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Control of a Robotic Arm Using Low-Dimensional EMG and ECoG Biofeedback

Timothy M. Blackely and William D. Smart

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Department of Computer Science & Engineering

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CONTROL OF A ROBOTIC ARM USING LOW DIMENSIONAL EMG AND ECOG BIOFEEDBACK

by

Timothy M. Blakely

Prepared under the direction of Professor W. Smart

A thesis presented to the Sever Institute of
Washington University in partial fulfillment of the
requirements for the degree of
MASTER OF SCIENCE

May 2007

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Chapter 1

Background

This document describes our experiences while designing and testing a system that allows control of a robotic arm through electromyographical (EMG) and electrocorticographical (ECoG) biosignals. We address three main questions:

- *Can we design a system to control a robotic arm via a form of biological systems?*
- *Would using these biosignals be comparable to conventional control?*
- *Can this system be extended to different types of biosignals?*

1.1 Autonomy

Currently, successful autonomous completion of complex, high-level strategies by a robot relies heavily on human input for control. In order for robots to do all but the simplest of tasks, such as obstacle avoidance or color segmentation, human intervention and guidance play a major role. Even tasks as simple as moving through a doorway can be surprisingly tough for an autonomous robot. The unpredictability and density of information provided by the environment surrounding a robot, combined with inaccuracies in sensor measurements make these tasks difficult for a robot to complete.

Human brains, on the other hand, are capable of processing large amounts of information and are better at making rational decisions based on these data than current autonomous systems. Because of the need for guidance and supervision, it is necessary to devise control schemes that allow the human operator to manage and direct a robot. These control layouts must be both simple to use yet robust enough to complete the intended tasks.

1.2 Control Limitations

When the concepts of simplicity and robustness are considered, it is not hard to imagine emphasizing one will inherently complicate the other. As more actions and abilities are designed into a robotic system, the different selection and transition paths between actions grow in number. In addition to balancing these issues, situations may arise where robots become complicated to the point that controlling all the degrees of freedom[1] synchronously in order to complete a task may prove too complex for the operator to efficiently direct the robot. Honda's ASIMO humanoid robot for instance, requires the operator to be constantly aware of and control 26 degrees of freedom nearly simultaneously to guide the robot through tasks while avoiding damage to it or its surroundings.

In some cases, robotic motions and behaviors can be pre-recorded so that the operator only needs to satisfy a simple condition to trigger playback of the action. Assembly line robots that produce many of the same type of vehicle will repeatedly go through identical motions, making pre-recorded actions a good solution for control. While this works well in static settings, when the world is dynamic situations may arise where a pre-determined movement may not be appropriate or possible. In such cases human intervention may provide a more desirable or efficient outcome than an autonomous response may suggest. In order for this switch to be as smooth as possible, the operator needs to be able recognize the internal state of the robot and be able to direct the robot efficiently.

[1] Informally, "Degrees of freedom" refers to the number of ways that a robot may move. For example, a robotic arm that can rotate along exactly three different axis is said to have three degrees of freedom.

