Non-Explicit Communication with Robotic Manipulators: A Review (December 2016)

Paul M. Calhoun, *Member, IEEE*

***Abstract*— This paper reviews current applications of non-explicit, direct communication between human users and robot actors for the purposes of manipulation. A brief overview of each input type (Intracortical Electrode, Surface EMG, etc.) is followed by a novel categorization of current applications into Replace (full replacement of capabilities externally), Replace-In-Place(replacement of capabilities integrated directly into the user), and Augment (capabilities being added to the user beyond those of an unaugmented human). Where an input type is currently not in use but may be used in an application, a brief argument is made for doing so. There is also a discussion of the prevalence of certain input types for specific applications, and the possible reasons behind cross-usage trends.**

I. Introduction

Communication with robots either occur both explicitly and directly, or neither. A robotic interface can be a joystick, graphical window, or even gestures and words. All of these methods of communicating what we want a robot to do are both explicit and direct. We communicate *x* and the robot does *y(x)*. Communications which are non-explicit, and non-direct are also well defined. The robot sees that an event has occurred such as an item left on a work surface and it takes the item and puts it away, or there's a person between it and its target configuration so it waits until the person is no longer there. Few communications currently are non-explicit and yet direct. We want the robot to do x and our desire needs to be communicated, but we can't tell it that through a symbolic interface where a certain combination of known inputs result in a deterministic action. These communications are expressly for the robot, but cannot be explicitly given to it. There must be an interface which taps into those intentions; not looking for cues or using a well defined interface, but reading deeper into us through either the patterns in our brains or our muscles. These communications are usually reserved for those who cannot use explicit means – or for whom those means would be a distraction from the purpose of the robot. In most cases, these are prosthetic hands and robots which assist the physically disabled.

There are approximately 735,000 people in the United States who have lost either one or both upper limbs [1], 3 million worldwide [2], and of them 70% have amputations distal to the elbow. 30-50% of people in the United States who have lost all or part of their arm are not using a prosthetic [3]. Expense is the primary reason [4] behind this lack of adoption, followed by the current status of progress in making effective replacement limbs. In addition, there are up to 347,000 people currently with spinal cord injuries, and 58% of those patients are suffering from a form of tetraplegia [5], degrading or removing voluntary control of their extremities and in some cases removing all voluntary muscle control.

These applications and others which involve an operator using a robot which is either unusable with or degraded by the use of an interface which requires the operator to provide explicit input must find a different method – non-explicit communication. As mentioned before, the two prevalent means are those which look at our brains for guidance, brain-machine or brain-computer interfaces [6] (BMI/BCI, for the purposes of this paper I will use the term BCI though there is currently active discussion of the appropriateness of the term in the context of robotics) and those which tap into our muscles to get inputs, electromyography (EMG) [7]. For the purposes of this paper, we will look only at interfaces with facilitate manipulation (hence the focus on upper limb amputation), with a view towards classifying them with regards to their current uses. For this purpose, there are three labels which will be used – Replace, Replace-in-Place, and Augment. These labels will be elaborated on more in section IV. By breaking up the applications of non-explicit communication this way, we can understand better how robotics professionals currently view the input methods currently available by not just looking at the uses, but the lack of certain interfaces in each application.

The rest of the paper will look at each interface type, starting with BCIs (section II), then EMG (section III). With this background fully realized, the paper will then go through each type of application and the current work being done, broadly keeping to elaborating on applications realized with BCI, followed by EMG (section IV). Section V will discuss how these applications fit together with observations about the cross-*applicability* of certain papers, and the lack of cross-*application* of certain methods, as well as the total lack of other methods in practical use. It will then conclude (section VI) with a conclusory statement as well as future work.

Submitted December 13, 2016 as the final paper in Manipulation Algorithms, RI, SCS, CMU

Paul Calhoun is with the Robotics Institute, SCS, CMU, The Robotics Institute 5000 Forbes Avenue Pittsburgh PA 15213-3890 (e-mail: pcalhoun@andrew.cmu.edu).

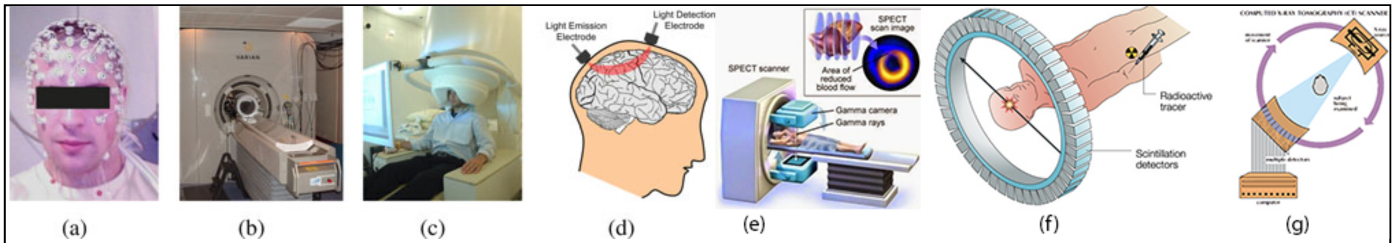

Figure 1 - Noninvasive BCIs, (a) EEG. (b) fMRI. (c) MEG (d) NIRS [6], (e) SPECT [56], (f) PET [57], (g)CAT [58]

II. Description Of Methods – Brain Computer Interface

Brain Computer Interfaces are currently the prevalent means of communicating with and giving agency to people with tetraplegia and other 'locked in' syndromes [8]. They read the intention of the user by acquiring through various means the signals which pass through the user's brain as they think about taking actions. For the purposes of this paper, most signals being acquired are centered in and around the motor cortex [9]. Signal processing is currently a major avenue of research, as most types of BCI are limited by bandwidth and by the speed with which they can process very complex data. Most common BCIs operate near or below the Nyquist criterion for the number of updates per second needed to capture a signal well, and none at the speed at which most robots update [9].

Some BCIs incorporate direct bio-feedback [6], a process in which the BCI sends a signal to the user through its connection or an ancillary connection to tell them that an event has occurred, similar to haptic feedback. This remains rare within most applications [9], with most biofeedback being in the form of visually observing the robot [10] due to the difficulties of activating the specific neural patterns that produce sensations of touch and proprioception [11] (fig. 2).

As with any system, there is a learning curve involved in the usage of BCIs, in this case both for the machine and human [10]. The machine to better learn each individual human's signals to better filter noise and categorize input, and the human in producing clear and unambiguous signals, to the point where a user who is very familiar with BCIs will have adapted some of their neural structure to produce clear, machine readable signals [8]. There has been some discussion [12] over whether the changes in brain structure and function caused by various forms of neurodegenerative conditions significantly change how a BCI would need to read a user, though learning may remove that particular issue by having the system conform to the users' neural features.

In BCIs, the dominant difference in controlling manipulatory prosthetics (beyond degree) is that of shared autonomy. In many cases, a task being done by the robot is one which it is familiar with and it is more likely to succeed if it uses its own autonomous decision making process to complete. As such, many systems leave the task planning to the human and once the robot knows what the human wants, motion and grasp planning is completed by the robot [13]. The open questions in this situation is when to have the robot take over, how much control the human should have during motion/grasp planning, and when to turn control back over to the human in a way that feels seamless.

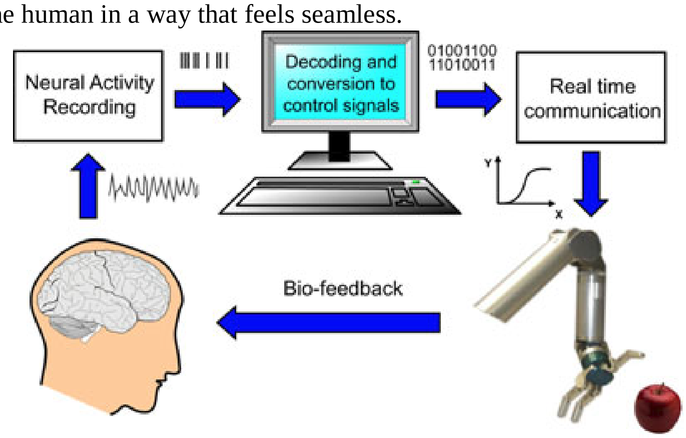

Figure 2-High Level BCI Schema [6]

BCIs are generally split between noninvasive forms which read signals through the scalp and skull via external sensors, and invasive, which are either on the surface of the brain itself or introduced intracortically – for our purposes into the motor cortex. Each type of sensor has its own benefits and drawbacks unique to the method, though broadly speaking noninvasive methods are either slower or less accurate. An overview of BCIs is presented in table 1.

A. *Noninvasive*

Noninvasive BCIs are a family of sensors which either rest on the scalp to directly read the electromagnetic emanations of the brain or use some manipulation of electromagnetism to look through the skull and image brain activity.

Noninvasive BCIs make use of Evoked Responses (ER) and Induced Responses (IR). These correspond to phase and amplitude of signals respectively.

ERs are evoked by continuous sensorial signals such as light or sound, and so are related to the signals captured by the BCI by their phase. These can be visual evoked potentials (VEP), in which a flashing light is shined in the subject's eyes and their neural response varies at the same frequency. This is difficult to reproduce voluntarily and rarely used.

Induced Responses are a potential that occur as a response or in advance of an event and are broken into Event-Related Potentials (ERP) and Event-Related Synchronization/Desynchronization (ERD for simplicity). Both are used more commonly than ERs. ERP is broken into the very common P300 which occurs as the result of a random stimulus and can be easily trained to reoccur by remembering that same stimulus, and SCP which uses cerebral rhythms trained with biofeedback and there is some evidence that many people cannot train themselves to produce them voluntarily [6]. ERD methods are even more common than P300, and while they require training, they are very effective in use because of their discretization. Each type of signal exists on a different frequency band and with training a system can distinguish between the sensorimotor rhythms of different parts of the body [6], and are in part based on local field potentials (which will be discussed later).

1) Electroencephalography (EEG)

EEGs are scalp mounted electrodes (figs 1a and 3) which attempt to directly capture the activity of large groups of neurons. It has a bandwidth of 0-50Hz and a spatial resolution (smallest area of the brain it can read) in the centimeter range and milliseconds of temporal resolution (shortest signal it can detect), directly capturing neural activity rather than most other noninvasive methods which must infer neural activity from other sources. It suffers from significant noise issues as the signals it attempts to capture must pass through several thick layers of liquid, bone, and skin to reach the scalp electrodes, so a system using them needs sophisticated means of noise reduction [6]. EEG is by far the most common noninvasive BCI, with consumer applications, and is also the most portable and least difficult to use, adding up to a strong incentive to fix issues with it rather than find other means of capturing signals.

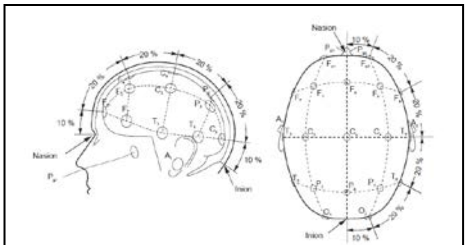

Figure 3 - Electrode Placement on Scalp [8]

2) Functional Magnetic Resonance Imaging (fMRI)

fMRI uses changes in magnetic fields produced by an MRI scanner on the order of 3T to 7T [8] to detect changes in blood flow as the result of the oxygenation and deoxygenation of hemoglobin(fig 1b). These correspond with changes in brain activity due to the blood-oxygen-level dependence (BOLD [8]), an indirect means of inferring neural activity from blood movement. It has a spatial resolution of 1 to 3 mm [6], and an information transfer rate on the order of 1 bit per minute [8]. It is currently not used in many applications and will likely never be used outside of very specialized situations since though it is accurate and does not require invasive surgery or expose the user to radiation, the magnetic exposure may have side effects, and the equipment needed to produce up to 7T of magnetic field strength will likely never be small enough to make it worthwhile without significant advances in material science. One significant difference between BOLD and any other type of information gathered in non-explicit communication (BCI or EMG), is that BOLD uses image processing using Computer Vision methodologies (fig 4) rather than signal processing of the electromagnetic emissions of brains and muscles. In the figure below, the image from an fMRI is shown, being segmented into a voxel grid (only two dimensions shown).

