, Closed-loop

Contents

1 Introduction

Users of state-of-the-art prosthetic hands face a difficult learning challenge. Dexterous robotic prosthetic hands are unnatural to control and clumsy [57], requiring constant attention when in use. While amputees may desire the dexterity and functionality of a real hand, they also require for the hand to feel like their own, and to be able to use it without conscious effort. As dexterity increases, patient acceptance decreases, thus the state-of-the-art is an underactuated hand with limited degrees of control. We hypothesise that a fundamentally limiting aspect of the amputee's learning process is the lack of feedback, and that a closed-loop device would be significantly advantageous for both acceptance and dexterity.

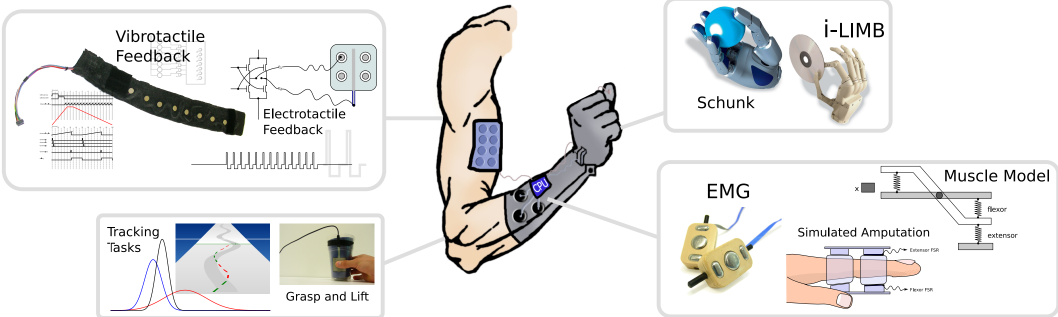

Figure 1: Components of the closed-loop prosthetic hand project. Our research aims at improving prosthetic hand function and understanding the underlying sensorimotor processes.

In this project there are three themes under investigation:

- The benefits and limitations of a closed-loop prosthetic hand for amputees.
- The neural and cognitive mechanisms underlying sensory substitution.
- The underlying mechanisms of sensorimotor learning and control.

In this report I will introduce a closed-loop prosthetic hand model, combining the i-LIMB a state-of-the-art prosthetic hand, with custom built artificial feedback interface. My project aims to address the limiting factors of the closed-loop model, with an aim of understanding the underlying sensorimotor processes from a neuroscientific and rehabilitative persepctive. Rather than attempting to engineer a new robotic hand, we propose to take the healthy hand as the gold standard and strip it gradually of its (feedback) components by means of anaesthesia, providing a novel experimental angle on sensory restoration. We present a simulated amputation, which will allow us to control for the limitations of the brain computer interface such as noisy EMG. Having idealised these control components of the closed-loop model we should be able to obtain objective results regarding the benefits of sensory feedback for amputees. We should be able to observe a transition from the apparently sub-optimal performance of prosthesis users on tasks such as approaching, grasping, identifying and manipulating objects to behaviour that is more like that of healthy individuals. This technical report outlines the technological and theoretical progress thus far, and details the experiments we are presently undertaking.

2 Background

2.1 Closed-loop prosthetics

2.1.1 The gold standard

The healthy human hand is remarkably dexterous, seemingly effortless to control and equipped with a vast sensory system. Replicating these features in a robotic hand is the holy grail of prosthetics. In aiming for humanoid robotics we must consider why it is that human hand control, despite the high level of variability and redundancy in sensory and motor systems, has such remarkable capabilities, and why current prosthetic hands fall far from this target.

2.1.2 Sensory Substitution

Bach-y-Rita, pioneer of the first tactile vision substitution system (TVSS) [4], made astonishing findings regarding the latent plasticity of the adult brain. He described a vision substitution system which provided video camera footage to the lower back using 400 vibrating solenoid stimulators. Initial training with horizontal and vertical lines was advanced to objects, multiple objects and faces. Blind subjects could perform complex scene classifications that would normally be only possible by the sighted [4, 5, 6]. TVSS experiments reported near-immediate acquisition of basic skills such as orientation to light sources, tracking target objects and discriminating orientations.

Since his landmark work he has restored vision to the blind through electrotactile tongue electrodes [37] and balance to the vestibularly impaired [51]. The amazing capacity of the peripheral nervous system to make sense of artificial sensory data has important implications in any system of sensory deprivation, notwithstanding the loss of a limb such as with amputees. For restoration of hand sensibility we can ask *what* items of information are required, and *how* to best communicate them to the subject. The potential bandwidth of the tactile channel is phenomenal, but with limited remaining plasticity in the nervous system it will be a challenge to harness the full potential of the available cognitive resources.

It is also interesting to note that learning is poor unless the subject can manipulate the camera themselves. This highlights the importance of a closed loop for learning.

2.1.3 Sensory feedback for amputees

Hand-amputees have lost not only control but sensation from their hands. The development of highly dexterous and functional robotic replacements is useful only to the point where the hand is still controllable. Unfortunately, this means amputees rely on underactuated and therefore "clumsy" devices [57]. Lack of functionality, controlability, sensory feedback and feeling the hand as part of your own body are the most common complaints by amputees, and 30-50% of upper extremity amputees do not use their prosthetic hand regularly [14]. To solve this, the idea of adding feedback to prosthetic devices emerged in the late 1970s [39, 40, 41].

Prosthetic systems providing vibrotactile force feedback are non-invasive and safe, and are readily accepted by amputees [28]. Cipriani *et al.* show that 'reach, pick and lift' trials are improved in amputees with a single element of force feedback [14], and they report increased acceptance and usability. Similarly, amputees respond positively and rely less on visual control when picking up a soft ball [35]. These subjective results highlight the importance of sensory feedback, motivating an objective quantification of performance, learning rates and degree of integration.

Cincotti *et al.* examined the benefits of tactile feedback in a spatial navigation task designed for EEG control [13]. A screen provided task information (the position of a placeholder within a maze of rooms), while tactors on the shoulders and a separate screen gave feedback of a cursor representing the subject's navigational decision. The subject was required to select a 'go left' or 'go right' option with a noise-corrupted cursor, placing high demands on feedback of the cursor position. To make the task even more visually demanding, a coloured key would occasionally pop up on the screen, and the subject was required to verbalise this colour correctly. Two modes of operation were tested - visual and vibrotactile. The vibrotactile channel proved effective in reducing errors in naming the colours (indicating decreased visual load), while remaining comparable to the visual channel for navigating. It is unknown how subjects would perform with a multimodal version of the task. The effects of training on performance are also not shown. However, it is clear that when visual attention is compromised, the tactile modality can be of quantifiable benefit.

The benefits of feedback for control have not yet received rigorous quantification. This could be due to either technological or cognitive limitations. We therefore choose a more theoretical approach in the present research project. From the perspective of human sensorimotor control we will isolate the components of human hand function that enable successful manipulation; only then can we begin to transfer this to the amputee.

2.2 Human sensorimotor control

2.2.1 Sensory Systems

Manipulation of objects is a skill we take many years to refine. A typical daily task which healthy individuals take for granted is that of reaching, grasping and lifting an object. Each of these phases requires careful modulation of muscle forces, which is very difficult for an open-loop control policy.

The tactile sense is not only capable of determining grip force, but also object roughness [23], surface patterns [11], curvature and force direction [25], object taper [22], torque loads and mass distributions [25], softness [45], shape [53] and orientation [21], to name but a few. While it is known that we *can* interpret these properties, it is not known which items of information *are* exploited by the nervous system to aid manipulating objects. This is made even more challenging due to the predominantly unconscious processing of the tactile modality. Understanding the role and function of different feedback sources is thus still an open question.

Each fingertip contains around 2000 tactile sensors, with different temporal and spatial characteristics. Fast adapting sensors indicate onset and offset of tactile events, while slow adapting sensors give absolute feedback. The fast adapting neurons are suspected to inform the brain of 'goal completion', spiking on object contact, lift-off and slip [25]. On the other hand the visual modality is slow, inaccurate and requires conscious effort to decode these features, presumably resulting the slow, sequential and un-natural hand control we observe in amputees.

Aside from the sense of touch, another important sensory signal arises from muscles and joints. This proprioceptive feedback gives us knowledge of the position of our body in space. Without vision monkeys can accurately point to targets, but proprioceptive deafferentation impairs this capacity [49]. As well as being of functional importance, proprioception is linked to the feeling of body ownership and therefore prosthesis acceptance. Proprioception is a readily adapting sense (relying on visual feedback to maintain its calibration). In modulating grip aperture, for example, one can use a virtual reality set up to shift proprioceptive feedback. However, while we adapt readily to changes in offsets in aperture size we are less adaptive to changes in the slope [36].

Amputees controlling a prosthesis with residual muscles may have some access to proprioceptive feedback – through intrafusal muscle fibres they can detect muscle contraction. This feedback could be utilised by using a control strategy in which *perceived* muscle force were mapped directly to *applied* muscle force of a robot simulating a human hand. No additional learning or re-mapping would be needed in this case. It has been shown in amputees that in the absence of visual and proprioceptive feedback, muscle-activity and the efferent copy of the motor command are what create the perception of movement in the phantom limb [26]. In closing the loop we ought to consider the relationship between perception and action to make learning as simple as possible.

In summary, proprioceptive, tactile and force feedback are key components of the healthy human hand. How does the nervous system integrate these percepts to provide dexterous, adaptive and dynamic interactions with the world, and how do we exploit latent neural plasticity, the adaptive capacity of the senses and residual feedback to enhance prosthesis control and reduce mental effort? Our experimental setup will allow us to address these questions.

2.2.2 Muscles

Muscles are elastic, and induce torques around joints. Joints are equipped with agonistic and antagonistic muscles, and it is the combined contribution of these muscles that determines the final joint torque generated. In joints such as the fingers a curled 'rest state' exists due to the viscoelastic properties of the hand and forearm muscles. Under no external load there is an approximate one-to-one mapping between a muscle activity and finger position. This is could be replicated in a servo motor with a *position-control* policy. When the hand is in contact with an rigid load such as an object being grasped, there is an approximate one-to-one mapping between muscle activity and the force applied. This could be termed a *force-control* policy. These are both *absolute* control policies. Contrastingly, the i-LIMB a state-of-the art robotic prosthetic hand, adopts a *relative* control policy, meaning that muscle activity sets the movement speed of the fingers (it sets the torque on the worm gear motors, which is a *speed-control* policy under no external load, or a *yank-control* policy for a rigid load). To set your fingers to a desired position or force in a relative control policy you would need to integrate the control signal over time (a potentially challenging task), which may explain the demand for visual attention for users of the i-LIMB.