1.3 Dealing With Insufficient Input

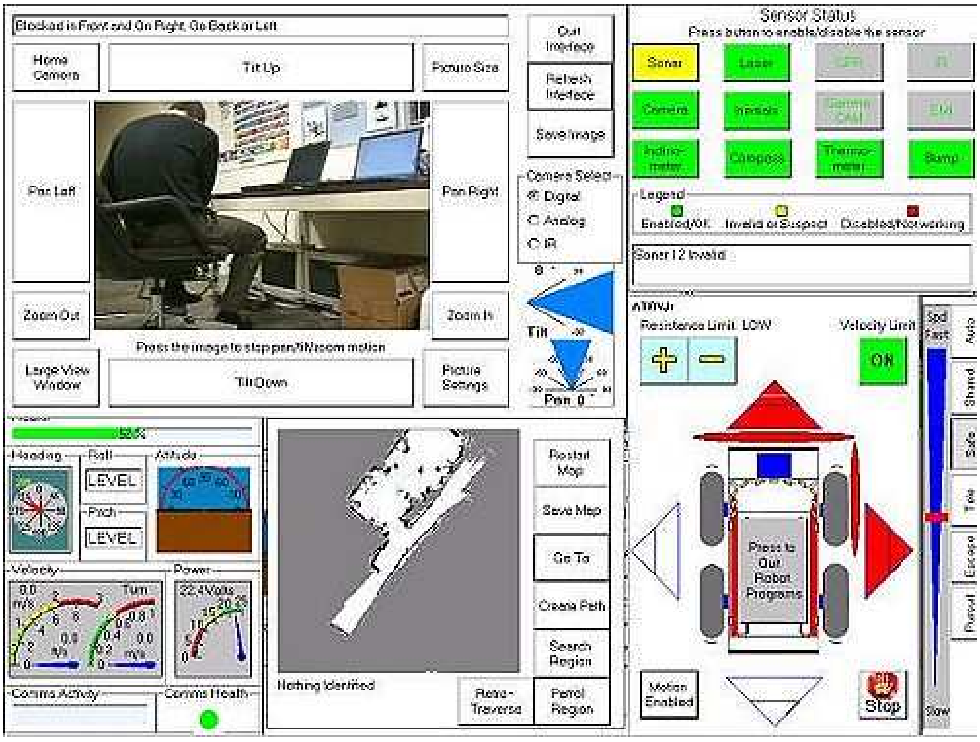

Figure1.1 The Multi-Robot Interface GUI [2]

Because robotic systems are complex, there is a significant amount of research going into how to control robots as efficiently and simply as possible. In our work, we use the Idaho National Laboratory multi-robot interface (MRI)[2]. The MRI program was created with the goal of providing the user with a variable amount of control over the robot, a concept known as 'Sliding Autonomy'.

At one end of the spectrum, the user controls the robot directly via a joystick. In this mode, the robot will immediately respond and take any action that the user requests of it, regardless of the current situation of the robot. While this allows for fine and predictable control of the robot, it also allows the user to inadvertently put the robot in undesirable situations, such as a collision with a wall or accidentally running down a set of stairs

At the other end of sliding autonomy, the user controls the robot on the highest level possible. For example, moving the robot from one place to another only requires the user to input a location in the world. The robot then plans a path from where it currently is to the place the user directs it to go using a map generated as the robot moves around in the world. This approach greatly simplifies the control the user needs to exert over the robot while at the same time increasing the computational load on the robot's controlling program. Since the user does not have direct control over the robot, the path or action the robot chooses might not be the appropriate or desired action.

Both extremes have their own respective pros and cons. The idea behind 'sliding autonomy' is that in any given situation there is a setting somewhere between these two extremes that maximizes the utility and control the user has over the robot while at the same time minimizing the amount of low level control the robot requires. In our experiments, we explore this idea using two different input systems and consider the utility of different settings along the spectrum.

The idea of sliding autonomy can be applied to our proposed system. If direct control via biosignals is not comparable to conventional control, sliding autonomy can be introduced to test if assisted control can aid the user in completing a task. Further research can be done to determine if certain types of tasks such as mapping are more efficient at a certain point along the autonomy scale.