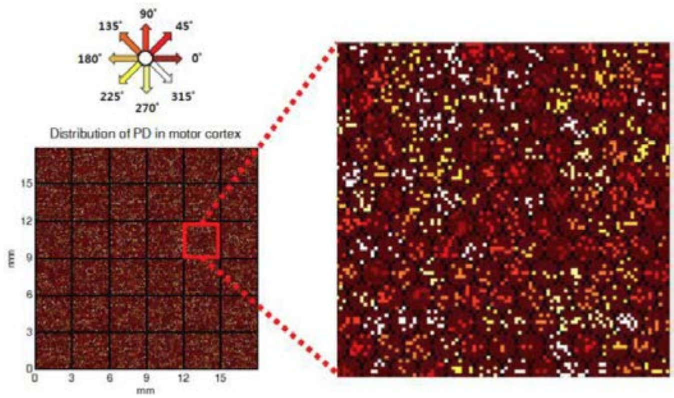

Figure 4 - fMRI BOLD Image [14]

3) Magnetoencephalography(MEG)

MEG is a similar method to fMRI, using magnetic induction to view the direct magnetic activity around the brain, a sort of hybrid of fMRI and EEG, making use of the fact that magnetic fields are less distorted by biological impediments (the user) than electric fields. The device makes use of superconducting quantum interference, and is cooled to within 0.15K of absolute zero [8] and requires a magnetically shielded room in which to operate, as the ambient magnetic noise from electronics would overpower what it detects from a human brain. It has higher temporal resolution than fMRI but lower spatial resolution [6]. As can be inferred from the description of the equipment, it is also not likely to become portable without significant improvements to signal processing and material science, though it does require less preparation than fMRI, and the patient need not be prone (fig 1c) to make use of it.

4) Near-Infrared Spectroscopy (NIRS)

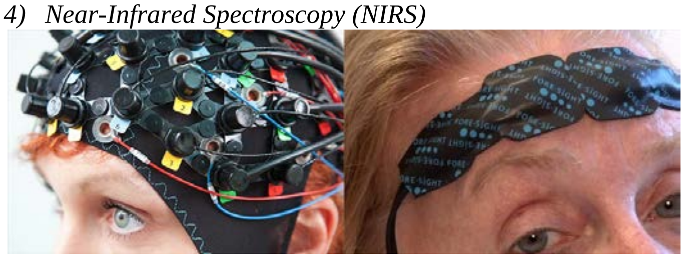

Figure 5 - NIRS sensors. Research grade fNIRS 'helmet' (left) [15] and consumer grade patch (right) [16]

NIRS is similar to fMRI in its use of BOLD to infer neural activity. It uses an infrared LED to shine infrared light through the skull (fig 1b), though attenuation means that it only reaches into the outer cortical layer. It has a spatial

Method	Invasiveness	Portability	Resolution	Bandwidth	Data Spread	Reaction Time
EEG	None	High	1cm/ 1ms	0-50Hz	High	High
fMRI	None	None	1-3mm/1s	1 Hz	High	Low
MEG	None	None	1cm/1ms	0-330Hz	High	High
NIRS	None	High	1cm/100ms	1-10Hz	High	Low
CAT/SPECT/PET	None	None	N/A	N/A	High	Low
Intracortical	Very High	Low	10µm/1ms	0.1-10kHz	Targeted	Very High
ECoG	High	Moderate	10µm/1ms	50-500Hz	Moderate	High

Table 1 - Overview of BCI Capabilities

resolution around 1cm and a temporal resolution around 100 ms [8]. It does not require much training on the part of the user, and is as safe and portable as EEG, requiring even less preparation time as it does not need to place electrodes on the scalp (fig 5 right). However, due to the slow nature of inferring neural activity from blood flow, its uses are still limited [6]. It is also degraded by hair obstruction and head motions, which are usually mitigated in research and clinical applications by molding NIRS helmets to individual subjects' heads (fig 5 left).

5) Other Non-Invasive Methods

There are other noninvasive BCI methods, but are as yet unused in manipulation. These include PET (positron emission tomography), SPECT (single positron emission computed tomography), CAT (computerized axial tomography), and fNIRS. PET, SPECT, and CAT are likely unused because they require not only bulky and costly machinery, but also introduce radioactive isotopes into users to image the brain [6]. As such, they are not suitable for long term BCI usage. fNIRS is a variant of NIRS which uses the helmet (fig 5 left) to get a 3D image of the brain, and is often used interchangeably with NIRS in research.

B. Invasive

Invasive BCIs are a family of methods which introduce the sensor either to the surface or inside the brain (fig 6). By directly reading neural activity, they significantly decrease noise and improve resolution both spatial and temporal [6].

Their main tradeoff is the complexity of implanting an invasive sensor, requiring costly and complicated surgeries, and if there is an error or fault in the hardware can require surgery to repair. They are also often wired connections, leaving the user with a port or wire extending from inside their skull. As such, there are no invasive sensors in use for non-medical applications.

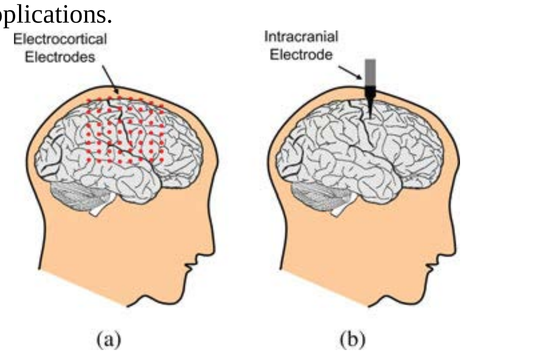

Figure 6- Invasive techniques. (a) ECoG. (b) Intracortical [6].

1) Intracortical Electrode

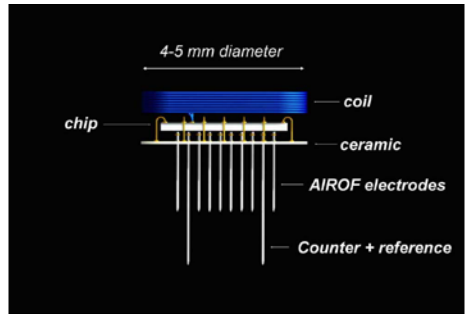

Figure 7 - Diagram of Wireless Intracortical Electrode [17]

Intracortical electrodes use a microelectrode (fig 7) to penetrate into the brain to read signals with as much as 1 neuron of resolution. They can read single unit activity (one neuron), multiunit activity (groups of neurons) [6] and local field potentials (very large groups of neurons) with most implants being a 96-channel array. The first two can be directly translated to digital output as they record the firing of neurons while local field potentials are read as analog signals [8]. The minimum estimated number of neurons needed to control a basic prosthesis is 15-30 [6]. However, signal quality can degrade over time as the microelectrode accumulates damage from the motion and fluctuation of the brain, though this is a continuous process and so does not require discreet retraining until the electrode is recalibrated or replaced [8]. The larger problem, however, remains inflammation, scarring, and rejection, which leads to the area around the electrode becoming unreadable. There are currently efforts to produce an electrode which either helps to regenerate tissue around it or to not provoke damage at all, but these have yet to produce consistent success [6].

2) Electrocorticography (ECoG)

ECoG introduces a set of electrodes similar to an EEG to the surface of the brain (fig 8). They read the LFP, getting a much higher resolution version of the ERD than EEGs. They have a spatial resolution on the order of 100 times that of EEG, and a bandwidth on the order of 10 times more than EEG [6] while remaining wireless in some applications.. Currently there are

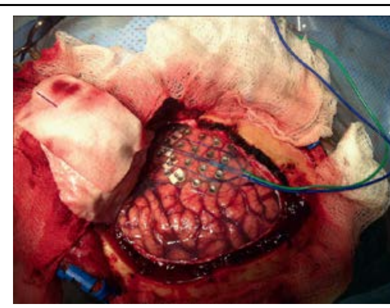

Figure 8 - A Brain with ECoG Sensors [59]

studies which have shown ECoG remains stable and can function for months, and methods exist to introduce the electrodes using minimally invasive surgery [8]. Much newer than intracortical electrodes, ECoG has not had as many applications, though given its properties this is likely to change.

C. Multimodal

BCIs which make use of two or more (sometimes both invasive and noninvasive) methods occur with some regularity, usually a mixture of EEG and another method such as NIRS or visual tracking. As there is no consistent or recognized pairing which occurs with regularity, these multimodal combinations of methods will be addressed on a per-application basis in section IV.

III. Description Of Methods – Myoelectric

Myoelectric systems are the prevalent means of controlling replacement hand and arm prosthesis [18]. While BCIs can view intention at a high level and need ever increasing resolution to read specific manipulatory intent from the motor cortex, Electromyography (EMG) reads the amplitude of electric signals from muscles [19]. This bypasses much of the need for sophisticated learning and electronics of a BCI, with the drawback that there are a very limited number of muscles that can be independently read from, limiting the system to few simultaneously controllable degrees of freedom (DoF) [18].

An EMG signal is – broadly speaking – digital. A set of muscles receive the activation signal from the nervous system, which causes the muscles to contract. This occurs in two stages: first a transient state as the muscles go from rest to contraction, and then a steady state of a contracted muscle [7]. There is an amplitude component, which can be used to define the torque or speed to be used to move a myoelectrically controlled prosthesis, however this is rarely implemented as the signal processing necessary makes myoelectric control more of a classification issue than an amplitude issue [20] (fig 9).

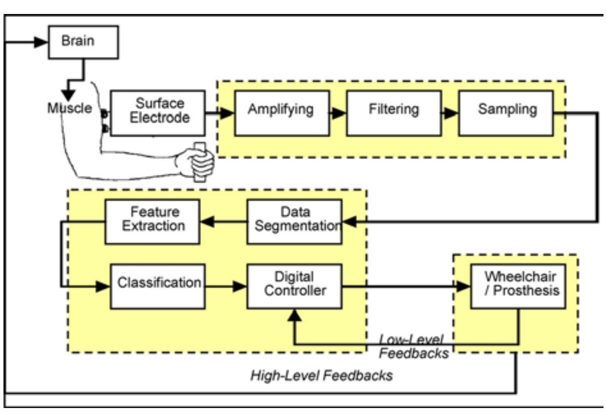

Figure 9 – Block Diagram of a Myoelectric System [7]

There is an analogue to BCI's biofeedback methods, which make use of "stimulation of the sensory portion of the spinal cord nerves, which would normally innervate the hand and forearm" [21] producing feeling in the location of a limb whether it remains or has been removed. In manipulation, myoelectric systems often have their own version of shared autonomy as well, where instead of the prosthetic performing full actions autonomously, it must read a user's intent to form a grasp primitive [19] (fig 10). This is done via attempting to map muscle synergies [22] to intent, finding which muscles coactivate at which amplitude to produce specific motions.

The number of primitives a prosthetic is capable of ranges from 7 to 20 in most commercially available prosthetics [18] to 41 primitives in research [19]. The most common grasp primitives are – unsurprisingly – very similar to those found in computer controlled manipulators.