In 1968 Long *et al.* used electromyographic recordings of hand and forearm muscles to classify finger control [32]. Three major muscles were identified as critical for basic movements, namely the flexor digitorum profundus (FDP), extensor digitorum (ED) and the lumbricalis (L). FDP and ED are located in the forearm, and L in the palm. The fingers are at rest in a slightly curled posture under the elastic influence of FDP. When ED is contracted alone the fingers 'claw', bending at only the distal joints. Simultaneous contraction of FDP with ED is sufficient to fully flex the finger joints. L opposes and does not contract simultaneously with FDP. L extends the knuckle joint and relaxes the elastic effect of FDP, allowing ED to extend the fingers.

Previous hand prostheses have adopted the idea of 'extended physiological proprioception' (EPP), the ability to use proprioceptive feedback to infer the state of an external tool. An *absolute* control policy facilitates this. Shoulder-powered prostheses use the shoulder position to set the arm position, and grasp closure, and such a direct mapping from signal to action has been shown to be superior to speed-controlled prostheses [16].

- Are current prostheses limited by their absent senses of touch and proprioception or by an inadequate control policy?

2.2.3 Anticipatory behaviour

Johansson and colleagues have accumulated a large body of evidence over the past two decades pertaining to the simple precision grip. Healthy individuals adjust grip force to an amount just greater than is sufficient to avoid object slip. Rarely do healthy subjects over-grip objects, a mechanism which serves to avoid muscle fatigue and breaking the object in question [23, 24]. We are able to predictively estimate the grip force required based on object surface properties detected by the skin. Visual and tactile memories serve to speed up this process so that we can behave in a feed-forward manner.

When we lift an object we increase the grip force in parallel with the lifting (or load) force (figure **2**). The slope of the increase will depend on the frictional properties of the surface; a higher 'grip to load ratio'. By ramping the grip in parallel with the load we need only accurately predict the grip-to-load ratio in order to lift the object, not the final mass, as we simply increase grip and lift together until object lift off, making movement robust to unexpected loads. Amputees on the other hand do not appear to gauge these forces, and tend to over-grip.

Not only do we predictively accommodate loads of varying magnitude and surface properties with economical grip forces, we anticipate the load changes during acceleration of the object [20]. For example, for cyclic movements we continuously increase and decrease our grip force with the upward and downward deceleration components of the motion respectively, even though it might be simpler to just maintain our grip force at the maximum expected. Interestingly, while digital anaesthesia impairs modulation of grip force magnitude, it does not impair the timing of these

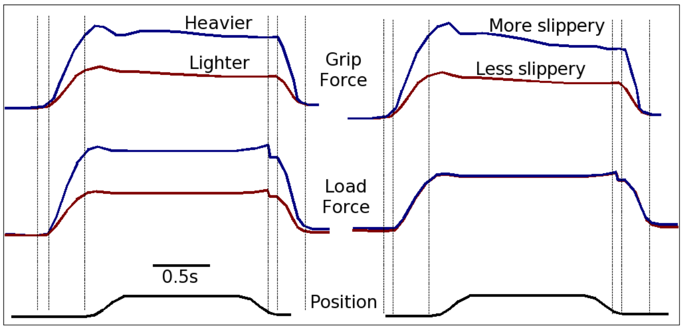

Figure 2: Anticipatory scaling of grip force in parallel with load force for objects of different surface properties (from [24])

anticipatory grip force increases and decreases. The peak of grip force aligns temporally with the peak of load force in both healthy and anaesthetised subjects [3]. In a study of stroke patients with severe sensory (but not motor) loss it was noted again that anticipation of grip increases was present, even in a patient with 23 years of peripheral sensory neuropathy [20]. Grip force magnitude scaling, on the other hand, is not preserved under anaesthesia. We tend to over-grip objects, presumably as a strategy to avoid slip under the added uncertainty. We are also unable to maintain this force at a steady value, and slip is common [3]. This suggests that cutaneous cues are required to allow us to maintain our forward model of grip force. In a study comparing the ability of patients with ALS versus stroke patients (corresponding to motor versus sensory deficits respectively), it was suggested that neither the sensory nor the motor component could be held solely responsible for these observed impairments, and instead some sensori-motor correspondence is required [20].

- When equipped with artificial tactile and proprioceptive feedback, will the amputee tend to the behaviour observed in healthy individuals?

2.2.4 Feed-forward and feed-back based control

Prediction turns motor commands into expected sensory consequences, while control turns desired consequences into motor commands. The neural processes underlying prediction and control are termed 'forward' and 'inverse' models respectively [18]. The presence of these models allows us to both predict and act, refining our predictions and mapping them to refined actions. We are able to gather information and act simultaneously (avoiding delayed action). In order to understand human motor control, computational architectures that combine both forward and inverse models have been developed [54, 8]. The interplay between a forward and inverse components is complex, though these models have received some experimental support.

Flanagan *et al.* attached subjects to a manipulandum with novel dynamics and asked them to move the hand along a straight line trajectory [18]. In learning to control elbow position and grip force, subjects showed rapid learning of grip force (in around ten trials) but slower learning of arm control (around 70 trials), suggesting that there are separate internal models for grip force and arm position and a transfer from reactive (feedback) to predictive (feedforward) control. Flanagan *et al.* argue that this is evidence for separate complimentary forward and inverse processes, with prediction (grip) aiding the learning of control (arm movement).

We can schematically describe sensorimotor processes as feedback loops between separate modules of prediction, observation and correction. With the aim of selecting the best action at a particular juncture to achive our higher goals we require feedforward (predictive) and feedback (corrective) actions. The same cycle exists at different scales, too, so we can learn at a muscle level, a kinematic level (end-effector trajectories) or a task level (end-point errors). The process of selecting the appropriate action given higher level goals is explained by the Optimal Feedback

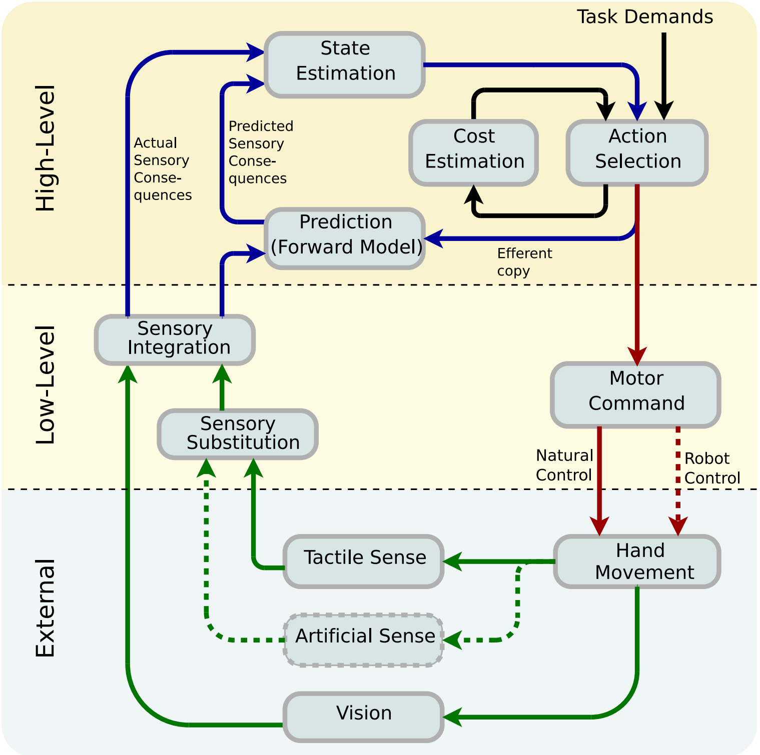

Figure 3: A schematic model for generating goal directed movements in a task involving visual and tactile processing. Unavoidable delays in feedback (indicated by the large sensory feedback loops) highlights the importance of an internal forward model, while feedback is necessary for correcting unavoidable errors in the forward model for state estimation and prediction. In our research, robotic hand control, artificial tactile feeback and sensory subsitution will replace natural hand control and the natural tactile channel. (adapted from [38]).

Control framework. Figure **3** summarises this framework for the present application, showing both the high-level optimal feedback controller and the low-level sensory and motor components.

The 'optimality' of motor control is defined with respect to a *cost function*, assigning a measure of value or reward to different actions. In the presence of delayed feedback from the world, we optimise our motor output (i.e. minimise the cost) based on our *estimate* of the current system state and the *predicted* sensory consequences of our actions. We can correct this *internal model* when feedback eventually arrives from the world. Take the example of picking up a cup. The cost function might be to minimise energy expended. Primarily we would wish to avoid dropping the cup, as this would cost us the most effort. Secondarily we might avoid over-grip as this wastes muscle energy. An emergent consequence of minimising global cost function is the behaviour observed in healthy individuals, predictively applying a minimal necessary force with sufficient margin for error. Assuming healthy people optimise their control policy based on globally imposed costs, then in order to reduce the costs associated with a given action we need to make optimal use of the available information. If amputees are equipped with the 'relevant information' they should show appropriate grip force modulation of their prosthetic hand.

Lesion studies suggest that these kinds of processes (state estimation, prediction, cost-estimation and action selection) do indeed occur in the brain (parietal cortex, cerebellum, basal ganglia and motor cortex respectively) [38]. We will compare our behavioural results with the optimal feedback control framework. We are able address this concept of optimality in human behaviour because suboptimality can be induced by removing parts of the sensorimotor circuitry. For example, we can manipulate control or feedback and compare the resulting behaviours to those predicted by computational models with the same parts altered. Our proposed paradigm, the closed-loop prosthetic hand, offers a unique level of access to the sensorimotor system, allowing us to readily test predictions made by such computational models.

3 System Design

In this section we outline the technological and theoretical components of our model closed-loop system.

3.1 Control System

3.1.1 End-Effectors

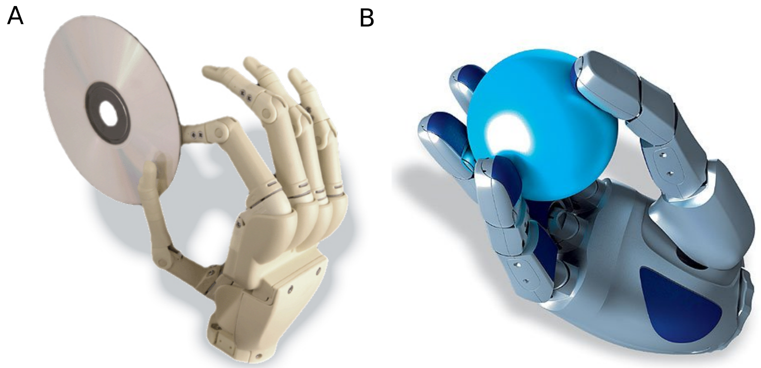

Figure 4: ***(A)*** The Touch Bionics i-LIMB and ***(B)*** the Schunk anthropomorphic hand

We are using two robotic hands (figure **4**) in our research:

- Having established a collaboration with the Livingston-based prosthetics company Touch Bionics, who in 2007 released the i-LIMB, the world's first commercially available prosthetic hand, we will investigate the current capabilities of users equipped with this device. The i-LIMB is the state-of-the-art in prosthetic hands. Using a miniature worm gear motor system, each finger of the i-LIMB is individually powered, and "stalls" when the grip reaches a set threshold, enabling object-specific grasp shapes. We can quantitatively examine the performance improvements when including feedback for everyday tasks, object identification, grasping, lifting, and vision-independent control. The i-LIMB will be the end-product on which the developed technology will be deployed.
- The Schunk anthropomorphic hand, which is far superior to the i-LIMB in terms of degrees of freedom, degrees of control and sensors, serves as a device for controlled experiments. It is servo-controlled, so the position of the fingers and fingertip forces can be precisely set, unlike the i-LIMB. The Schunk hand can be programmed to behave as simply as the i-LIMB, or as complex as a real human hand. We don't expect amputees to achieve this level of mastery, but the inclusion of feedback should allow subjects to gain greater control. We will explore different control strategies and use sensitive force and joint angle data to provide suitable feedback to experimental subjects.