Chapter 2

System Description

2.1 Robotic Arm

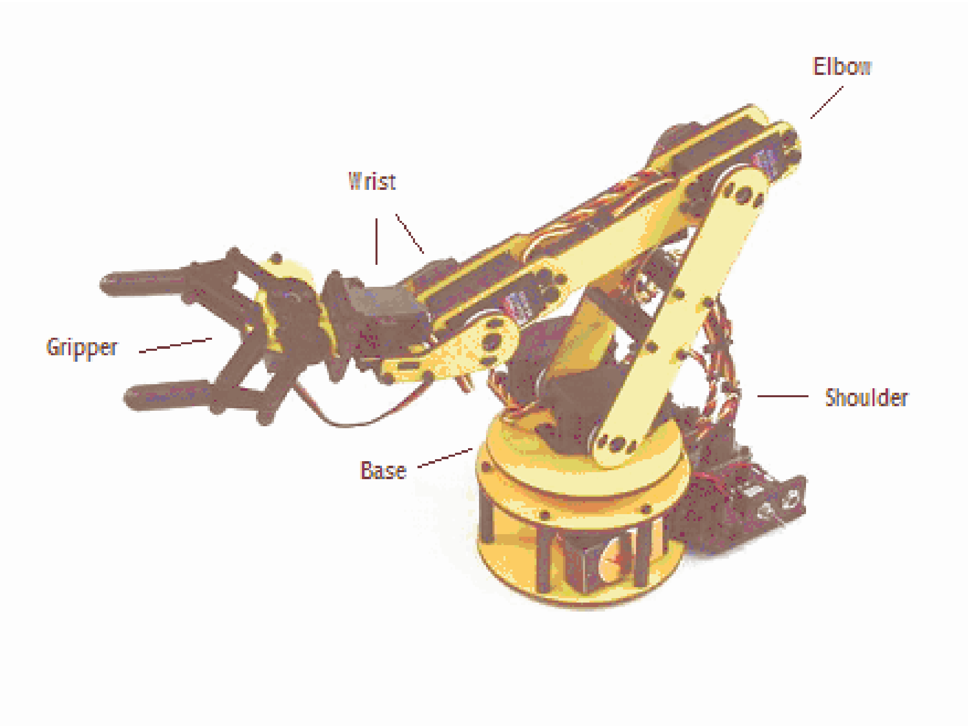

Figure2.1 The Lynx 6 arm used in our experiments

In our system we use the Lynx 6 arm from Lynxmotion; see figure 2.1 The arm has six degrees of freedom and seven servo motors, one for each joint except for the farthest vertical joint from the gripper, known as the "shoulder".

2.1.1 Description of Arm

The shoulder joint requires reinforcement by two servo motors in order to increase the torque driven through the joint, to counteract the weight of objects in the gripper. The other five motors each drive their own joint. Starting from the base, there is a rotational base joint, a vertical shoulder joint (driven by two coupled motors), a vertical elbow joint, a vertical wrist joint, a rotational wrist joint, and a motor that drives the opening and closing of the two-fingered gripper. In total, it has a total of six degrees of freedom.

2.1.2 Programming

The Lynx 6 arm comes packaged with an external breadboard that contains a SSC-32 programmable microcontroller. In order to program the breadboard, the SSC-32 circuit is connected to a computer using a standard DB9 serial cable. Programming the microcontroller is done by writing ASCII programs on the computer and transferring them directly to board via a COM port. These ASCII programs control the servos by pulsing the signal to each motor. The servo sensors are designed so that a continuous pulse of 1.5ms sent to a motor results in the servo positioning itself in the center of its range of motion. Varying the pulse width from 500 to 2500 μs will position the motor all the way left or right, respectively. Some simple example commands can be seen in table. Full command descriptions can be found in the SSC-32 programming guide found on the Lynxmotion website [12].

Table 2.1 Example SSC-32 Commands

Command	Description
#0 P1500	Send a continuous pulse of 1500μs to motor on channel 0, resulting in the servo centering itself
#0 P2500	Send a continuous pulse of 2500μs to motor 0, moving the servo 90 degrees clockwise
#2 P500 #5 P1500	Move servo 2 90 degrees counterclockwise and center servo 5
#1 P1000 S250	Move servo 1 from current position to -45 degrees counterclockwise, changing pulse width at a rate of 250μs/second
#3 P1000 T300	Move servo 3 from current position to -45 degrees counterclockwise, taking 300ms to do so

The SSC-32 controller has the ability to store a series of commands – in the form of programs – on the chip, allowing playback of pre-recorded actions using a single command. However, since we use closed loop control we wanted to have the arm react to user input immediately instead of using the input as a switch to trigger certain actions.

2.1.3 Inverse Kinematics

To control a robotic arm, we can use forward kinematics to predict the gripper position based on joint commands, and inverse kinematics to determine the commands to reach a given position. The forward kinematics have the form

$$M_{final} = \prod_j T(x_i, y_i, z_i)_j \, R(\theta_i)_j \tag{2.1}$$

where $T(x_i, y_i, z_i)$ is the transformation matrix from one joint to the next and $R(\theta_i)$ is the rotation matrix to transform one local frame of reference to the next joint's frame of reference. A simplified version of equation 2.1 can be described given a set of known joint variables **q**:

$$x = f(q) \tag{2.2}$$

where **x** is the final position of the end effector (tip of gripper). In order to calculate the required joint positions, an inverse mapping needs to be found. Given a location in space **x**, the joint variable solution **q** can be found by

$$q = f^{-1}(x) \tag{2.3}$$

Our initial attempt at finding this inverse mapping used an iterative inverse kinematic solution. The inverse kinematics take a specific point in space and gives the angles that the joints need to be at for the gripper to be at exactly the desired point. We used the Inverse Jacobian method[5].