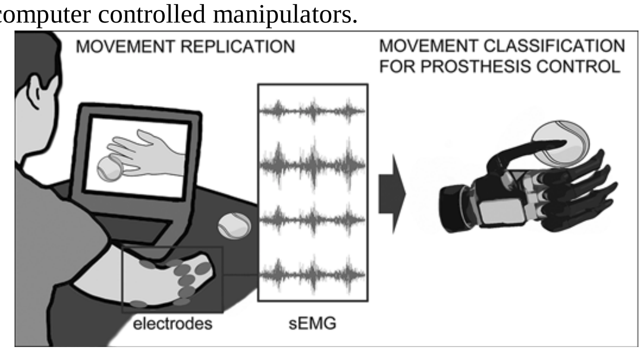

Figure 10 - Robot Learning Grasp Primitives using sEMG [19]

The number of different ways of acquiring EMGs are fewer than BCIs, mainly because the signal being acquired is in a more localized, easier to reach area and the signals themselves are less complex than found in the brain.

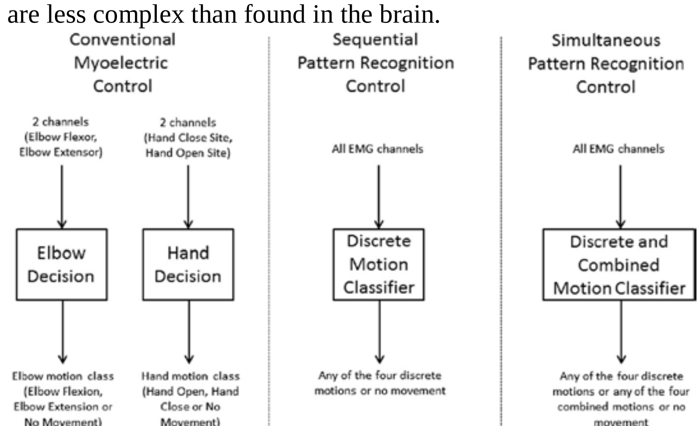

Figure 11 - Overview of Basic EMG Strategies [23]

A. Surface EMG (sEMG)

sEMG is the most common, simplest, cheapest, and least information rich version of EMG. A set of electrodes are placed on the pairs of agonist-antagonist muscles and the strength of the signal dictates the action, occasionally adding an ulnar element for more sophisticated processes. There is a great deal of interference from skin and fat layers, resulting in a need for sophisticated noise reduction techniques in order to get a strong signal [22]. In most cases only two sites can be read from at the same time due to the proximity of muscles interfering in each others' signals [23]. The methods of how to use these two-site signals vary, but the classical way is for the user to engage both flexion and extension (cocontraction) at the same time repeatedly to cycle through modes or joints (fig 11 left, 12), and then to use the difference between the two to decide which direction to move and how quickly. This is useful for prosthesis that have a very limited number of predefined grasp primitives or very few degrees of freedom, but is not suitable for complex motions.

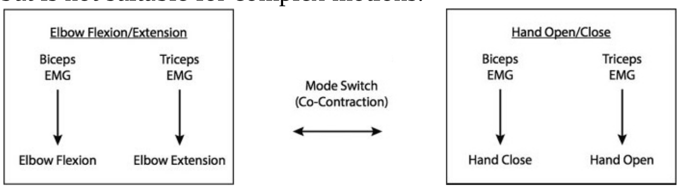

Figure 12 - sEMG Switching Method [22]

More complicated but similar methods include using flexion, extension, and ulnar deviation to 'mix' signals into a custom grasp (fig 11 center, 13), but this requires the user to go through a lot of training [24]. sEMG is also used in learned systems [19] but the lack of dedicated muscles and confusion of the signal can often make the process difficult (fig 11 right).

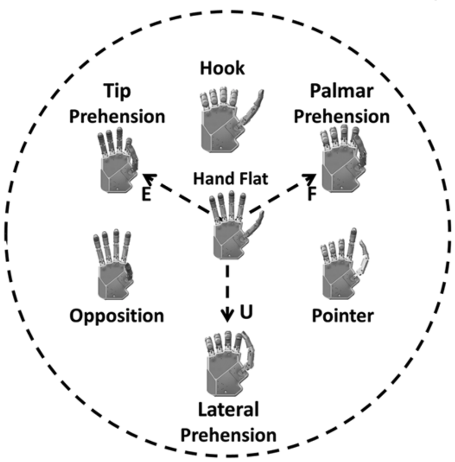

Figure 13 - Mixing Three EMG signals for the hand E = extension EMG signal, F = flexion EMG signal, U = ulnar deviation EMG signal [24]

As mentioned earlier, there is a method of using learning to try to find muscle synergy patterns and classify them into grasp primitives, which is difficult with sEMG due to the issues caused by removing and reapplying electrodes, however classification gets around the two-site problem by including crosstalk between muscles as part of the classification model, in some cases even avoiding a direct reading of any specific muscle.

The final downside of sEMG is that because the user has no dedicated site (they pull the electrodes off and reapply them using either a dry electrode stuck on with adhesive or one with Ag/AgCl gel [25]) the signal can vary from day to day, making learning even more difficult.

B. Targeted Muscle Reinnervation (TMR)

Figure 14 - Patient Post-Surgery with Grafts and Flaps [22]

TMR is not strictly speaking an EMG strategy, but instead a way of significantly improving the results of an sEMG source by increasing the number of degrees of freedom that can be simultaneously controlled. This is done by surgically transferring residual nerves which had been attached to muscles in the portions amputated to new muscle groups made up of muscles still extant which are separated from their motor nerve input during the surgery. An added benefit of the surgery is that 'flaps' can be added which get closer to the muscle, decreasing the dampening of intervening fat and skin (fig 14), and isolating the hybrid sEMG from interference. [22]

The number of sites of a TMR recipient is usually four (fig 15), as opposed to the two which are the limit of an unmodified sEMG recipient. By doing so, a user can use a full arm prosthetic with greater ease, dedicating two sites to the elbow and two to the hand.

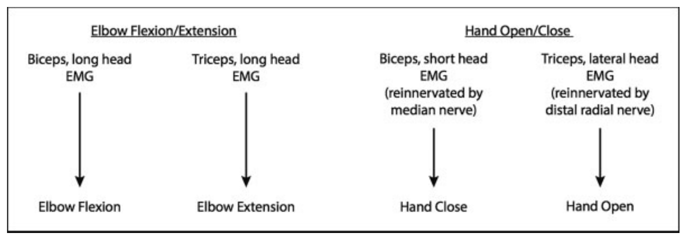

Figure 15 - Four-Site Model (no learning/grasp primitives) [22]

There are few papers on the use of TMR in manipulatory prosthetics (and only 60 users [23]), so this paper will make the distinction later on between sEMG with and without TMR and try to highlight the differences in how they are being applied.

C. Percutaneous

A relatively new way of obtaining EMG signals, a percutaneous implant pierces through the first layer of skin, but not does not pass through the subcutis (fig 16). This has the benefit of creating a dedicated, fixed site which has much lower attenuation than found in sEMG, but without a need for expensive equipment or surgery. The percutaneous implant can be inserted in the same way as a microdermal body piercing and has no upper limit to how long it can remain [25].

Percutaneous implants lack the precision of an intramuscular implant, but are also significantly cheaper, easier to work with, and can be easily implanted and removed.

The current major downside of small Percutaneous implants is that it is a very new technology, with the one seen above only having been extant since early 2016. As such, no manipulatory prosthetic has been shown to function with it, and so it is being discussed here as a promising avenue rather than a method in use.

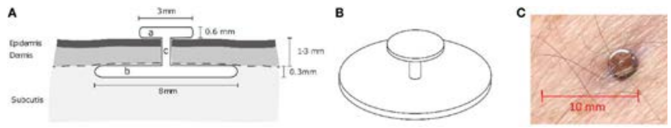

Figure 16 - Schematic, Drawing, Photograph of Percutaneous Implant [25]

D. *Intramuscular*

Similar to the concept of intra*cortical* implants in BCI, intra*muscular* implants in EMG place the sensor inside the target to be sensed. In this case, a sensor is surgically implanted inside a muscle. This has the benefit of insulating the sensor from muscle crosstalk and outside interference [26] while also removing the attenuation caused by intervening layers [27]. There are several forms this can take, with power either by wire or wireless induction, and data being relayed in either a wired or wireless form [26]. By isolating individual muscles, many sites can be combined to control a prosthetic with multiple simultaneous degrees of freedom [27].

Intramuscular is accurate and stable because the implant does not move, though there is a large variance between systems (fig 17) when it comes to returned telemetry and complexity of surgery. Wireless solutions are usually smaller, easier to implant (sometimes even without major surgery), and do not have mechanical strains, while those with external leads have a much higher bandwidth due to the wires and the ability to draw more power [26].

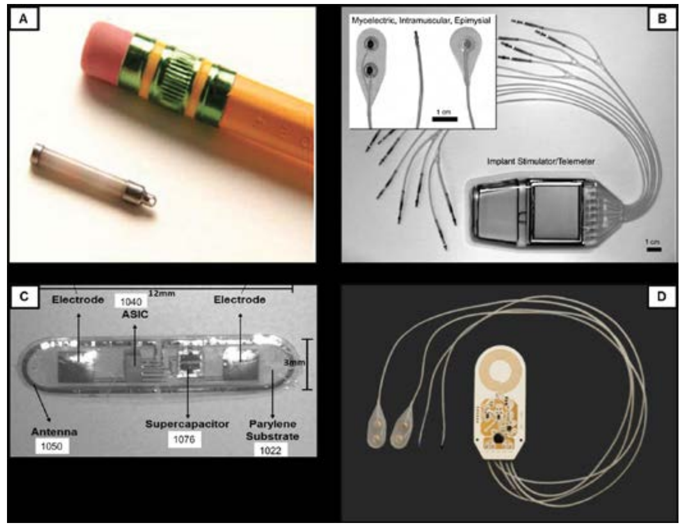

Figure 17 - Lead (B,D) and wireless (A,C) implants [26]

IV. Uses of Non-Explicit Communication

Non-explicit communication (comprising of BCI and EMG) can be broadly considered as either fully replacing a capability, replacing a capability in the location a former capability was removed, or augmenting to add a new capability. This taxonomy was arrived at by inspecting the cross-usage of methods of understanding non-explicit communication by looking beyond the invasive/non-invasive modality, as well as the dividing line of muscle and brain

Taxonomy	Goal	Dominant Users	Sub-Taxonomies	Definition
Replace	Restore significant to total physical capability to user (manipulation, presence, personal autonomy)	Users have little or no remaining voluntary motor capability (tetraplegics), those unable to perambulate without aid		
			Full Autonomy	Robot gives user finite choices in actions to take
			Shared Autonomy	Robot gives user control of high level motions, take more control as user closes on recognizable goal object
			Direct Control	User controls all motions and manipulation actions
Replace-In-Place	Restore one or more limbs user no longer has	Amputees with varying quantities of residual limb		
			Maximize controllable DoF	User can directly control the most number of degrees of freedom
			Maximize grasp library	User can perform the maximum number of discrete grasps (usually requires more residual limb)
Augment	Add extended capability to user above that seen in unmodified human	Anyone, usually able-bodied, but no theoretical reason not to augment users of R and R-I-P		
			Increase Ability	User gains a new personal capability such as an integrated limb, manipulator in a key area of workspace, or extended endurance/speed (not in this paper since they aren't related to manipulation)
			Increase Presence	User can occupy a location they are not physically proximal to using a robotic surrogate

Table 2- Taxonomy Summary

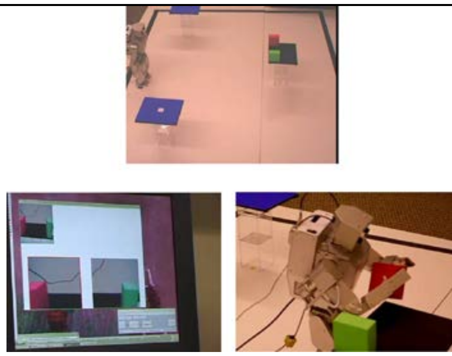

Figure 18 - (A) Robot sees objects of interest, (B) Presents them to the user (C) Picks up the one chosen [30]

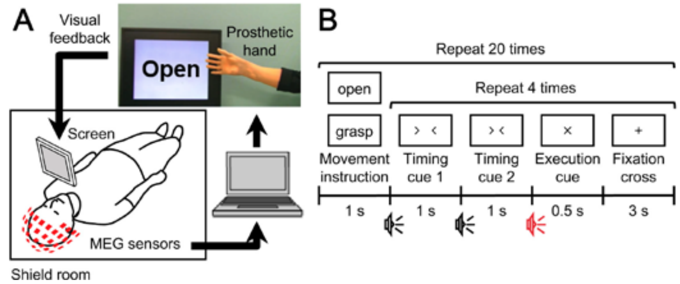

Figure 19 - MEG Based Hand Control. A) User controlling a prosthetic hand using MEG sensors (B) Training structure with user moving their hand as instructed to show the system what to look for [32]

interfaces. By looking at the use to which non-explicit communication is put, we can see how these boundaries often hide a shared necessity.