As well as using these robotic hands, we will use simulation. On-screen visualisations of the hand or a cursor are advantageous for quantifying and comparing feedback and control techniques because data is much easier to acquire and interpret in these controlled conditions. It is nevertheless still important to show that the method can be deployed in the real world.

3.1.2 Control Signals

Present-day prosthetic hands are controlled by Surface Electromyography or EMG sensors, which amplify small electrical changes in muscles under contraction. Typical muscles exploited by prosthetists are the wrist flexor and extensor, and finger flexor and extensors. When EMG sensors are placed over these muscles in the forearm they measure the amount of muscular contraction, which can be used as a control signal to open or close the prosthetic hand. Figure **5** shows the EMG sensors used to control the i-LIMB.

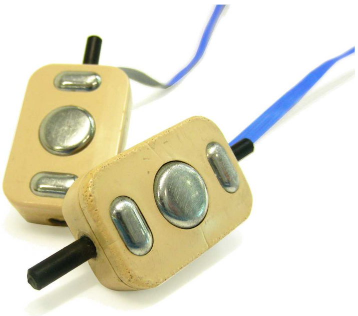

Figure 5: Otto Bock EMG sensors

For pursposes of experimentation, healthy subjects will be given a *simulated amputation*, by anaesthetising and rigidly splinting or binding the hand. Following amputation, partially amputated muscle heals onto remaining bone and tissue in the stump, which we simulate by locking the hand in pace. The purpose of the anaesthetic is to avoid tactile cues from providing additional tactile or force feedback from the hand. EMG sensors could be applied to the simulated amputee in the normal way.

Controlling the hand by recording EMG signals from the residual muscles of the amputee has its limitations. A low signal to noise ratio means that considerable signal smoothing is needed, limiting the responsiveness and accuracy of the EMG signal. Learning to control EMG signals is a big challenge for prosthesis users, and it may be that noise in the signal is the fundamentally limiting aspect of effective prosthesis control. Using the simulated amputation technique, sensitive force sensors or strain gauges can be applied to the end effector of the bound limb. This is equivalent to recording EMG signals, only at the end effector of the muscle rather than from the muscle itself, and with a much higher signal to noise ratio. Taking this a step further, rather than anaesthetising the whole hand, we need only splint a single joint, such as the middle interphalangeal (figure **6**). This is less costly and simpler to perform, and in the same way is a noise-reduced alternative to EMG.

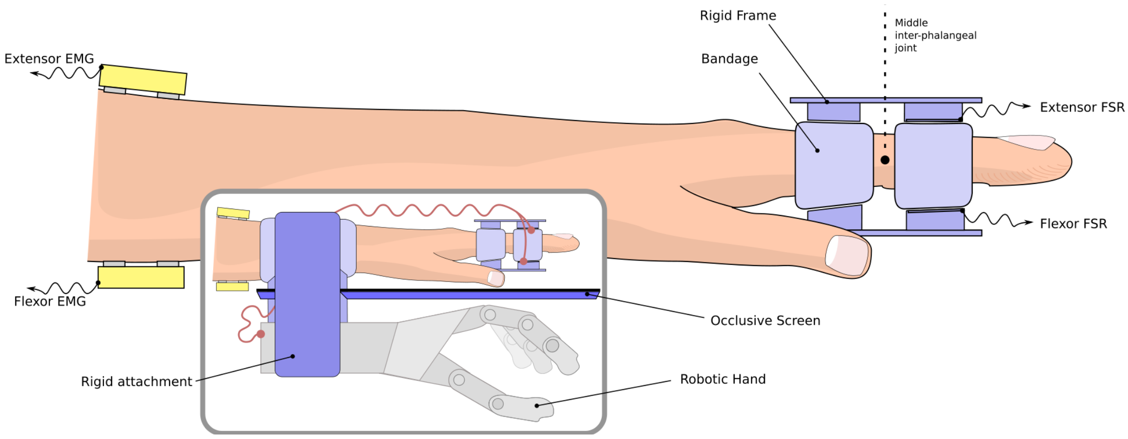

Figure 6: Rigid splinting of an anaesthetised hand, to simulate an amputation. Either EMG or force sensors can be used as control signals for an attached prosthetic device.

3.1.3 Control Method

In section 2.2.2 I discussed different control policies. *Absolute* control features a direct mapping from control signal to output behaviour, while *relative* control maps to a *change* in output. *Absolute* control has the advantage of extended physiological proprioception, while *relative* control may be easier to learn and fine-tune. The latter is the dominant control method in modern day prostheses.

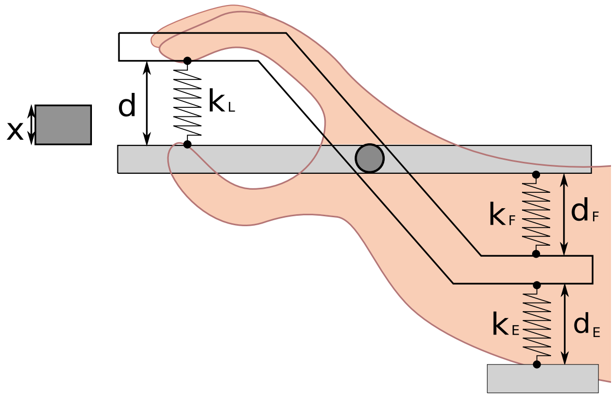

Figure 7: A viscoelastic spring model for human hand aperture control

We can describe the operation of the healthy human hand using a spring model (Figure **7**). Basically, the torque at the finger joints is set by the difference between a flexion signal, an extension signal and a position-dependent opposing force that restores the rest state. The extensor (ED + L) and flexor (ED + FDP) muscle actions are described by linear tension springs, with spring constants k_E and k_F respectively. These spring constants are connected to the control signal, allowing control of the tension provided by each spring. A passive tension is also provided by the elastic properties of the spring, with magnitude k_P. The tensile force supplied by each spring is therefore given by:

$$F_E = \begin{cases} k_E d_E + k_P(d_E - 1) & \text{if } d_E \geq 1 \\ k_E d_E & \text{if } d_E < 1 \end{cases} \tag{1}$$

and similarly for the flexor spring.

A non-linear compression spring L represents the variable load experienced by the hand, which varies with hand position depending on the presence or absence of an object. If $d > x$ then $L = 0$, otherwise $L = kL(x - d)$, where kL defines the stiffness (springiness) of the object being manipulated.

We can compute the instantaneous acceleration of the end-effector, $\ddot{d}$, given the control signals k_E and k_F and the current aperture size d:

$$\ddot{d} = b\dot{d} + k_F d + k_P(d - 1) - k_E(2 - d) - L \tag{2}$$

where positive accelerations are in the direction of flexion, and negative accelerations of extension. A damping term $b\dot{d}$ smoothes the motion.

We can compute velocities and aperture sizes by integration. For a given control signal the hand accelerates towards a 'steady-state' aperture d_{ss}, at which point the the forces from all the springs are in balance (i.e. $\ddot{d} = 0$). It is given by:

$$d_{ss} = \begin{cases} \frac{2k_E + k_P}{k_F + k_P + k_E} & \text{if } d > x \\ \frac{2k_E + k_P + k_L \cdot x}{k_F + k_P + k_E + k_L} & \text{if } d \leq x \end{cases} \tag{3}$$

This simple model encapsulates many key features of the real hand. The aperture size decreases with increasing flexion, and increases with increasing extension. With no signals present the passive elasticity drives the aperture to an equilibrium point. Stiffness increases with co-activation of flexion and extension signals.

This is clearly an *absolute* control policy. When no load is present the control signal maps to the position of the hand, and when a load is present the control signal maps to the force exerted by the hand (the two cases in equation 3). Controlling a prosthetic hand with a policy like this may be more natural and intuitive to operate. This strategy has the further advantage of providing additional state information, i.e. positions or forces can be inferred from the control signal (either proprioceptive feedback from the controlling muscle or the efferent copy of the motor command).

We will compare *absolute* (human-like) and *relative* (i-LIMB-like) control in this research, and ask why the dominant method is not the most biologically realistic.

3.2 Sensory feedback system

3.2.1 Vibrotactile feedback system

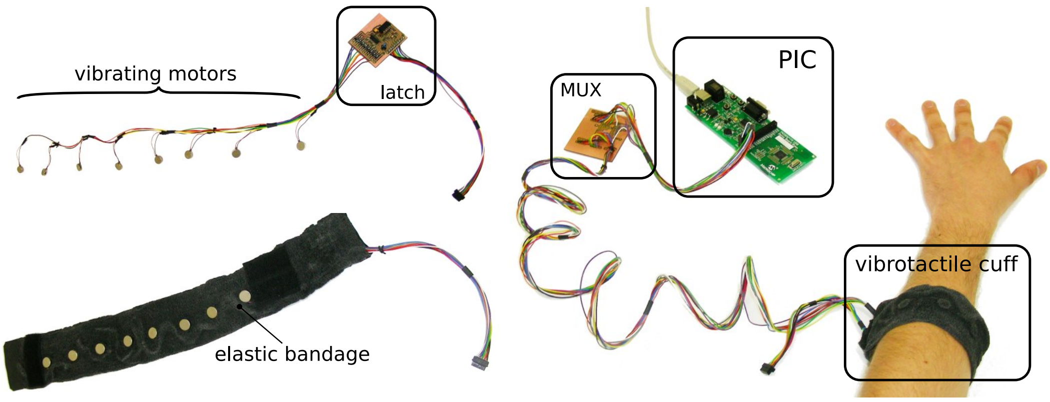

Figure 8: Vibrotactile Feedback System

Vibrating motors and piezoelectric transducers are two common sources of vibratory stimulation. 2D arrays of such stimuli have been used to communicate to users in virtual reality environments [9]. Discrete feedback interfaces have also been developed, such as by embedding an array in the shoulder pad of a jacket [50]. These multi-tactor displays report an increased mental load with more tactors, just as more control sites for a prosthetic hand increases effort. Vibratory patterns get increasingly difficult to distinguish with increasing overlap [19]. However, the healthy tactile modality is capable of integrating a massive quantity of information in parallel, which is processed unconsciously. Patients were certainly able to learn to see again using Bach-y-Rita's very high bandwidth TVSS. Crucially Bach-y-Rita employs closed-loop learning, so the user is in control of the webcam, which may not have been exploited in the virtual reality studies. Of course the present application is a closed-loop system.