This section will look at a wide variety of manipulator applications and tests which made use of every elaborated non-explicit methodology previously expanded upon. The arrangement will illustrate how each method fits into the broader manipulation concept by exploring the taxonomy.

To help aid structure, each section will be further segmented by a sub-taxonomy which is based on the overall goals seen in the systems – for example in Replace the taxonomy is broken up by the quantity of shared autonomy. By segmenting by this taxonomy as well as system goal, we help see the differences in effectiveness and uses more clearly by seeing how well they perform manipulation tasks based on the intent of the user. Table 2 summarizes the taxonomy.

A. *Replace*

Replace can be thought of as the classical invasive BCI format (and indeed, invasive BCIs are found almost exclusively in this category). A user has lost a significant capability (in most cases, the voluntary use of all muscles controlled via spinal reflex), and requires a service robot. As the Replace taxonomy is specifically interested in manipulators, most cases will involve a manipulator arm on a static base, though some mobility will be explored for the purposes of comparing it to R-I-P and Augment.

This taxonomy shows the stark divide in usage between invasive BCI and all forms of EMG (for the understandable reason that EMG cannot function if there is no voluntary muscle control). That said, contrasting with R-I-P and Augment, we will see that conceptually this is a one way street. Cases of Replace cannot mix with EMG, but the other two can freely take from BCI without conceptual violation, even if this is in practical terms almost unheard of for invasive BCIs. The taxonomy will be split by degrees of *shared autonomy* each robotic system grants the user, from systems which take minimal input to perform preprogrammed behaviors to those with almost total control over the robot's behavior. An example which contains the two extremes of shared autonomy is [28] where the author has an EEG controlled mobile robot which is either controlled manually or told what waypoint to go to, at which point it engaged in autonomous navigation. The user can see through a camera mounted to the robot, and in the first version has total control of the robot's trajectory with the EEG through the experiment, and in the second has no control at all once they've chosen a target location.

1) *High/Full Autonomy*

When the robot has the most autonomy, the user is effectively acting as the decision making node in a finite state machine. We can see this in [30] where the robot finds objects of interest and displays them on a screen as such. If the user chooses to interact, the robot picks the object up and then can give another set of choices. In the case of this 'object choice' system, the situation is even more interesting because it is the same type of user choice system but this time with a humanoid robot and interface that could be used to fully replace a human unable to leave a control facility, which is why we will also see the same system in Augment with a different application. A system with a little more sophistication is [29] in which an ECoG was used to measure a desire to grasp an object in conjunction with an eye tracker to measure visual fixation, with an array of three objects in the test. When the user was looking at an object *and* showed intent, a preprogrammed behavior would pick up the object and place it in a container.

In [31], we see a very interesting concept of using anticipation rather than evocation ('I intend to/want to do something' rather than 'I'm pretending to do it in my mind'). However, because the sophistication of the interface (surface EEG), and of the processing algorithm (CVN flip-flop), the maximum number of differentiable signals is three. In that case, each signal started a predefined behavior, so again the system is as sophisticated as 'press one of these three buttons, do something, repeat.' As such, this system was categorized as Replace less because of its interface or author intention but simply because there are few cases where the usability passes the threshold of usability needed for R-I-P or Augment (usability threshold will be discussed in section V).

In the most extreme cases, the user's input is *when or whether* a system executes a predefined action rather than being given a choice between possible actions. In [32] there is a case of using MEG to train with a user and then detect whether they wanted to open or engage a grasp with a prosthetic hand, a promising avenue but very early in development and because it uses MEG, it works at a speed which may place it in the Augment category in future as a 'lightswitch' app assuming a portable MEG-like device is produced. The 'lightswitch' is almost explicitly called out in [33], a NIRS based method of estimating how much force a user is applying with an isometric movement of their arm, which they were able to separate into '1','0', and '-1' inputs, referring to it as 'ON/OFF' motions. A variant of [29] which expands the system by giving the user the ability to place the object anywhere is [34] falls into the 'lightswitch' category because it has only been tested using a single object, making an eye tracker unnecessary but also reducing the choice to when the robot will pick the single object up, though promising in that it gives the user the choice of where to put it, and is fairly inexpensive compared to other systems explored here. The user choice aspect may eventually move the system to the 'shared' category.

2) Shared Autonomy

In the next layer up in terms of shared autonomy, we see robots which still choose grasps and angles of attack, but modify their behavior in real time based on user input. In the case of [13] and [35] we see a Barrett WAM arm being operated in a shared autonomy setting using an intracortical implant without any auxiliary visual inputs. The user guides the robot hand to an object by directional intent alone and the robot decides what to do, smoothly increasing its share of the work as it grows closer to the object. The robot never assumes full control, and can be guided away from the object at any time, or told to place the object in a location or manipulate it in a way other than the one it had expected to when it began planning. The authors succeeded in integrating the shared autonomy to the degree that the test subjects were not informed in any given trial whether they were operating using direct control or shared autonomy, with only the ease of use to give them an idea of what mode the system was in. Some of this is due to the significant work done by the creators of the system in making the transition smooth, and also the use of grasping strategies which do not rely on a model set, instead finding grasp patterns online. This system is explicitly contrasted with those like [29], seen in the previous subsection, in that it does not ever cede total control to the robot, and does not require an explicit eye tracker to function. There is also a significant contrast in terms of grasp strategies; with the user more free to decide what they want to grasp, there is a lower reliance on the system deciding what objects are of interest and so much greater flexibility. As of now, there is only one system in this category, though others may soon join it.

3) Direct Contol/Maintenance-Only Autonomy

Finally, there are cases where the system has minimal autonomy, effectively only handling tasks to avoid colliding or reaching unsafe joint velocities (if that). While entirely theoretical at present, [14] demonstrates a possibility of using fMRI to learn muscle control patterns in subjects' brains and use that to control a manipulator, giving the user complete control within joint limits. While this process looks a great deal like a BCI version of R-I-P, the philosophical necessity of free motion in R-I-P excludes it from that category, and it is excluded from Augment because fMRI (and indeed any method that makes use of BOLD) has a slow response rate, making it difficult to place in Augment, which already incorporates a general assumption of a remote system which has feedback delays, making the addition of input delays a significant roadblock to inclusion (though as seen later not an insurmountable one). One thing the authors did that may mitigate this in future is begin work on an algorithm that predicts the next motion primitive from the previous one, though this may push the system into a different layer of shared autonomy.

A system with more results is [36] in which a tetraplegic user with an ECoG was trained with higher degree of computer assistance, but decreased it until they had full control of a 3DoF prosthetic arm with hand. This produced very good results, with the user able to move the arm to the correct location with very small jerkiness, however there was no control of the hand at the end of the arm, giving it very limited capabilities. As resolution increases, no doubt this will change. A very similar system is in [37] where the user had a classical two pair sEMG configuration which gave them two DoFs to control, moving a robot arm to touch its palm to a cup, where in a real system the user would have to change DoF configurations to have the system grasp the object. It is important to note in this case that the system would not be useful to someone with upper limb paralysis but instead as a helping hand for those with mobility issues. In the same vein, [38] would be appropriate for users with lower limb paralysis. This system controlled a 7 DoF arm (3 arm, 3 wrist, 1 'open/close' hand control) by using a camera to visually track arm motion to get the orientation of the arm joints, and then an EMG for the wrist and hand, using a neural network of their own design, the log-linearized Gaussian mixture network (LLGMN). This had an average success rate over 97% when it came to classifying motions. While neither this nor the previous EMG example are classical Replace candidates, they do allow for arm motion at a distance, replacing the capabilities that would be lost by someone who cannot reach or cannot move to a location which the teleoperated arm can. By moving the arm into place, they can use natural motions to reach and grasp, rather than a harder to use joystick or GUI.

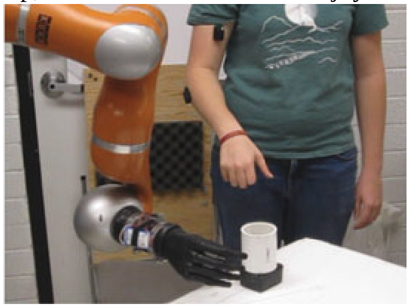

Figure 20 - User Controls Robot Arm By Moving Own Arm [37]

A more effective result was achieved in [39] in which a user with intracortical electrodes was trained in a similar way using not only computer assistance at first, but also machine learning of the individual's specific patterns to help it learn the user's intent as the user was learning the system. By the end of the trial, the user had no autonomous assistance and was able to control a 3 DoF arm with a 3 DoF wrist and 1 DoF ('open'/'close') articulated manipulator to grasp and move objects with consistently good outcomes. In both of the previous examples, calibration and training took weeks or months to complete, with computer assistance ending on day 18 in [36] and week 10 in [39]. In contrast, the training required for the BrainGate interface in [40] and [41] took 4 minutes of watching a robot arm and imagining themselves doing what the arm was doing to train a Kalman Filter, which continued to refine itself online – though it is important to note that the users from [36] and [39] had their BCIs implanted at the time of the study, whereas the two from [40] had theirs for 5.3 years and 5 months respectively. The results, then, are more surprising since the first user had a success rate of around 60% whereas the second had a success rate similar to the other invasive BCI systems – around 96%. They used either a 7 or 6 DoF arm with articulated hands which only registered 'open' or 'close' for the purposes of the test, and used impedance control to help keep from continuing to contract after a successful grasp. The two arms were a DLR arm meant for assistive usage and DEKA, which is a replacement upper arm prosthetic [42]. The first user improved by 10-15% using DEKA and the second user used DEKA exclusively [40].

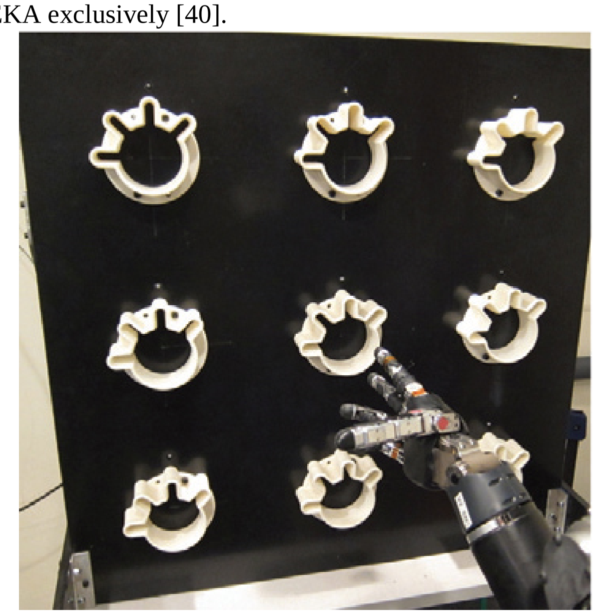

Figure 21 - Test Facility for Non-Grasping Manipulator Arm [39]

B. Replace-In-Place (R-I-P)

Whereas Replace is specifically non-integrative, and Augment is anthrosynergistically agnostic, R-I-P is specifically an integrative process in which the manipulator becomes part of the human user, replacing a hand or arm with a robotic prosthetic. Like Augment, there is no theoretical boundary that keeps any method from being used to control it. Two physical operations which are specific to R-I-P are Targeted Muscle Reinnervation (TMR) [22] (discussed here and later on) and Osseointegration [43]. The first alters the user by effectively adding muscles to control a system, and the second physically makes a prosthetic part of the user, implanting not just intramuscular electrodes but also grafting a socket to plug the prosthetic into directly to the bone of the residual limb; as of now the only user with the latter also has undergone the former, gaining the sometimes redundant benefits of TMR, intramuscular implantation, and integration into the bone.

Though all but one solution for R-I-P are EMG based, by exploring the taxonomy we'll see that there is no specific reason why this is the case other than anthropological imperative towards replacing human parts with prosthetics that are as functionally similar as possible, even when the effect is to in fact decrease its functionality and the familiarity with which a user might operate it. Non-explicit communication is, at its root, *intention*, which means that the most effective means of communicating that intention is the best interface. There will be two sub-sections: methods that are focused on *simultaneous control* of arm DoF, and methods focused on *variable grasp* patterns. These correspond to the two priorities of upper limb replacement, the hand and the arm. As can be seen by the descriptions of the methods, these are not mutually exclusive goals, but for the purposes of study and research are usually pursued separately.

1) Simultaneous Control (SC)

Simultaneous control seeks to restore as similar a function as possible, focusing on having the user directly control their prosthetic. While this can include hands with grasp primitives, due to the difficulty in differentiating between muscles being read from in sEMG and expense of intramuscular methods, most of the time these efforts are focused on the elbow and wrist, with only one or two grasp primitives programmed into the hand. This section is arranged by the number of simultaneously controllable DoF.

The smallest number is of course one. The usual case there is a hand which can open and close or an elbow joint. In [44], the system takes a holistic view of creating a hand prosthetic system, not only producing their own algorithm for EMG control but also a compliant 'soft hand.' Their system was not exhaustively tested with users, but did show good results with grasping objects using a grasp similar to cylindrical prehension (wrapping fingers around object and thumb on opposite side), and mechanically it appears to have many properties of compliance which is valuable in making a biomimetic prosthetic, but given its highly limited applicability, the system itself was less important than the architecture of the hand.

In [45], two simultaneous degrees of freedom were controlled, with three minutes of calibration followed by online learning of the users' requirements. They made use of 14-16 sEMG sites, which were combined into 4 distinct channels – two per DoF as has been described above. The difficulty they face currently is that neither of their chosen DoFs were in the hand – instead being focused on two wrist motions, with one TMR user instead doing hand open/close and elbow motion - meaning that grasping was very basic with the system they produced, though the TMR patient showed that it could be extended to grasping by altering which DoF was being controlled.

There are also two simultaneous DoF and three in total being controlled in [22], however this is a significant advance because by altering the user's physiology with TMR surgery, which had only been able to handle one DoF at a time, they doubled his control capability. Prior to TMR, the patient did not have enough residual muscle to control more than one DoF at a time, so while almost all other methods rely on improving the machine, this method directly altered the user to improve control capabilities. As such, the user may benefit from the advances in control offered by other methods, further increasing capability. Similarly, [25] does not test with a prosthesis real or virtual, but instead demonstrates a new physical device which like TMR integrates permanently with the user in a non-intrusive way, controlling 2 simultaneous DoF, and removing the effects of vibration and between-day changes in the location of electrodes. The intramuscular EMG tests in [26] were also not used on any type of prosthesis, but showed good results with both able bodied users and transradial amputees, with over 99% classification accuracy and approximately 60% path accuracy when controlling three simultaneous degrees of freedom. However, the system makes use of fine wire intramuscular electrodes which are implanted and removed as part of the experiment and hooked into non-portable systems, making it only an R-I-P candidate because of author intent, and not a candidate for Replace because there is not enough control for a system that is physically separate from the user.

Three simultaneous degrees of freedom are further investigated in [46], which while more concerned with laying out the procedure for a method of testing upper limb prosthesis in the Target Achievement Control (TAC) test does itself have a 3 DoF control schema which it uses to show how the TAC test can be used. As far as this paper is concerned, the only other mention of the TAC test is in [23], where it is used to evaluate several systems as part of a review. They used the TAC test in [46] to test their own system, which controlled two wrist directions and an 'open/close' grasp on a virtual upper limb prosthetic. Six electrodes were placed on amputee users' residual muscle locations, and trained classifiers (linear discriminate analysis, fuzzy logic, and artificial neural networks) to recognize motion of those DoFs. They recorded an average 94% classification accuracy, but only 69% completion rate of the TAC test, suggesting to the authors that while systems can accurately classify motions, often this does not translate into useful behavior. It is important to note that this paper was written in 2011, whereas most of the other R-I-P papers which tested on physical prostheses came later, and produced better results. This includes the very early stages of IMES® [27] which had only one long term user as of publication, and so was not able to provide any statistical analysis of usage. There was, however, a great deal of promise in the system, which has three simultaneous DoF, one in the wrist, one which pinches the thumb and index finger together, and one which curls the other three fingers. It is wireless and powered by induction, but is limited in that it can only be used by amputees with significant residual lower arm musculature due to its reliance on those muscles for fine control. They included the capability to add a fourth DoF to the system, but this has yet to be implemented in a user.

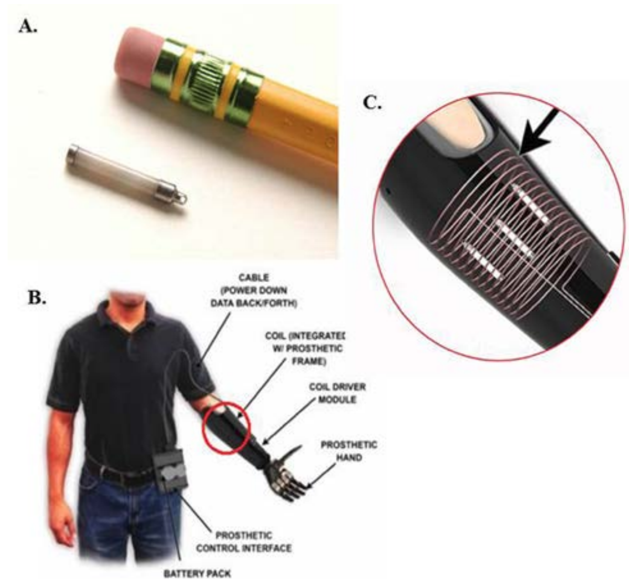

Figure 22 - IMES Concept and Execution [27]

There has been some progress in very fine hand control with very high simultaneous DoF control. In [47], there is a theoretical basis for a 16 DoF control (a degree of actuation/motor(DoA) for each finger which contains 3 coupled DoFs, plus another DoF with its own DoA for thumb ab/adduction, so arguably only 6 DoF control with another 10 coupled to 5 of those) with only two EMG channels by approximating muscle synergy using Principal Components Analysis. They showed a hand that could be controlled continuously through several grasp primitives, effectively giving total hand control. They, however, chose not to use real EMG inputs, instead feeding their algorithm simulated EMG readings, which while artificially noisy to try to simulate a real human user, and they acknowledge at the end of their paper that they need to extend their experiment to human users and in [48] they did. When human users were brought in to do trials, they found that by the third day the users were able to complete more than 90% of grasps in a range of 5-10 seconds per grasp, with the worst results in the 'precision' category at 87.5% completion with 'power' and 'lateral' grasps over 95%. While this method does not have complete hand control (only the index finger and thumb could be moved independent of the other fingers and the thumb in two directions, with the middle through pinky bending roughly as one unit), they can claim at least 4 simultaneously controllable DoFs on able-bodied subjects, meaning that using PCA they can do at least as well as a TMR patient, so perhaps by combining the two, an amputee user could add another dimension to their PCA graph and control more DoFs.

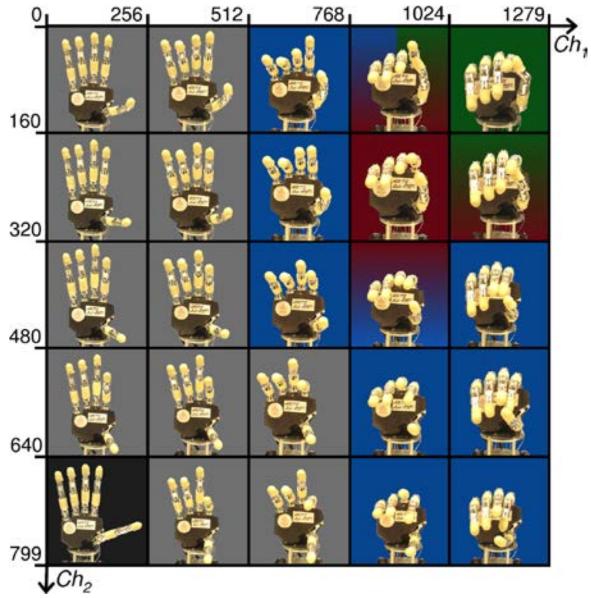

Figure 23 - Hand Postures Mapped Using 2D PCA [48]

The highest proven DoF control was investigated in Replace earlier in this paper. In the BrainGate trials [41], a 6 DoF arm with a 'close' and 'open' DoF on the hand was shown to function on an arm intended to be an upper limb prosthesis. While intracortical implants may seem unnecessarily invasive for an upper limb replacement, given that it translated intention to function so well, there is likely no reason why some of the channels could not be moved further down, putting 2 DoF on the wrist and 4 on the hand, and if an invasive BCI could be made portable and non-intrusive in daily life, there is no reason why the BrainGate system could not be used for amputees as well as tetraplegics apart from possible difficulties in separating input for one arm from the other. There is also some argument that [38] does better as a 7 DoF arm, however the difficulty there is that 3 of those DoFs are controlled visually, which would make it difficult to make it a portable system as required in R-I-P. Were the visual portion removed, it would be very similar to many other systems proposed here. However, if the visual system could be made portable or turned into some other form of measuring the location of the upper arm, it would also be a very useful system for people with no residual forearm.

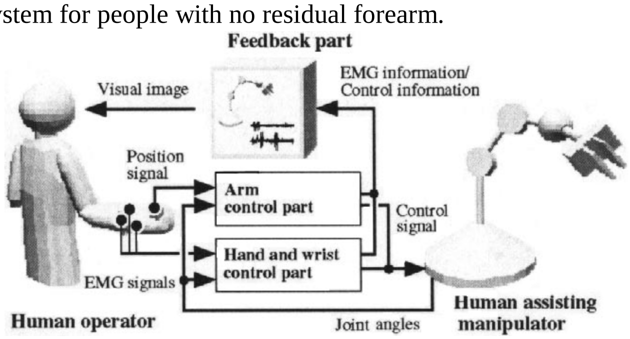

Figure 24 - Concept of a Hybrid Visual-EMG System [38]

2) Variable Grasp (VG)

Rather than trying to restore the feel of controlling a prosthetic, VG looks at restoring as many functions as possible, seeking to differentiate signals in ever more subtle ways to increase the number of grasp primitives a prosthetic hand can support. Often these methods focus on the hand to the point that the rest of the upper limb is controlled by mechanical means if it is even considered at all. There are two main examples in this section, one with more grasps and the other with a better control of the grasps implemented.