Cholewiak *et al.* investigate a number of parameters affecting vibrotactile localisation and perception. As with electrotactile stimulation, body locus is a significant factor in the successful interpretation of vibrotactile stimuli. The shoulder and upper arm (and in fact near to any joint of the body) appear to be effective locations as tactors placed here can be distinguished with greater accuracy [12]. A tactor spacing of 1 inch is significantly worse than two inches for correctly localising the stimulus [12], though this may improve with training, as for electrotactile learning [42]. Finally, older people tend to be poorer at tactile localisation, and require larger steps in stimulus intensity to perceive a change [12].

It is suggested that Pacinian receptors are more sensitive to 250Hz stimulation, while other structures prefer lower frequencies. Pacinian corpuscles have notoriously poor spatial acuity, and one of the criticisms of vibrotactile stimulation is that multiple channels can be hard to distinguish. When tactors are placed 25mm apart, changes in stimulus amplitude are more noticeable when the tactor vibrates at 100Hz rather than 250Hz. However frequency does not seem to affect localisation performance [12].

We these considerations in mind, we have developed and implemented a 32 channel vibrotactile feedback system. This uses 32 miniature vibrating motors to signal sensory information to the amputee. We can increase the vibration frequency and amplitude to each sensor, to deliver 32 discrete sensations of frequency or intensity. Our custom hardware samples forces from sensors, and upates the frequency of the 32 motors at 200Hz. We record the force sensor data onto PC for analysis. An array of these motors allows us to to experiment with frequency codes, spatial and temporal codes, body locations, tactor spacing and many more channels than are currently available to amputees. See Appendix 1 for further details.

3.2.2 Electrotactile feedback system

As an alternative to vibratory stimuli, which may be harder to localise, noisy and more power-consuming, we will consider electrotactile (electrocutaneous) stimulation. The general principle involves passing small currents (∼10mA) for brief intervals (∼100μs) to the free nerve endings which reside in the dermis of the skin, typically using surface-mounted electrodes.

There are a wide range of parameters describing electrotactile stimulation: electrode geometry, material and spacing; voltage and current available; frequency, duration, shape and magnitude of pulses. The choice of the parameters depends on: body location, subject age and skin resistance; the number of perceivable levels desired; avoidance of adaptation; and most importantly, safety. These details are included in a separate report, and summarised in Appendix 2.

3.2.3 Feedback codes

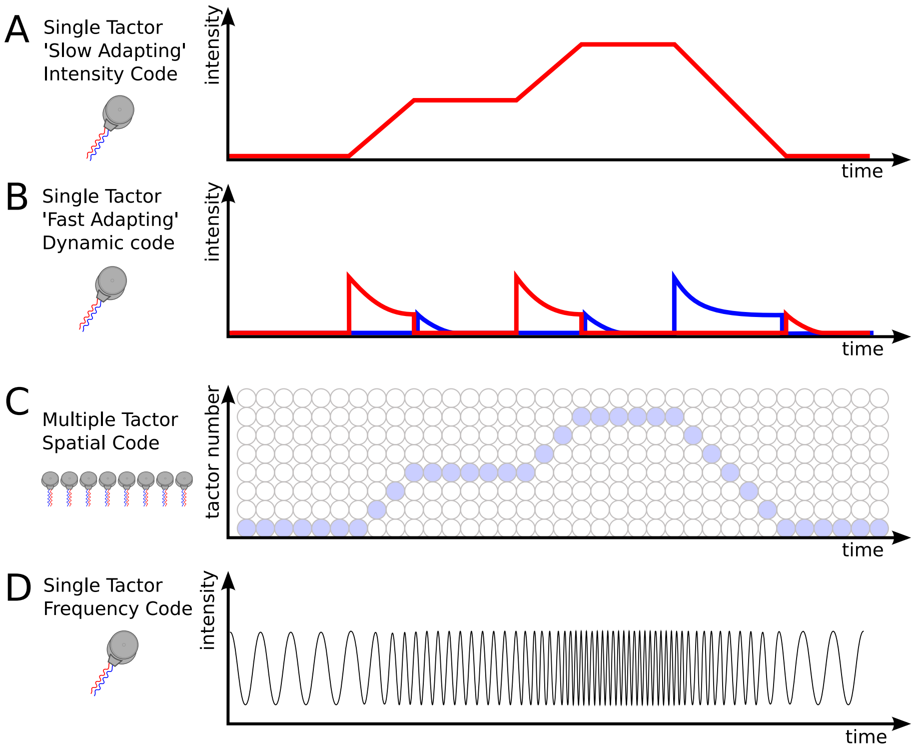

Figure 9: A selection of possible feedback codes.

We can give feedback of fingertip forces, finger positions, and/or their derivatives with respect to time. We can have many channels (e.g. one for each finger) or just a few (e.g. an amalgamated signal), trading increased information for decreased mental effort. We can issue the feedback using electrotactile or vibrotactile stimulation. We can use numerous feedback codes, such as intensity, frequency, spatial and temporal. In intensity and frequency codes the amplitude or frequency of vibration or duration or frequency of current bursts represents the signal. In spatial codes an array of vibrating motors or electrodes are used, each one representing a different signal value. In temporal codes we vary the order of stimulation of a set of motors or electrodes.

4 Experiments

4.1 Research Goals

4.1.1 Overview

Figure **10** shows the questions we will ask with our research, using the sensorimotor control framework we described previously. In this figure we illustrate the proposed experiments to understand the low-level transformations involved in artificial sensation and prosthesis control. This *artificial sensorimotor circuit* is open to experimental manipulations that can elucidate the underlying mechanisms of sensory integration and sensorimotor learning.

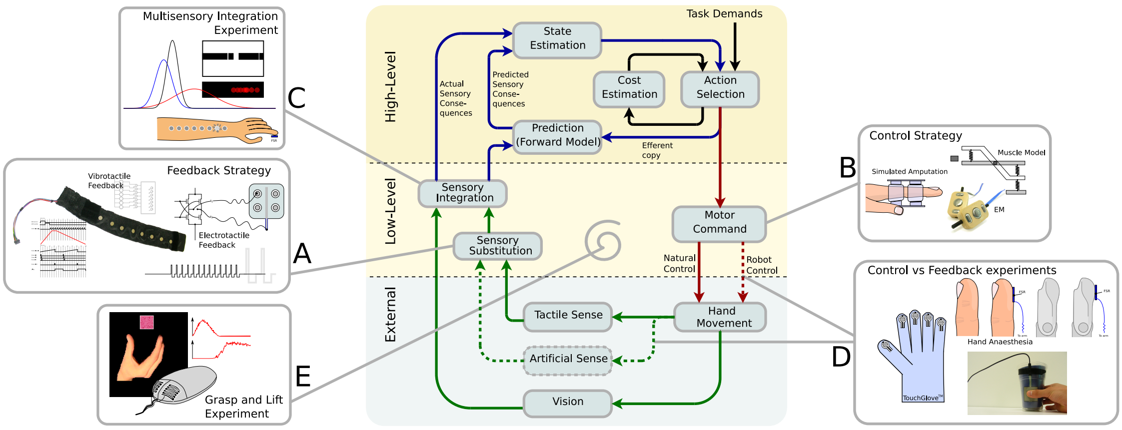

Figure 10: Experiments addressing the problem of closing the feedback loop. ***A***, What is the best method of delivering feedback, and the best feedback code? ***B***, What is the best control policy for the robotic hand? ***C***, How do we integrate visual and (artificial) tactile information? ***D***, Are the performance limitations of current prosthetic hands due to lack of control or lack of feedback? ***E***, Can functionality, responsiveness and performance be improved, and optimal behaviour attained by closing the loop?

We will conduct three key experiments:

- **Optimal Sensory Integration.** Figure 10A and C. Section 4.2.
- **Control *vs.* Feedback.** Figure 10A, B and D. Section 4.3.
- **Reach, grasp and lift task.** Figure 10E. Section 4.4.

4.2 Optimal sensory integration

4.2.1 Background

Healthy people integrate visual and proprioceptive feedback from the world in order to make decisions about where their hand is, and the aperture of their grasp. Even without vision we are able to pre-shape grasps and position ourselves, and conversely those with proprioceptive loss are able to position themselves relying on vision alone [52]. When there is a discrepancy between visual and proprioceptive information, which do we rely on?

It has been proposed that in healthy individuals sensory integration is statistically-optimal, in that it takes into account prior knowledge and sensory uncertainty. For the present application we are interested in asking if an artificial feedback channel integrates with our other sensory modalities in the same way. For example, in deciding the location of a target x given visual and tactile cues x_v and x_t with independent noise, Bayes theorem implies:

$$\Pr(x = k|x_v, x_t) = \frac{1}{Z} \Pr(x_v|x = k) \Pr(x_t|x = k) \Pr(x = k) \tag{4}$$

For the special case where visual and tactile stimuli, and prior uncertainty are all drawn from Normal distributions of different mean and variance, $x_v \sim N(\mu_v, \sigma_v)$, $x_t \sim N(\mu_t, \sigma_t)$ and $x_{prior} \sim N(\mu_p, \sigma_p)$ we get a posterior probability which is also distributed according to a Normal distribution:

$$x_{posterior} \sim N\left(\frac{\mu_v\sigma_t^2\sigma_p^2 + \mu_t\sigma_v^2\sigma_p^2 + \mu_p\sigma_v^2\sigma_t^2}{\sigma_t^2\sigma_p^2 + \sigma_v^2\sigma_p^2 + \sigma_v^2\sigma_t^2}, \frac{\sigma_v^2\sigma_t^2\sigma_p^2}{\sigma_t^2\sigma_p^2 + \sigma_v^2\sigma_p^2 + \sigma_v^2\sigma_t^2}\right) \tag{5}$$

Two discrepant cues in different modalities are often perceived as the same. One can compute the weight attributed to each modality by comparing perception to statistically optimal integration as shown in equation 5. The weight has been shown to be a function of sensory uncertainty for vision and proprioception [15] for audio-visual integration [7] and visual and haptic integration [17], just as Bayes theorem suggests. Prior knowledge also plays a part in this sensory integration, and it has been shown that we integrate this prior knowledge with sensory uncertainty for tasks of force estimation [30] and pointing movements [31].

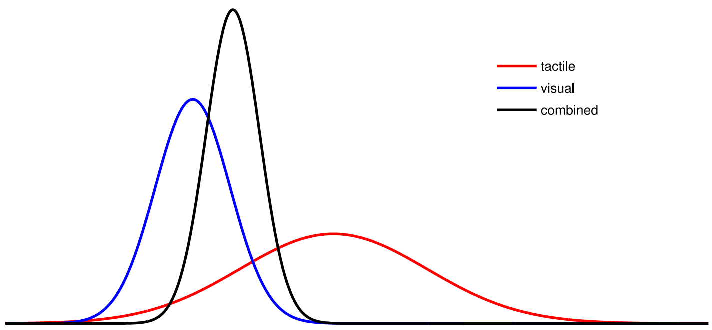

Figure 11: Bayesian multisensory integration for discrepant stimuli with different variances.

The underlying mechanism of this integration process is unknown. The findings can be explained by a neural model in which different modalities are interconnected and probabilities are represented by population codes [15]. It has been argued that the brain uses Bayesian models when interpreting sensory information [31, 30]. However it is also possible that this optimal behaviour is the consequence of basic Hebbian learning in a 2 layer neural network, with prior experience being encoded by increased potentiation of more frequent events and sensory uncertainty being represented by a more diffuse population response.

It is also not yet known whether statistically optimal multisensory integration this extends to a "new" (artificial) sense. This is a very interesting from a neuroscienctific perspective. Moreover, if it is revealed that we rely on our senses based on their information content (i.e. sensory uncertainty), irrespective of what modality it presents itself in, this is a very promising result for amputees equipped with an artificial sense of touch and proprioception.

4.2.2 Methods

In order to address these questions we will use a tracking task, shown in figure **12A**.

The prior distribution, $\Pr(x = k)$ of stimuli will be uniform. We will increase visual uncertainty either by adding noise (fig **12B**) or jitter (fig **12C**), and similarly for the tactile channel. There will be no discrepancy between the two modalities other than that imposed by the noise.

Each target presentation is approximately 5 seconds long, and subjects are alerted of success or failure by the target turning green (success) or red (failure). 90 randomly placed targets are presented in a 5 minute run. The jitter in the visual and tactile channels, σ_v and σ_t respectively, will be varied every 5 trials to one of three variances (*low*, *medium* and *high*). In a run each subject

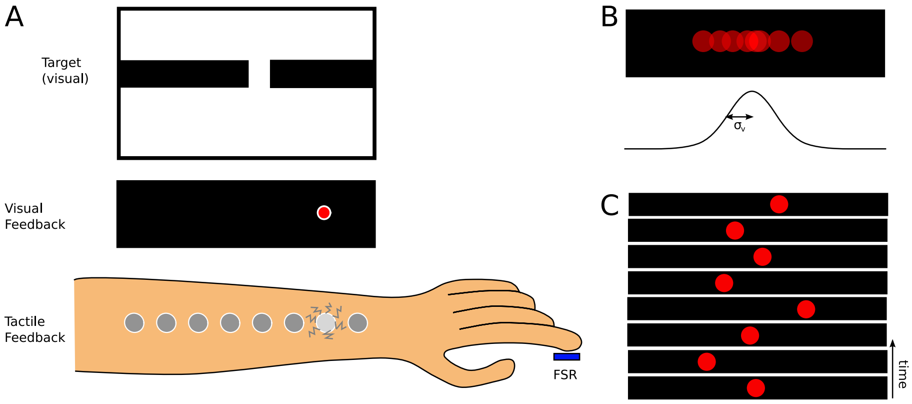

Figure 12: ***A***, Schematic of the tracking task. Subjects are required to track a cursor to a target position using visual and tactile feedback of cursor position. ***B***, Spatial uncertainty of variance σ_v (noise) applied to the visual modality. ***C***, Temporal uncertainty (jitter).

will therefore experience 10 trials for each combination of visual and tactile variance. Subjects will perform three such runs, separated by brief breaks.
The following quantities will be measured at the granularity of a single trial:

- Success / failure;
- The distance of the cursor from the target at the end of the run;
- The trajectory taken to reach the target, compared to the statistically optimal trajectory.

We will also examine the learning effects within each block of 5 trials, and across runs. If subjects are behaving in a statistically optimal way their performance will be a function of the Bayesian combination of the variances.

We will analyse the gross behaviour by comparing it to predictions from Baysian statistics. In the jitter case (fig **12C**), we will further examine the trajectories chosen by the subject as the sensory uncertainy decreases with time. We will compare these trajectories to those predicted by a Kalman filter model as evidence accumulates.

4.3 Control versus Feedback

4.3.1 Motivation

One of the aims of this project is to restore sensation to prosthesis wearers and show a quantifiable improvement in day to day tasks. However, it is critical to realise that any improvement will necessarily lie within the limitations of the setup. One must be aware of the the difficulty in learning to control new muscle patterns, the inherent noise in EMG sensing equipment, the responsiveness and accuracy of hand actuation, the availability and sensitivity of the sensory receptors, the efficacy of the feedback method and the limited latent plasticity of the nervous system. While we hypothesise that sensory feedback is of fundamental importance for hand control, it may be that technological and neural limitations also inhibit progress.

We wish, therefore, to decouple the components of the closed-loop setup. However, rather than starting with the prosthetic hand and trying to make it better by improving the components of the loop, we start with the healthy human hand and gradually strip it of its analogous components. We consider five conditions, shown in figure **13**.

The five conditions in figure **13** allow us to separate control and feedback. Comparing task performance in condition ***A*** with condition ***C*** we can quantify the degree of *sensory* restoration, independently of control method. Comparing ***C*** with condition ***E*** we can quantify the degree

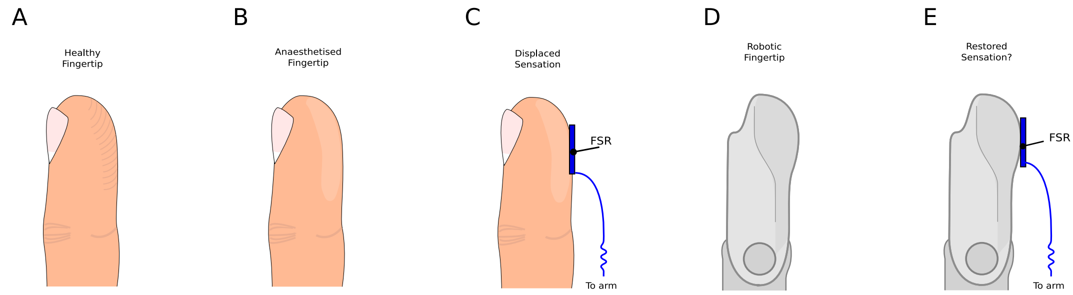

Figure 13: Five experimental conditions to elucidate the limiting factors in prosthesis functionality. ***A***, Those using their healthy hand have full control and full feedback. ***B***, Full anaesthesia of the fingertips eliminates tactile and force feedback. ***C***, Force feedback can be artificially restored using vibrotactile stimulation. ***D***, Full control can be removed by using a robotic hand. ***E***, Force feedback can again be artificially restored using vibrotactile stimulation.

of *control* restoration, independently of feedback method. ***B*** and ***D*** provide lower bounds on performance for the two comparisons. ***D*** is of course the state-of-the-art.

Five similar conditions can be created to provide full anaesthesia (both proprioceptive and tactile), by injecting the whole hand.

4.3.2 Research Questions

- Which items of sensory feedback are utilised in different tasks for healthy individuals, and what is the best *feedback* method for the healthy hand?

We will take a task which a healthy subject (***A***) performs well, but an anaesthetised subject (***B***) does not. We hypothesise that we can restore sensation to the anaesthetised subject by sensory substitution (***C***), re-enabling task performance. Under these *ideal conditions*, where the subject has full control of the movement of their hand, we obtain a measure of performance *independent of control method*. Whatsmore, we hypothesise that different tasks will require different types of information. The task of aperture modulation will benefit from proprioception, and of object lifting force perception. We will continue to explore different feedback types, modalities and encodings until significant performance improvements are observed in a simple battery of day-to-day tasks.

- Do these ideal conditions transfer to use of the the robotic hand, and what is the best *control* method for the prosthetic hand?

The anaesthetised hand will be compared to the prosthetic hand with the same (artificial) feedback provided to the subject in both cases (***C*** *vs* ***E***). The only difference in these conditions is the ability to control the hand, so a comparison of these cases will yield performance improvements due solely to control. Having already selected the best type of feedback to restore task performance for the anaesthetised healthy hand condition (***C***), we hypothesise that this improvement will be similarly reflected in performance improvements of the prosthetic hand. If so, then the feedback should be instantly adopted in the prosthetics community. In the more likely case that performance is not improved to the level for the ideal condition, we will try different control methods until significant performance improvements are observed.

4.3.3 Tasks

A battery of tasks will be performed by five groups of subjects for each of the experimental conditions in figure **13**. To be suitable for currently available robotic hand control technology we will take a battery of relatively straightforward tasks. These are tasks fundamental to daily living:

- Reaching to pick up an object;

- Grasping the object;
- Identifying properties of the object (size, shape, weight, compliance);
- Manipulating the object (setting and maintaining suitable grip under acts of lifting, displacement, rotation);
- Placing the object on a target location.

The objects will be of many varying properties:

- size (small, large);
- shape (flat, round, cylindrical, square, natural objects);
- weight (light, heavy);
- compliance (rigid, springy).

There are obviously more advanced tasks of daily living which may be of interest. Some of these tasks may be out of the range of present day robotic hands, but nonetheless it is important to show that artificial feedback can be utilised in more complex tasks:

- Tying a shoelace;
- Fastening a shirt button;
- Turing a door handle;
- Turning a key in a lock;
- Using a knife and fork;
- Striking a match;
- Catching and throwing.

4.3.4 Methods

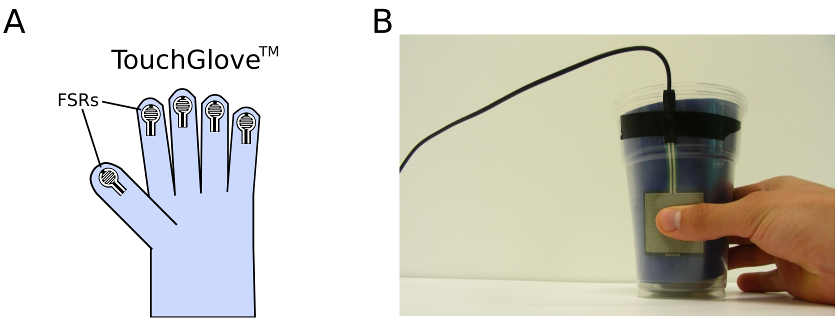

Figure 14: ***A***, Diagram of the TouchGlove, for sensitive fingertip force measurements. The glove is wired directly into the vibrotactile feedback cuff, so anaesthetised glove wearers can use vibrotactile feedback as a cue to absent fingertip forces. ***B***, A cup equipped with a force sensor. We vary the load in the cup, and analyse the forces applied when lifting.