In [49], the system used an array of 4-12 sEMG electrodes evenly spaced around the proximal third of their forearm, specifically placed to keep from targeting a specific muscle. By using vector summation of each RMS value as well as a discrete integration, they were able to determine the 'position' of a virtual cursor (visually shown in training sessions and then removed for hand control experiments) by finding the angle and velocity of its motion in a virtual circle. They defined six locations at the outside of the circle and one in the center to represent the seven grasp primitives their prosthetic was preprogrammed to use. The users were able to move the virtual cursor with over 90% completion, but about 3.5 seconds to reach a grasp from neutral, and less than 50% path efficiency. The users generally had ~4 hrs of time on the system by the end of the experiment, so with online learning to help improve the decision process and more time to get used to the system, this would be likely to significantly improve.

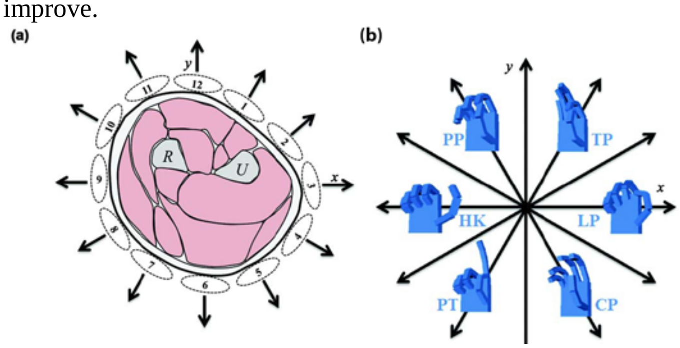

Figure 25 - Control Concept for 7 grasp system a) Location of Electrodes b) Grasps Mapped to Virtual Directions [49]

We see a more sophisticated methodology in [50] where there are only 5 grasp types, but the system also attempts to match how much force is to be applied by the grasp from 0 to 100N with 0.02N resolution. In this case, there are 10 sEMG electrodes, which are placed in groups along the muscles responsible for finger motions. The difference between [50] and [49] in this regard is that in [50] rather than trying to train a user to produce motions which correspond to a grasp, they are training the machine to learn the inputs from a user's natural grasping behavior. They test using a feed-forward neural network, support vector machine, and locally weighted projection regression, and found all three worked with approximately the same accuracy. The main contribution and centerpiece of their learning strategy was not the learning method, but the means of gathering training samples which used Online Uniformisation (OU), a method which would take each sample as it came in and look at the distance between it and all other points. If it is within a minimum distance of at least one point, it was discarded, otherwise kept as part of the sample set. By doing this, they maintained the minimum number of samples necessary for learning. Using a four fingered hand similar to [49] (so 5 DoA and 13 DoFs), they were able to accurately classify the 5 grasps of the user 90% of the time, and had an error of 7.89% on predicting the force of the grasp.

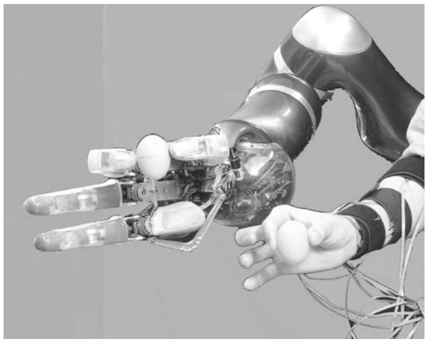

Figure 26 - DLR Hand Being Taught How Much Force to Grasp and Egg With [50]

C. Augment

While Replace and R-I-P look at returning functionality which has been degraded, Augment seeks to take a fully functional user and add further functionality. This is the philosophy behind most robotics today, though few make use of non-explicit communications for this, opting for the easier to parse and more direct methods such as voice, gesture, and GUI control. In these cases, the invasive methods are generally unseen, as few humans are interested in having electronic control methods integrated into their bodies in order to increase their capabilities (for now). However, there will be some invasive methods investigated as part of Augment to show the progress being made towards less intrusive invasive control schemes.

As such, this is the taxonomy that unifies all four concepts of invasive BCI/EMG and non-invasive BCI/EMG. Augmentation contains applications via all four methods since there is no preconceived opinion or condition of the user which precludes a method other than willingness to try them. While there will be no example of true Augmentation using an invasive BCI, an example will be included where the usage by a Replace candidate could easily be translated to an Augmentation case. As will be observed during the cases, many Augment situations are more geared towards mobile robots than manipulators, and so while the attention will remain on manipulation, some mobility will be included as illustration. In most cases, systems highlighted in Augment were not intended for the purpose but instead was shown to be good candidates because the experimental users were able-bodied and not the intended end user of the system, with about 70% being repeated in the Replace and R-I-P categories. In these cross-referenced cases, novel uses will be suggested for robots which were intended for other purposes. This section will be split in terms Augmentation based on increasing *ability* and that which increases *presence*, the difference between a helping hand / mobile helper and telepresence / surrogacy.

One system to highlight which might be a component in either is [25], which is a hardware solution that might make a system which is robust, portable, and sensitive enough to combine hand and arm control without the need for intrusive control mechanisms, but as this kind of unobtrusive percutaneous implant is less than a year old, tests using that hardware with real hand/arm systems have yet to be published, and so is not included as a direct Ability or Presence improving system.

1) Ability

Increasing Ability is the main thrust of robotics today. Robots do things humans can't or won't, from assembling cars to exploding bombs. They do the repetitive, dangerous jobs, and those which require speed, precision, or strength beyond that of a human. Ability increasing robots which make use of reading intention through non-explicit communication are robots which usually act alongside humans or as part of them. An example which is not manipulation but shows this well is [51], where a quadcopter is controlled with SSVEP potentials,

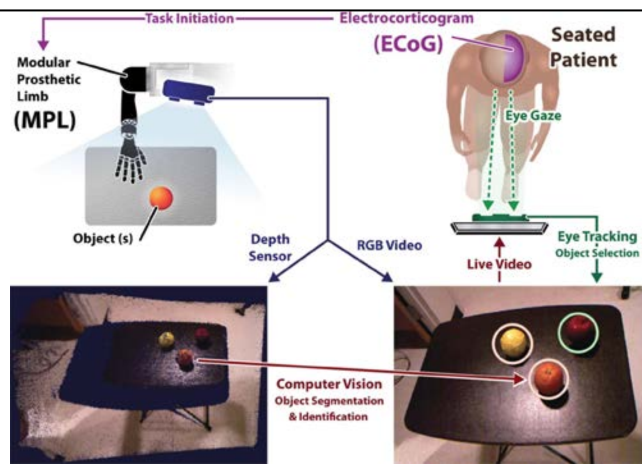

Figure 28 - User Controlling a Remote Manipulator which Finds Objects of Interest and Gives the User a Choice to Interact [29]

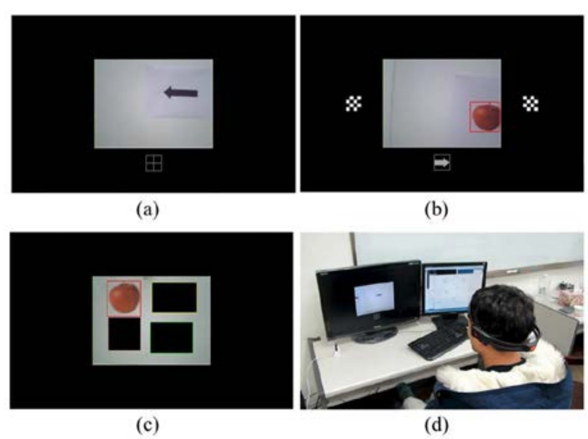

Figure 27 - Small Telepresence Robot. "The design of the display during (a) walking straight, (b) turning head, and (c) recognition. (d) The interface being used by a subject."

and a NIRS reading to improve accuracy. In this case, it is easy to see a human needing to see something far away or send a message and they send the quadcopter up, using the BCI to guide it and so be able to focus on a visual interface without the clutter of a GUI.

The considerations in [52] are for space systems as a whole rather than any specific armature or device, but the arguments made make sense for such a system which requires the level of reliability and performance a space system would need. They envision a situation where astronauts will need to pay attention to many different things, so the system will need significant noise tolerance. While their argument against fMRI, MEG, PET/SPECT, and NIRS (too bulky, requires shielding, requires radioactive injection, could be compromised by light emitting cosmic rays respectively) are compelling, their wholesale ruling out of invasive systems seems more about comfort and perception than anything else. In a situation where a pilot of a craft never leaves the ship and uses non-explicit communication to control functions, an invasive system might make the most sense, placing them in some kind of life support system as they focus their minds on the ship, which mixes Presence and Ability strongly into one concept. There is also no mention of EMG, which would make some sense for a manipulator like the ones used on the space shuttle, which are functionally similar to an upper arm prosthetic.

2) Presence

A strong theme in extending Presence is that the user is shown the view of the robot during operation, and has something closer to direct control, though stronger themes of autonomy can show up when it comes time for grasping and finding objects of interest. At the near end are robots meant to go where a user cannot because the area is dangerous, and the far end are robots which are surrogates for the user in situations where the robot is acting in place of the user in a day-to-day aspect.

We last saw [28] in the Replace category, briefly used as an example of the difference in autonomy between Full and No Autonomy groups. The Unlock system the author produced could have a BCI user pilot a mobile robot either by direct control of direction and a fixed velocity during motion, or by choosing a waypoint which corresponded to an object of interest identified by the robot. This system and the one in [30] (also cross-listed in Replace) are good candidates for Augment as they use a non-invasive methodology to control a mobile robot and in [30] that robot is also capable of manipulation, marking it as very useful in long distance teleoperation tasks, especially in dangerous but well known environments like a nuclear plant where the objects of interest are well defined, and so the robot need only be guided from waypoint to waypoint and told what to do there.

Augmentation using DC is generally seen in cases of true telepresence rather than in task-oriented scenarios since having the human totally immersed in robot control only increases the human's capabilities if the robot has more capability than the human or is in a location that is otherwise unreachable. In [53] we see a small humanoid robot which is trained entirely on individual user BCI data and uses three different signals to allow for several different types of input. The robot uses ERD to control when it takes steps, SSVEP to turn the head to look at things, and P300 to find objects of interest – and in all cases the rate of correctly interpreting a command was around 70%. This system is unique in all the systems that implement object recognition in that it can still be placed in DC, owing to the fact that rather than having objects be recognized based on a predefined database, the objects are defined by the *user* by having them look at the object beforehand and capturing the neural activity associated with it. This means that the humanoid can go into a variety of locations and as long as the location has been somewhat defined by the user in advance, help them find areas of interest. The downside is that this does not aid manipulation and would need to be coupled with a more sophisticated grasp planner – which is beyond what this system was able to provide, as it reached the point of actual manipulation without interacting with an object.

The system in [54] was intended as a telepresence robot, and tests were meant to take that as far as possible, with the user on a different continent from the robot (user in Israel, robot in France). They controlled a small humanoid robot using fMRI and their vision was through the camera of the humanoid robot. They could make the robot walk and move the arms up and down, but the robot itself did not allow for grasping, only blunt manipulation. The longest task was walking a figure 8 around two obstacles, with path radii about the height of the robot, which was completed in an average of 12 minutes. Users reported identifying with the robot as an extension or replacement of themselves and of feeling a strong sense of being where the robot was, to the point of feeling the motion of the robot when it was picked up by one of the experiment staff. The methodology is strongly biased towards surrogacy, with the user completely subsumed into the robot's identity since an fMRI would leave them unable to move their own body, and so their intention was focused entirely on the robot.