The subject will be presented with numerous objects, and required to perform the range of tasks discussed in the previous section. For the basic tasks of lifting and grasping we will use the touch glove, a tight elastic glove fitted with force sensors on the fingertips. We will use the Optotrak and Minibird tracking systems to monitor grasp size and aperture. We can also fit sensors to objects, as in figure **14**. Using these systems we can both track positions and forces over time, and issue force and position feedback to the subject. The following quantities will be analysed:

- Time taken to do the task;
- Trajectory taken (in geometrical space, in grasp aperture space and in grasp force space);
- Deviation from the 'optimal' (condition ($\boldsymbol{A}$)) trajectory.

We will compare the following feedback types (in order of priority until significant improvements are seen):

- Force feedback vs. grasp aperture feedback vs. both
- Vibrotactile vs. electrotactile
- Dynamic feedback codes (time derivative of force and aperture, such as that provided by type I afferents)
- Higher level feedback codes (slip onset, goal completion, etc...)

We will use the following control methods (in order of priority until significant improvements are seen):

- Relative control (like i-LIMB).
- Absolute control (like human hand).
- More bio-realistic control methods...

4.4 Reach, Grasp and Lift task

4.4.1 Motivation

A crucial task of everyday living is that of reaching, grasping and lifting objects. This is an ideal task to study for three reasons. Firstly, it characterises the key aspects of sensorimotor control: sensing, planning, predicting and acting. Secondly it is well researched in healthy and sensory-impaired individuals, which can be easily extended to amputees. Thirdly, it is well known that humans behave in an optimal way in these simple tasks, allowing us to target and remedy the sub-optimality of present day prostheses.

When approaching an object, healthy people will set their grasp aperture to be slightly larger than that required to successfully hold the object. Grasp apertures that are too small will not be sufficient to enclose the target. A grasp aperture of the same size as the object might also be unsuitable as sensory and motor systems are prone to noise and the world is not entirely predictable. Grasp apertures that are too large will increase movement execution time, and expend more muscle energy. When approaching an object, amputees do not behave in this apparently optimal way, but instead tend to select a size too large. A similar description holds for force modulation when lifting an object.

There are numerous possible reasons for this apparent sub-optimality. It may be that the adult brain is incapable of optimising the new sensory and motor patterns. However, it may also be that amputees are optimising with a different set of parameters. Firstly, sensory and motor noise may be greater, increasing the safety margin. Secondly, the effort required to accurately pre-shape or apply a force, perhaps requiring careful timing and visual attention, may be greater than the increase in effort resulting from behaving as healthy individuals do. Thirdly, it may be that there is insufficient sensory information to enable success at the task.

4.4.2 Methods

A simulated 2D grasp and lift task has been developed. The user moves a cursor, which is a simulated hand with variable aperture, and is required approach, grasp and drag the simulated object to a goal location. A modified computer mouse is used so that the subject can control the cursor position (like an ordinary mouse) but with force sensors rather than buttons the subject can open and close the grasp (figure **15A**). These two control signals correspond to either flexor and extensor forces or open and close signals depending on control strategy being tested. We analyse the 2 stages of the task separately (approach, T1; and drag to target, T2). In T1 we should modulate aperture size to the target object size, and in T2 the grip force to the target object weight. In T1 we have ample visual aid, and in T2 we do not.

The physics of the simulation are simple: The fingers and objects are treated as rigid bodies in a viscous environment. If the fingers hit the object it is shunted away. If the thumb and finger oppose one another on opposite sides of the object then the object is within the grasp and a force is applied to the object. If the grasp force is too weak the object will slip from the grasp when the cursor is moved. The target object varies in terms of its size and its mass. A larger object requires a larger aperture to enclose it before grasping. A heavier object moves slower and requires stronger grasps to drag without slipping (see figure **15**).

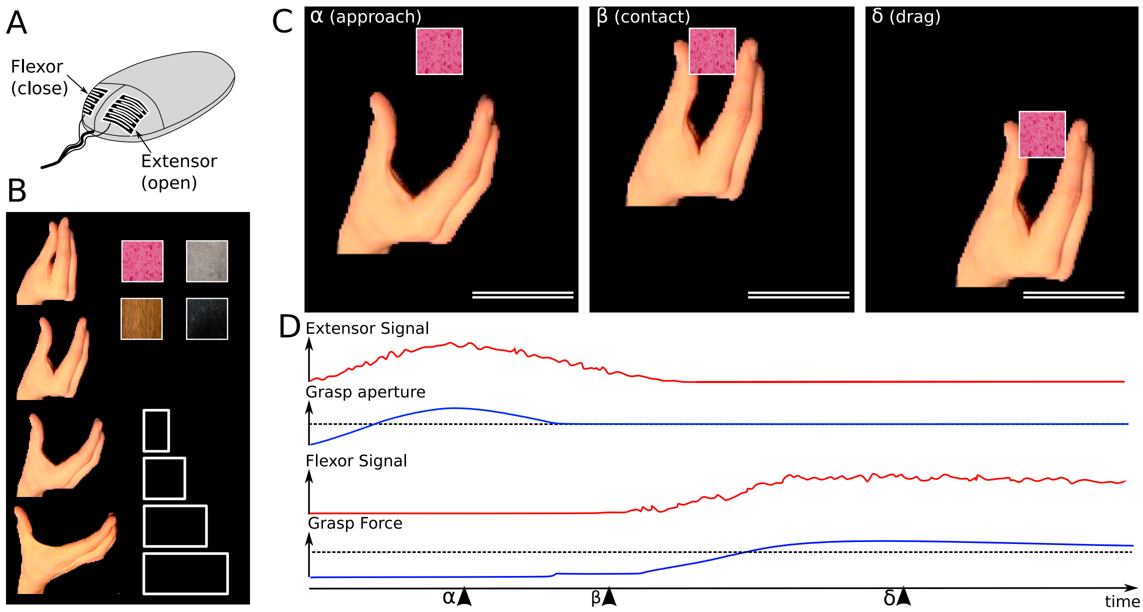

Figure 15: The simulated grasp and move paradigm. The user controls a cursor which is a simulated hand with variable aperture, and must approach, grasp and drag the simulated object. ***A***, The modified controller, a mouse with force sensors instead of buttons. ***B***, The cursor is an image of a hand with varying aperture size. Different object types and sizes are manipulated by the simulated hand. ***C***, Three stages of the task. α is the approach phase and β is the grasp and δ is the dragging of the object to the target. ***D***, Typical traces from the force sensors and of the aperture sizes. The dotted line shows the minimum aperture size to enclose the object and the minimum necessary force to successfully drag it.

The task is to successfully move as many objects to the target in 2 minutes. Subjects are rewarded for more objects successfully moved. We speculate that this imposes a simple global cost function from which optimal behaviour (grasp apertures slightly larger than necessary and grasp forces slightly larger than necessary) should emerge.

We train an optimal feedback controller (OFC) to do the task, and compare the observed to the optimal trajectories. With different control strategies and different sources of feedback we obtain different optimal trajectories in the model. Figure **16** shows preliminary results for the T1 task.

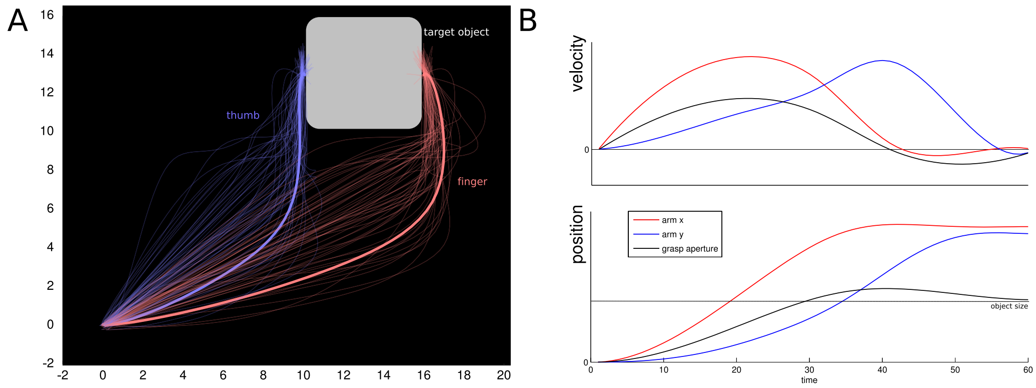

Figure 16: ***A*** The 'optimal' path of thumb and forefinger when approaching an object (T1). We model the human hand and assign a cost function that increses with energy expended (excessive muscle activity) and collision with the target object, and costrain the trajectory kinematics at the start and end points of motion. ***B*** The trade-off minimising the cost terms results in smooth trajectories and bell shaped velocity profiles, similar to healthy human behaviour.

4.4.3 Experiment Design

For the first experiment we will adopt a block design, 2 tasks $\times$ 2 control methods $\times$ 3 feedback codes. 18 subjects will participate in the study, each assigned a group (C1, C2) and a feedback type (F1, F2, F3). Both tasks (T1 and T2) are performed by all subjects. They repeat the two-minute blocks 10 times, with a break of 30 seconds between each (total time 25 minutes). In each 2-minute block the subject will experience between 15 and 30 objects, depending on how quick they are.
Task:

- T1: Grasp aperture modulation (approach phase)
- T2: Grasp force modulation (drag phase)

Controller:

- C1: Relative control (like i-LIMB)
- C2: Absolute control (like human hand)

Feedback type:

- F1: Spatial feedback code
- F2: Intensity feedback code
- F3: No tactile feedback

Quantities:

- The size of the grasp and the grip force applied k seconds into the task, relative to the target size and force;
- The number of objects dragged to the goal by the subject in two minutes;
- The time taken to complete a task;
- The shape of the size/force curve with time;
- For the first 200ms from the onset of movement in each task (feedforward performance):

- The size/force relative to the target size/force at $k = 200ms$;
- The slope of increase in size/force;
- Comparison of the observed perofrmance to the optimal trajectory.

Statistical comparisons:

- **T1 vs T2:** The effect of task will be examined (N=18 per group). This will highlight the benefit of vision in T1, which is not so useful in T2.
- **C1 vs C2:** The effect of controller type (relative vs absolute) for each task, and the interaction between control group and task will be examined (N=9 per group).
- **F1 *vs* F2 *vs* F3:** The effect of feedback type (spatial code *vs* intensity code *vs* no feedback) for each task, and the interaction between feedback type and task will be examined (N=6 per group)
- **Control and feedback type interaction** To examine an interaction between feedback type and controller group we will have 6 conditions: C1F1, C1F2, C1F3, C2F1, C2F2 and C2F3 (N=3 per group)
- **Learning across blocks** Over the 10 blocks we can look at within-subject learning effects (N=18), and the effect of task (N=18), controller group (N=9) and feedback type (N=6) on this. We can also look for an interaction between these factors (N=3 per group).

All of these measurables can be made across subjects or as a function of object size / weight. Depending on interactions we may or may not be able to pool data across controllers or feedback types, giving higher N values.

5 Summary

In this report I have briefly described the current state of the art in hand prosthetics and areas of human sensorimotor control research relevant to this field. My project aims to tackle the issues of present day prosthetics, by addressing the limiting factors of the closed-loop model. We will determine whether the problem in learning to control an artificial hand is due to control difficulties or the lack of sensory feedback, not by attempting to engineer a new robotic hand but by taking the healthy hand as the gold standard and stripping it gradually of its (feedback) components by means of anaesthesia. We will work with healthy subjects by creating a simulated amputation, which may also allow us to control for the limitations of the brain computer interface such as noisy EMG. Having idealised these control components of the closed-loop model we should be able to obtain objective results regarding the benefits of sensory feedback for amputees. We should be able to observe a transition from the apparently sub-optimal performance of prosthesis users on tasks such as approaching, grasping, identifying and manipulating objects to behaviour that is more like that of healthy individuals. This technical report outlines the technological and theoretical progress thus far, and details the experiments we are presently undertaking.

Following from these experiemnts we will address open questions in sensorimotor control, using our artificial hand as though it were a healthy hand. This model will serve as a novel manipulandum for testing current theories about sensory integration, feedforward and feedback cognitive processes and cortical (re)organisation. By removing or altering sensory feedback at a high temporal granularity we can potentially expose the underlying cognitive mechanisms in a way that is impossbile with the intact individual.

6 Appendices

6.1 Appendix 1: Vibrotactile feedback system

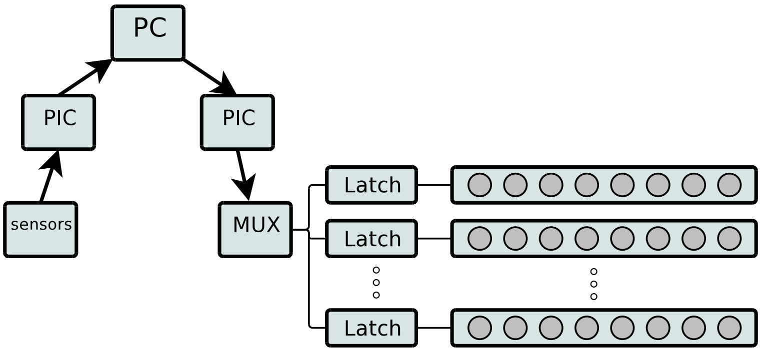

Figure 17: Vibrotactile Feedback System overview

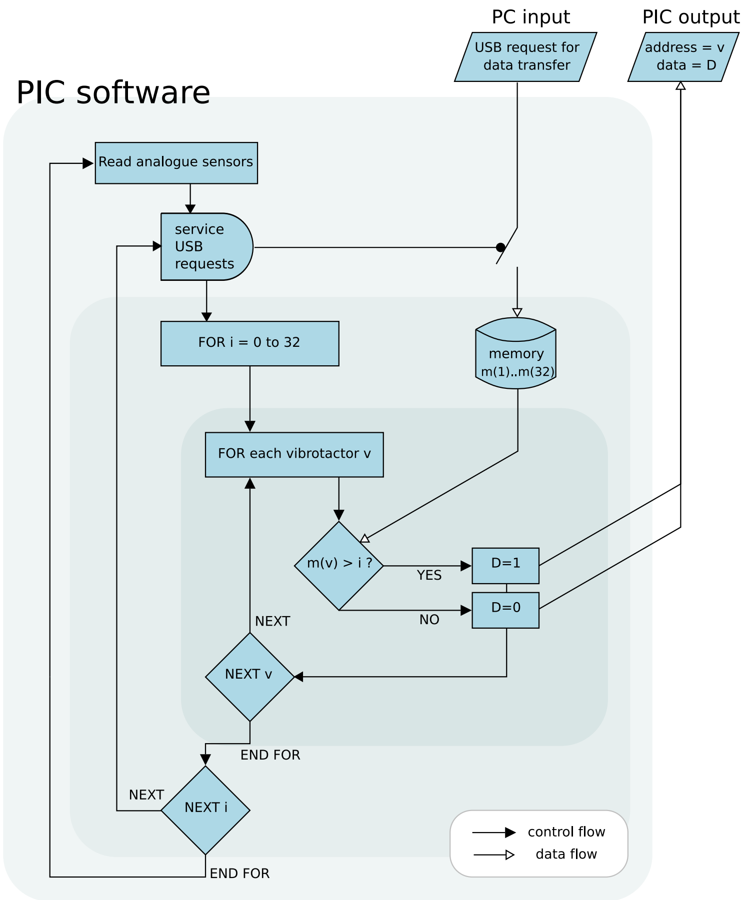

Figure 18: PIC Program. The software services USB data transfer requests to update on-chip memory for each of the tactor channels. The number in memory location $m(v)$, sets to the duration to turn on the vibrating motor on output channel v, setting its duty cycle and therefore vibration intensity.

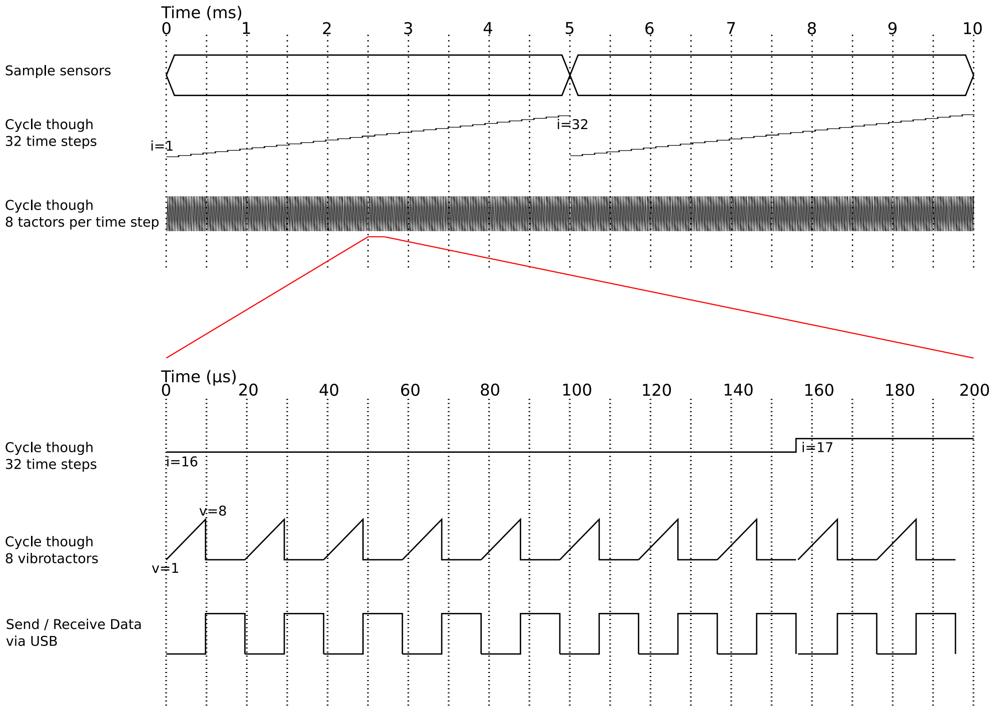

Figure 19: PIC Program timing diagram. At a frequency of 200Hz the software reads analogue sensors, communicates with a PC via USB, and controls the vibration intensity fo up to 32 vibrating motors (tactors)

Up to 32 channels of vibrating motors are controlled using custom hardware / software. Figure **17** gives an overview the vibrotactile feedback system. The vibrating motors are split into "cuffs", of 8 motors, which are daisy-chained together to provide 32 channels in total. These cuffs are elasticated, so that the motors can be firmly applied to the different locations, and the control circuitry is embedded in each cuff. Figure **8** shows the construction.

A Microchip PIC 18F4550 Microcontroller (PIC) has been programmed to interface with a PC via USB. When operating in PC mode, the PIC receives 32 8-bit values from the PC representing the amount of vibration required for the 32 motors. The PIC also contains an ADC, converting analog signals from force sensors into digital values. When operating in standalone mode, the amount of vibration depends on the forces detected by these force sensors. Figure **18** illustrates the microcontroller assembly language program to control the motors This all happens 200 times per second, making the system responisive (important for feedback). Figure **19** shows the timing diagram for the microcontroller software.

6.2 Appendix 2: Electrotactile feedback system

Key safety considerations, summarised in a separate report, are:

- Skin resistance
- Current source versus voltage source
- Biphasic stimulation
- Optimal waveform parameters
- Electrode material and geometry
- High voltage handling, charge density and charge buildup
- Electrode-skin interface
- The two-point discrimination threshold (TPDT)
- The pain/sensation ratio (P/S)

We will use a biphasic waveform (figure **20**), with parameters inspired by previous literature (table 1). We calso consider electrode geometry, given preious literature (table 2).

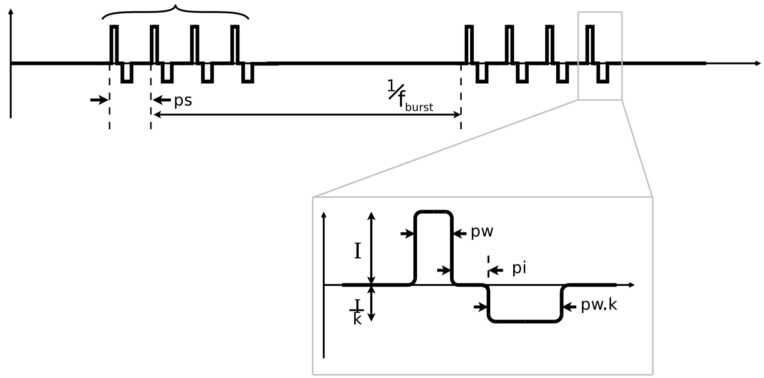

Figure 20: Biphasic Current Waveform

We have designed and built a current source to drive electrodes. Figure **21** shows the circuit diagram.

- A 50V DC source (V) drives the electrodes.
- The design assumes electrode (skin) resistance of 5KΩ. This means with a 50V supply, and assuming no losses across the switch, we should achieve 10 mA through the electrode.
- Biphasic currents are achieved by switching the direction of current through the electrode. When C_1 and C_2 are both 0V, no current flows through the MOSFETs, and the electrode is switched off. When $C_1 = 5V$ and $C_2 = 0V$ current flows in the forward direction, from active centre to passive surround. When $C_1 = 0V$ and $C_2 = 5V$ current flows in the opposite direction through the electrode. (see figure **22**).
- The constant current through the electrodes is limited by an amplifier feedback loop, with a gain set by an analog voltage A_1. The current is given by $I = A_1/R$. As A_1 ranges from 0V to 5V the maximum current attainable through resistor R ranges from 0mA to 10mA.