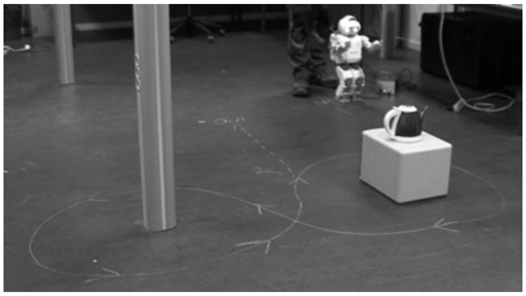

Figure 29 - Small Telepresence Robot Navigating a Path with Obstacles [54]

The system in [38] is very interesting as it is effectively a telepresence arm. The intended use is as a desktop helper, but it could also form part of a telepresence or a system for interacting with objects in a place a user cannot go, such as a lab with hazardous material or a highly regulated environment where extremely sensitive experiments are being done. There is no reason why both arms cannot be used, granting the user the ability to reach and manipulate objects at long distances. Given that they have to move their own arms for some of the joints, they would likely begin to identify with the robot with those arms, and using an EEG controlled mobile platform as previously described, would become even more integrated into the robot's agency. With a soft hand [44], such a system could be highly adaptable to being a long term telepresence solution.

V. Discussion

As can be seen in the above sections, the taxonomy of Replace, Replace-In-Place, and Augment bring out some very interesting trends in non-explicit communication of intention. One thing is the concept of cross-usage, where a system in one category crosses over to subsequent categories, being useful in a variety of ways that in most cases the systems' creators didn't intend. Another is the prevalence of methodologies in each category, with Replace predominantly BCI and R-I-P mostly populated with EMG solutions. Finally, there are the cases where a system might seem like it would belong in a category – and in some cases was intended so by the creator – but does not fit in very well. While I have respected the creators' intent in these taxonomies, I have also tried to observe when their system did not necessarily belong where it was placed by them. The conceptual tests which place a system and these borderline cases will be explored.

A. Cross-Usage

There are several systems which appear in multiple sections – indeed almost half of the systems in Augment are cross-listed from either Replace or R-I-P, and [38] appears in all three. While that may make it seem as if the taxonomy does not produce strong identities, I would argue that it is a good thing. Non-explicit communication is in very early stages and so many of the applications being written about have broad usage because they are still investigating many of the basic needs of the discipline.

B. Predominance of Methodology

It is not surprising that the first two taxonomies favor BCI and EMG respectively, while the third does not favor either.

Those who make Replace systems are more likely to use BCI mainly because the users are often unable to produce voluntary muscle signals, meaning that EMG has no input and so cannot be used. In cases where users still have voluntary input – such as those with lower limb paralysis – explicit communication via GUIs and joysticks remains the prevailing method.

There is also the philosophical issue that R-I-P heavily prefers EMG because it 'connects' in a more conceptually appealing way, restoring functions using exact same channels as the limb which is being replaced. This despite this paper's showing that BCI can – and in some cases does – outperform many EMG systems when used in upper arm prosthetics. This is especially true with prosthetics for those with very little residual limb, as even with TMR surgery it is difficult to get enough data to control an upper limb prosthetic, whereas BCIs can control an entire upper limb with more DoFs. If a person is thinking 'I want to move my arm', it doesn't matter what path that thought travels along if the arm itself moves as directed.

Augment has few cases of EMG which cross over from R-I-P, though as noted before the split between EMG and BCI is about even. In the following section this will be investigated, but the main reasons are simply those of capability and usability. Many of the systems in R-I-P are either *pieces* of a larger system that has yet to be put together into a meaningfully useful Augmentation, or are in some way difficult or intrusive to use and so would not make the transition easily.

C. Rationale of Categorization and Borderline Cases

There were a simple series of tests which were used to categorize these systems. The first was designer intent. I respected the designer even when I felt that their system was not necessarily as effective – or even minimally effective – for the purpose it was made for. An example is the hybrid visual EMG system in [38] which was intended as an upper limb prosthesis. This was put into Replace-In-Place, but otherwise failed the next most important test, who can use it? Replace is meant to restore physical capability for those with little to none; Replace-In-Place must be integrable into the user in order to restore the physical limb. Augment is not considered in this question since the addition of capability is user-agnostic for the most part. As we see in [38], there is no provision for how the system will maintain visual contact in the long term, and so the system cannot be integrated into the user since it by definition must have a component which is external. In fact, several systems including the force learning system in [50] may not satisfy the requirement since the tests on able-bodied users allowed for many shortcuts which could not be taken with eventual end user for Replace-In-Place. The test for Augment was a bit more qualitative. It looked at whether the system added capability to an able-bodied user in such a way that it was feasible to be used in the long term by an able-bodied user, and that the capability it granted could not be easily replicated. For example, many Replace and Replace-In-Place systems restored basic capabilities to the user which an able-bodied user would not consider an extension since they themselves could do those actions more easily and with more effectiveness themselves. The best way to see some of the rationale in action is by looking at borderline cases.

The category that is most typified by borderline cases is Augment. There were several EMG robot arms, for example, which were tested on able-bodied users and so would have been listed in the Augment taxonomy if not for their lack of usability. There is a remote controlled arm is in [45], which had no control of the hand for non-TMR users, so while it may one day be integrated into either a Presence or Ability based system, further progress needs to be made, as would a system like [37] which also allowed for only arm control with no hand capabilities. Likewise [47] and [48] have very good hand control, but lack arm control, which might make sense for a system that uses both something like [45] or [37], but switches between them as needed, or a yet-to-be created system that can differentiate well enough to do both arm and hand control. In these cases, while they might be good progress for R-I-P – and will often need to be combined as suggested here – Augment has the unique situation of addition rather than substitution, meaning that if the system cannot do a job *at least as well* as a human in the same situation (especially one encumbered by a survival system in harsh environments), then it cannot be considered a true Augmentation.

In a very similar case to the percutaneous implant in [25], [26] was tested on able-bodied users and showed good progress, but used invasive intramuscular implants which were not only uncomfortable, but not portable. They were, however, easy to implant and remove, so if it weren't for more sophisticated intramuscular implants which show just as much resolution but are much easier to retain in an unobtrusive way, this system might be a worthwhile Augment candidate.

The IMES® [27] intramuscular system is in some ways the opposite problem. Difficult to implant but very portable, it makes a very attractive choice for Augment but for the fact it requires expensive surgery to implant. If it could be placed in users in minimally invasive surgery, it might make a very effective telepresence *or* ability expanding system, as the small electrodes could be placed on muscles all over the body and perhaps have a biofeedback mechanism included.

BCI systems which use object recognition are likewise problematic. In cases where a user expresses intent to grasp an object, the system must *recognize* an object as being important when it's a Highly autonomous Replace system or at least graspable, otherwise no amount of intent will make the system interact with it, which is beneficial in that the user cannot try to make the robot do something it is completely incapable of, but with a much larger drawback that the user is stuck with whatever the robot has learned/been told is something it can grasp. In this way, the systems all express their grasping in terms of *known* objects, looking through a database to find a close match and then computing grasps from there. While this is likely sufficient for non-telepresence Replace candidates who are in the same environment all the time, telepresence Replace, R-I-P, and Augment users will need greater capabilities. As noted in Augment, these systems might have a place in emergencies when a robot is going through a well known but unreachable area, but pose issues for general usage.

VI. Conclusion

The needs of users to communicate to robots through direct transmission of intention is still mainly restricted to users who are either unable (in the majority of Replace cases) to do so, or for whom such a communication would be infeasibly cumbersome (for R-I-P). However, as seen in Augment, this will almost certainly change in the near future, and systems once meant only for people with specific needs may spread to users of all abilities to make them more than they could ever be without integrated robots rather than returning them to a level close to their previous capability. The taxonomy which has been suggested here helps show that though usage may differ, often the end result or methodology is the same, and some methods which were intended for one audience are better suited to others.

A. Future Work

The taxonomy remains somewhat fluid, and a more rigorous exploration of each category would no doubt find better ways of including certain methods. Specifically those discussed in section V-C, which were rejected from Augment but included in R-I-P, despite in truth not being particularly effective as R-I-P systems for the same reason. An arm, for instance, which can only reach but cannot grasp is only a marginal improvement over a purely mechanical upper arm prosthetic, though systems with only hand functionality are at least useful for those who retain most of their forearm. In addition, some systems categorized as Augment may in fact be very effective Replace candidates, but were not explored as such due to author intent. The strongest candidate is the fMRI telepresence robot in [54] which could conceivably be an all-in-one Replace system, and in a future revision may be placed there if it can not only extend presence but also restore manipulation capability.

There is also going to be rapid changes in many systems cited here, so another survey in 2 years will no doubt significantly change the landscape, and possibly replace many systems cited here with their successors and novel systems not yet devised. There are also some systems mentioned which have only a very tenuous connection to manipulation, included because they are the very beginnings of systems which will likely include manipulators. There is also room for investigating those methods which have never had a system built to use them, such as radiation based BCI. The process to even testing many of these systems is long, and getting them approved for wider use even longer [55] but the result is well worth it.

VII. Acknowledgements

The author would like to thank Carnegie-Mellon University for having a wonderfully diverse set of subscriptions, Professors Henny Admoni and Katarina Muelling for advising in the course this was prepared for – and even moreso Professor Admoni for reviewing earlier concepts of the paper and Professor Meulling for directly contributing to the advancement of non-explicit communication.

References

[1] "Limb Loss Awareness Month," The Amputee Coalition , April 2016. [Online]. Available: http://www.amputee-coalition.org/events-programs/limb-loss-awareness-month/.

[2] M. LeBlanc, ""Give Hope - Give a Hand" - The LN-4

Prosthetic Hand," Stanford, 09 11 2008. [Online].

[3] M. Kulley, "Hand Prosthetics Statistics," Brown University, 28 April 2003. [Online]. Available: http://biomed.brown.edu/Courses/BI108/BI108_2003_Groups/Hand_Prosthetics/stats.html.

[4] L. Diep and G. Wolbring, "Communication Technologies Including Brain-Machine Interfaces Revealed from the Perspectives of Special Education School Teachers Through an Ableism Lens," *Education Sciences,* vol. 3, pp. 30-49, 2013.

[5] "Spinal Cord Injury Facts and Figures at a Glance," National Spinal Cord Injury Statistical Cente, Birmingham, Alabama, 2012.

[6] J. Becedas, "Brain–Machine Interfaces: Basis and Advances," *IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS,* vol. 42, no. 6, 2012.

[7] M. A. Oskoei and H. Hu, "Myoelectric control systems—A survey," *Biomedical Signal Processing and Control,* pp. 275-294, 2007.

[8] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain Computer Interfaces, a Review," *Sensors,* vol. 12, pp. 1211-1279, 2012.

[9] H. K. Kim, S. Park and M. A. Srinivasan, "Developments in brain–machine interfaces from the perspective of robotics," *Human Movement Science,* 2009.

[10] J. M. Carmena, "Advances in Neuroprosthetic Learning and Control," *PLOS Biology,* vol. 11, no. 5, 2013.

[11] S. J. Bensmaia and L. E. Miller, "Restoring sensorimotor function through intracortical interfaces progress and looming challenges," *Nature Reviews Neuroscience,* vol. 15, pp. 313-325, 2014.

[12] J. Stone, W. Landau and C. e. al., "Neuroprosthetic control and tetraplegia," *The Lancet,* vol. 381, p. 1900, 2013.

[13] K. Muelling, A. Venkatraman, J.-S. Valois, J. E. Downey, J. Weiss, S. Javdani, M. Hebert, A. B. Schwartz, J. L. Collinger and J. A. Bagnell, "Autonomy Infused Teleoperation with Application to BCI Manipulation," 2015.

[14] S. Nam, K. H. Kim and D.-S. Kim, "Motor Trajectory Decoding based on fMRI-based BCI - a Simulation Study," in *International Winter Workshop on Brain-Computer Interface*, 2013.