I (mA)	bi-phasic	f_{burst} (Hz)	pw (μs)	duty	pi (μs)	ps (ms)	n	k	ref
?	✓	1-300	10	—	>30	0.1	1-32	1	[48]
?	✓	30	40	—	45	33.3	1	3	[10]
10	✓	100-4000	?	6-34%	?	?	1	1	[1, 2]
N/A	✓	?	150	—	?	2.85	6	1	[29, 33]
25	✓	any	>30	any	any	any	any	any	[34]
?	✓	15	135	—	135	3.33	3	1	[56]
50	✓	1-1000	2-1000	—	0-1000	0.04-10	1-300	1	[27]
40		300	10-10000	any	—	—	—	—	[43, 44]
15		2-50	200	1%	—	—	—	—	[46]
10		2-100	100-150	?		—	—	—	[47]

Table 1: Parameters of Monophasic and Biphasic current waveforms from the literature. Key: Peak Current (I) and Burst Frequency f_{burst}, the Pulse Width (pw) and Duty Cycle of monophasic stimulation, the Pulse Width (pw), Biphasic Pulse Interval (pi), Pulse Spacing (ps), Number of Pulses Per Burst (n) and Biphasic Magnitude Reduction ratio (k) of biphasic stimulation.

Electrode Location	Cathode area (mm^2)	Anode area (mm^2)	spacing (mm)	Peak Current (mA)	Typical Current (mA)	Ref
Trunk	12.6	148	1	7	1.7	[48]
Trunk	8.04	232	1	10	?	[47]
Leg	314	3150	5	20	5±2	[10]
Fingertip	0.25, 1, 4 , 16, 64	large	?	7	?	[34]
Upper arm	3000	3000	50	10	?	[1, 2]
Lower Arm	8.42	<30	unknown	40	?	[43, 44]
Arm	4	4000	2	50	variable	[55]
Upper arm	23.7	387	25	–	–	[29, 33]

Table 2: Bipolar electrodes described in the literature.

- This circuit differs from the majority of electrotactile stimulators in that it does not require dual high voltage supplies, and does not contain any capacitors apart from decoupling ones. It is also quite economic on components (less to go faulty).

The electrodes will be made from standard TENS electrodes. Figure **23** shows the design. These have even current distribution, have an adhesive conductor, and are inexpensive. Whatsmore, for their intended purpose (considered safe for personal application) they are driven by higher voltages, and handle higher currents and frequencies than proposed for this application.

The circuit design takes into account the safety considerations from the literature (see separate safety report).

- The accepted lower limit of ventricular fibrillation for whole body, arm to arm current flow in humans is 75mA r.m.s. The current is actually limited to 50 mA d.c. by an ultra fast blow fuse. Furthermore the current flow is also not arm to arm, but only through the skin of one arm, and is switchable d.c. which is less than r.m.s. This scenario only would occur if the MOSFET in the current regulator circuit went short circuit (worst case component failure situation).

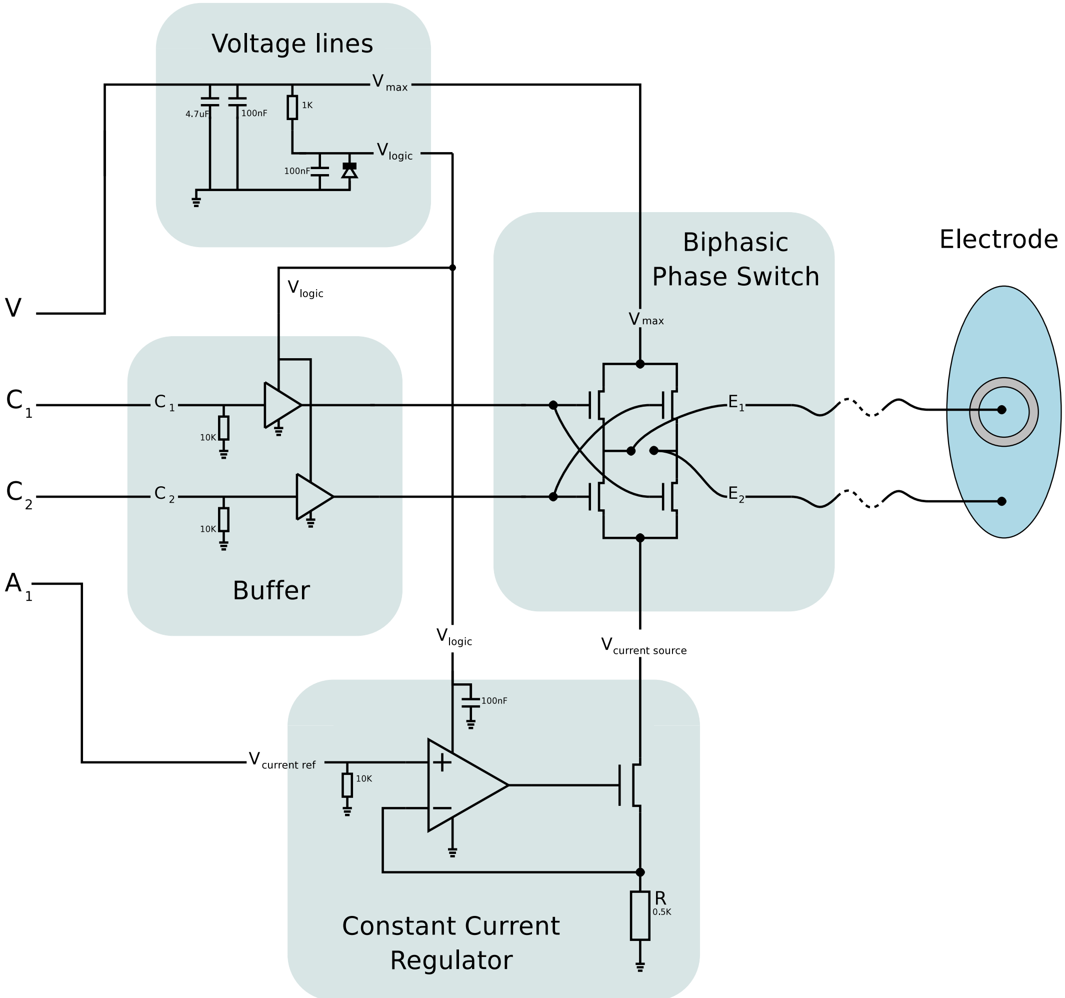

Figure 21: Circuit diagram for the constant-current electrotactile feedback system

- A hand or foot operated "panic button" will also be available to switch off the supply voltage if any discomfort is experienced by the subject. The electrode circuit itself does not use capacitors as do the majority of electrotactile stimulators, so there is no need to consider Charge Limiting Output Coupling.
- If during a session the electrode slips causing the electrode impedance to go well above 5KΩ, the circuit would have insufficient volts to produce any more current in the electrode than was demanded prior to this happening. It would produce less current in fact.
- If a bead of sweat caused the electrode to go short circuit, the high voltage source would be applied to the drive MOSFETs. These are capable of taking this voltage (plus more in fact). The current source would in fact just function as normal.
- Even under the worst case scenario / fault, the circuit should be unable to produce a current of greater than 50mA (the worst case fault condition). Even then this current would only be applied for milliseconds at most.

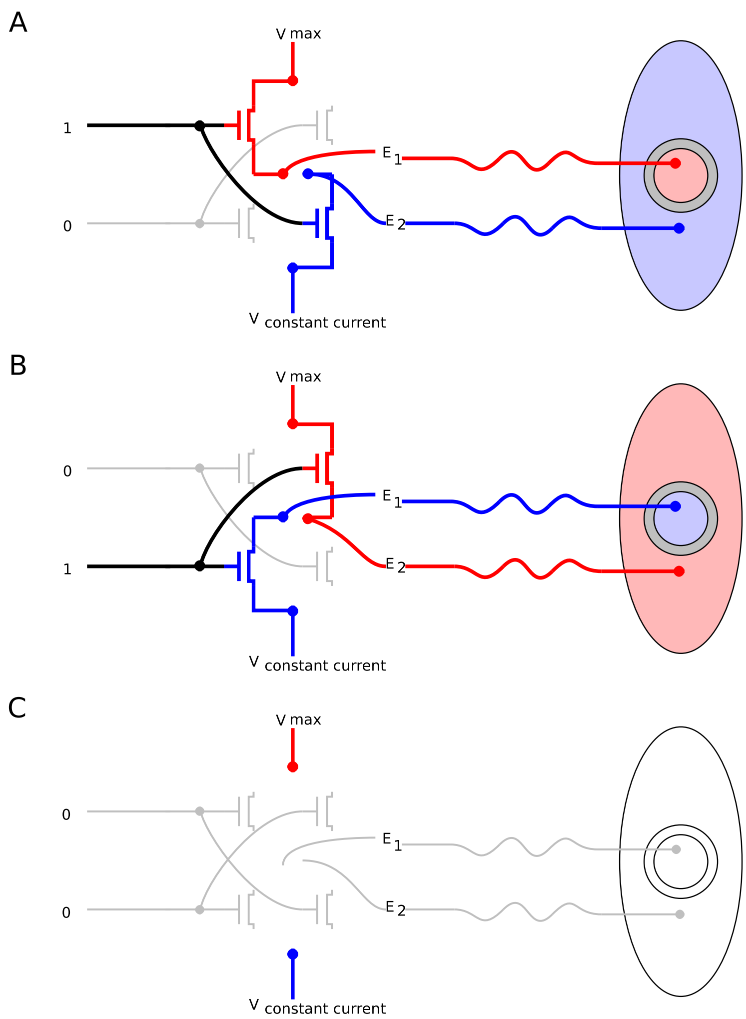

Figure 22: Biphasic current switching. For different values of control signal C_1 and C_2 the electrode has 3 modes of operation: ***A***, Active centre, passive surround. ***B***, Active surround, passive centre. ***C***, Disconnected electrode (no current flow).

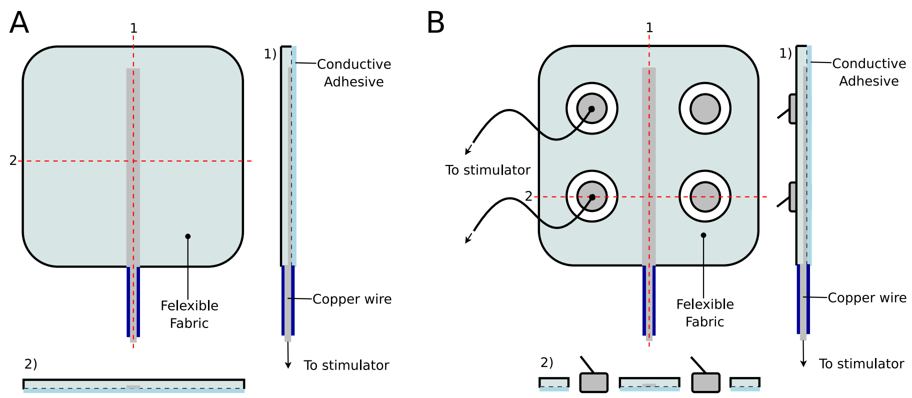

Figure 23: TENS electrodes. A standard TENS electrode (left) can be modified (right) to deliver punctate yet safe electrotactile sensations.

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