[15] "NirX," [Online]. Available: http://nirx.net/nirscaps/.

[16] G. Santos, "NIRS: A Head Patch That Monitors Brain Blood Flow and O2," 2012. [Online]. Available: http://www.geeky-gadgets.com/nirs-a-head-patch-that-monitors-brain-blood-flow-and-o2-05-02-2012/.

[17] "Intracortical Visual Prosthesis," Laboratory of Neural Prosthetic Research at the Illinois Institute of Technology, [Online]. Available: http://neural.iit.edu/research/icvp/.

[18] M. Atzori and H. Müller, "Control Capabilities of Myoelectric Robotic Prostheses by Hand Amputees A Scientific Research and Market Overview," *Frontiers in Systems Neuroscience,* vol. 9, no. 162, 2015.

[19] Atzori et. al, "Effect of clinical parameters on the control of myoelectric robotic prosthetic hands," *JRRD,* vol. 53, no. 3, p. 345–358, 2016.

[20] P. Parker, K. Englehart and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses," *Journal of Electromyography and Kinesiology,* vol. 16, p. 541–548, 2006.

[21] "Pitt Team Developing Technology to Allow Amputees to Feel with Prosthetic Limb, Improving Its Function," UPMC, 15 02 2015. [Online]. Available: http://www.upmc.com/media/NewsReleases/2015/Pages/improving-prosthetic-limb-function.aspx. [Accessed 2016].

[22] J. E. Cheesborough, L. H. Smith, T. A. Kuiken and Gregory A. Dumanian, "Targeted Muscle Reinnervation and Advanced Prosthetic Arms," *Seminars in Plastic Surgery* , vol. 29, no. 1, pp. 62-72, 2015.

[23] A. J. Young, L. H. Smith, E. J. Rouse and L. J. Hargrove, "A comparison of the real-time controllability of pattern recognition to conventional myoelectric control for discrete and simultaneous movement," *Journal of NeuroEngineering and Rehabilitation,* vol. 11, no. 5, 2014.

[24] J. L. Segil, M. Controzzi, R. F. f. Weir and C. Cipriani, "Comparative study of state-of-the-art myoelectric controllers for multigrasp prosthetic hands," *JRRD,* vol. 51, no. 9, pp. 1439-1454, 2014.

[25] J. M.Hahne, DarioFarina, NingJiang and DavidLiebetanz, "A Novel Percutaneous Electrode Implant for Improving Robustness in Advanced Myoelectric Control," *Frontiers in Neuroscience,* vol. 10, no. 114, 2016.

[26] L. H. Smith, "Use of Intramuscular Electromyography for the Simultaneous Control of Multiple Degrees of Freedom in Upper-Limb Myoelectric Prostheses," NORTHWESTERN UNIVERSITY, Chicago,IL,USA, 2015.

[27] Pasquina et. al, "First-in-Man Demonstration of Fully Implanted Myoelectric Sensors for Control of an Advanced Electromechanical Arm by Transradial Amputees," *Journal of Neuroscience Methods,* vol. 244, pp. 85-93, 2015.

[28] B. V. GALBRAITH, "A BRAIN-MACHINE INTERFACE FOR ASSISTIVE ROBOTIC CONTROL," ProQuest LLC, Ann Arbor, MI, 2016.

[29] Mcmullen et. al, "Demonstration of a Semi-Autonomous Hybrid Brain–Machine Interface Using Human Intracranial EEG, Eye Tracking, and Computer Vision to Control a Robotic Upper Limb Prosthetic," *IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING,* vol. 22, no. 4, pp. 784-795, 2014.

[30] C. J. Bell, P. Shenoy, R. Chalodhorn and R. P. N. Rao, "Control of a humanoid robot by a noninvasive brain–

computer interface in humans," *JOURNAL OF NEURAL ENGINEERING,* vol. 5, pp. 214-220, 2008.

[31] A. Božinovski, S. Tonkovi´c, V. Išgum and L. Božinovska, "Robot Control Using Anticipatory Brain Potentials," *AUTOMATIKA,* vol. 52, pp. 20-30, 2011.

[32] R. Fukuma, T. Yanagisawa, S. Yorifuji, R. Kato, H. Yokoi, M. Hirata, Y. Saitoh, H. Kishima, Y. Kamitani and T. Yoshimine, "Closed-Loop Control of a Neuroprosthetic Hand by Magnetoencephalographic Signals," *PLoS ONE,* vol. 10, no. 7, 2015.

[33] T. Tsubone, K. Tsutsui, T. Muroga and Y. Wada, "Estimation of Force Motor Command to Control Robot by NIRS-Based BCI," in *14th International Conference, ICONIP*, Kitakyushu, Japan, 2007.

[34] K. D. Katyal, M. S. Johannes, S. Kellis, T. Aflalo, C. Klaes, T. G. McGee, M. P. Para, Y. Shi, B. Lee, K. Pejsa, C. Liu, B. A. Wester, F. Tenore, J. D. Beaty, A. D. Ravitz, R. A. Andersen and M. P. McLo, "A Collaborative BCI Approach to Autonomous Control of a Prosthetic Limb System," in *IEEE International Conference on Systems, Man, and Cybernetics*, San Diego, CA, USA, 2014.

[35] K. Muelling, A. Venkatraman, J.-S. Valois, J. E. Downey, J. Weiss, M. Hebert, A. B. Schwartz, J. L. Collinger and J. A. Bagnell, "Blending of brain-machine interface and vision-guided autonomous robotics improves neuroprosthetic arm performance during grasping," *Journal of NeuroEngineering and Rehabilitation,* vol. 13, no. 28, 2016.

[36] W. Wang, J. L. Collinger, A. D. Degenhart, E. C. Tyler-Kabara, A. B. Schwartz, D. W. Moran, D. J. Weber, B. Wodlinger, R. K. Vinjamuri, R. C. Ashmore, J. W. Kelly and M. L. Boninger, "An Electrocorticographic Brain Interface in an Individual with Tetraplegia," *PLoS ONE,* vol. 8, no. 2, 2013.

[37] M. Ison and P. Artemiadis, "Proportional Myoelectric Control of Robots: Muscle Synergy Development Drives Performance Enhancement, Retainment, and Generalization," *IEEE TRANSACTIONS ON ROBOTICS,* vol. 31, no. 2, pp. 259-268, 2015.

[38] O. Fukuda, T. Tsuji, M. Kaneko and A. Otsuka, "A Human-Assisting Manipulator Teleoperated by EMG Signals and Arm Motions," *IEEE TRANSACTIONS ON ROBOTICS AND AUTOMATION,* vol. 19, no. 2, pp. 210-222, 2003.

[39] Collinger et. al, "High-performance neuroprosthetic control by an individual with tetraplegia," *The Lancet,* vol. 381, pp. 557-564, 2013.

[40] K. Kingwell, "Neurally controlled robotic arm enables tetraplegic patient to drink coffee of her own volition," *Nature Reviews Neurology,* vol. 8, no. 353, 2012.

[41] Hochberg et. al, "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature,* vol. 485, pp. 372-377, 2012.

[42] D. Stimson, "Paralyzed individuals use thought-controlled robotic arm to reach and grasp," National Institute of Neurological Disorders and Stroke, Lanham, USA, 2012.

[43] "APL's Modular Prosthetic Limb Reaches New Levels of Operability," 12 January 2016. [Online]. Available: http://www.jhuapl.edu/newscenter/pressreleases/2016/160112.asp . [Accessed 2016].

[44] M. C. Carrozza, G. Cappiello, G. Stellin, F. Zaccone, F. Vecchi, S. Micera and P. Dario, "On the Development of a Novel Adaptive Prosthetic Hand with Compliant Joints Experimental Platform and EMG Control," ARTS Lab, Pontedera (PI), Italy, 2005.

[45] N. Jiang, H. Rehbaum, I. Vujaklija, B. Graimann and D. Farina, "Intuitive, Online, Simultaneous, and Proportional Myoelectric Control Over Two Degrees-of-Freedom in Upper Limb Amputees," *IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING,* vol. 22, no. 3, pp. 501-510, 2014.

[46] A. M. Simon, L. J. Hargrove, B. A. Lock and T. Kuiken, "Target Achievement Control Test Evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses," *Journal of Rehabilitation Research and Development,* vol. 48, no. 6, pp. 619-627, 2011.

[47] G. C. Matrone, C. Cipriani, E. L. Secco, G. Magenes and M. C. Carrozza, "Principal components analysis based control of a multi-dof underactuated prosthetic hand," *Journal of NeuroEngineering and Rehabilitation,* vol. 7, no. 16, 2010.

[48] G. C. Matrone, C. Ciprian, M. C. Carrozza and G. Magenes, "Real-time myoelectric control of a multi-fingered hand prosthesis using principal components analysis," *Journal of NeuroEngineering and Rehabilitation,* vol. 9, no. 40, 2012.

[49] J. L. Segil and R. F. f. Weir, "Novel postural control algorithm for control of multifunctional myoelectric prosthetic hands," *JRRD,* vol. 52, p. 449–466, 2015.

[50] C. Castellini and P. v. d. Smagt, "Surface EMG in advanced hand prosthetics," *Biological Cybernetics,* vol. 100, pp. 35-47, 2008.

[51] M. J. Khan, K.-S. Hong and N. Naseer, "Hybrid EEG-NIRS based BCI for quadcopter control," in *SICE Annual Conference*, Hangzhou, China, 2015.

[52] Menon et. al, "Prospects ofbrain–machine interfaces for space system control," *Acta Astronautica,* vol. 64, pp. 448-456, 2009.

[53] B. Choi and S. Jo, "A Low-Cost EEG System-Based Hybrid Brain-Computer Interface for Humanoid Robot Navigation and Recognition," *PLoS ONE,* vol. 8, no. 9, 2013.

[54] Cohen et. al, "fMRI-Based Robotic Embodiment: Controlling a Humanoid Robot by Thought Using Real-Time fMRI," *Presence,* vol. 23, no. 3, pp. 229-241, 2014.

[55] Collinger et. al, "Collaborative Approach in the

Development of High-Performance Brain–Computer Interfaces for a Neuroprosthetic Arm," *Clinical Trans Sci*, vol. 7, pp. 52-59, 2014.

[56] C. M. L. West, T. Jones and P. Price, "The potential of positron-emission tomography to study anticancer-drug resistance," *Nature Reviews Cancer*, vol. 4, pp. 457-469, 2004.

[57] "Single Photon Emission Computed Tomography Market – Global Industry Analysis, Size, Share, Growth, Trends and Forecast 2016 – 2020," MEDGADGET, 2016. [Online]. Available: http://www.medgadget.com/2016/02/single-photon-emission-computed-tomography-market-global-industry-analysis-size-share-growth-trends-and-forecast-2016-2020.html.

[58] "computerized axial tomography: computed X-ray tomography (CT) scanner," Britannica, [Online]. Available: http://kids.britannica.com/comptons/art-54158/To-make-a-CT-scan-a-narrow-beam-of-X.

[59] San-Juan et. al, "Utility of electrocorticography in the surgical treatment of cavernomas presenting with pharmacoresistant epilepsy," *Epileptic Disorders,* vol. 16, no. 3, pp. 245-260, 2014.

Paul M. Calhoun (M'10) is a graduate student in the Master's of Robotic System Development (MRSD) program at Carnegie-Mellon University. He graduated with a dual degree in Electrical Engineering and Operations Management from Stony Brook University, after which he spent three years working for the US Navy as a project lead in the SEWIP program. He is a published science fiction author, a panelist and moderator at several science fiction and anthropomorphics conventions, and seeks to hasten the dawn of the transhuman era. As part of this effort, he is working on human robot interaction and integration, having recently finished teaching a Baxter to dance.