Given a vector containing the current state of the robotic arm's joints $q = [l_1, l_2, l_3, l_4, l_5, l_6]^T$, the relationship between the joint velocities and the end effector velocity can be shown to be

$$\dot{x} = J(q)\dot{q} \tag{2.4}$$

The Jacobian **J** of a 6-degree-of-freedom robot can be calculated by

$$J = \left[\frac{\partial q}{\partial x}, \frac{\partial q}{\partial y}, \frac{\partial q}{\partial z}, \frac{\partial q}{\partial \phi}, \frac{\partial q}{\partial \theta}, \frac{\partial q}{\partial \psi} \right] \tag{2.5}$$

If the inverse of the Jacobian can be calculated, the incremental changes in joint angles can be calculated using this mapping of joint velocities to end effector position.

$$\dot{q} = J^{-1}(q)\,\dot{x} \tag{2.6}$$

This equation, however, is subject to the condition that **J** is both a square matrix and non-singular. In practice, this assumption is not generally valid due to the existence singular configurations of the arm. When the arm is in a singular configuration, two or more rows of the Jacobian are linearly dependent. In addition, if the arm is not given six parameters to approach (an $< x, y, z >$ location with a roll, pitch, and yaw) and instead is only given a goal position $< x, y, z >$, the remaining free variables will not be linearly independent and thus the matrix will not be invertible[10].

Due to these limitations, we decided to instead compute the inverse angle positions via an analytical solution that guaranteed a solution given a goal matrix **G**. Each column of **G** represents the forward, right, up, and position vectors respectively. The final angles can be computed by

$$G = \begin{bmatrix} r_{11} & r_{12} & r_{13} & p_x \\ r_{21} & r_{22} & r_{23} & p_y \\ r_{31} & r_{32} & r_{33} & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2.7}$$

$$\theta_0 = \arctan \frac{p_y}{p_x} \tag{2.8}$$

$$\theta_4 = \arctan\left(\frac{s_0 r_{12} - c_0 r_{22}}{s_0 r_{11} - c_0 r_{21}}\right) \tag{2.9}$$

$$\theta_2 = \arctan\left(\frac{c_2}{\sqrt{1 - c_2^{\ 2}}}\right) \tag{2.10}$$

$$\theta_1 = -\arctan\left(\frac{\sqrt{p_x^{\ 2} + p_y^{\ 2}}}{(p_z - H)}\right) - \arctan\left(\frac{l_1 + l_2 c_2}{l_2 s_2}\right) \tag{2.11}$$

$$\theta_3 = \arctan\left(\frac{-r_{33}}{-c_0 r_{13} - s_0 r_{23}}\right) - \theta_2 - \theta_1 \tag{2.12}$$

where $\theta_0 \ldots \theta_4$ are the joint angles for the base, shoulder, elbow vertical wrist, and wrist roll respectively [11].

2.2 Joystick

We used a Microsoft Sidewinder Force Feedback Pro joystick in our system, though the system's design is not tied to a particular joystick. This has a standard output where the vertical and horizontal axes have numerical values assigned to them with a range of $0 \rightarrow 2^{15}$, where 0 corresponds to the left/bottom position. Since we are only gathering information about the x- and y-axis, this device can be considered a form of low-dimensional input with two dimensions. Haptic sensation (force feedback) was not used in our current setup.

2.3 Biosignals

Another source of low dimensional input that used in our work was biofeedback. Biofeedback involves the acquisition and analysis of intentional electrical signals, commonly known as biosignals, produced by a living organism. By analyzing and recognizing patterns of biosignals, biofeedback can provide a limited amount of direct human-computer interaction.

Because the currents that drive many of the human body's functions are very small (on the order of 30-100mV), amplification and cleaning of these signals is necessary. The amplifiers we currently use are g.USB amplifiers produced by Guger Technologies. Each individual amplifier records up to 16 discrete channels of information and can be connected to different input devices, such as an electromyogram (EMG) lead or an electroencephalograph (EEG) cap. Up to 4 amplifiers can be linked together and synchronized, producing a maximum of 64 channels of input. The amplifier is connected to the computer via a USB 2.0 connection, ensuring that data transfer between the amplifier and the computer does not prove to be a bottleneck.

2.3.1 EMG - Electromyogram

EMG, or electromyogram, consists of recording electrical information from the stimulation of muscles via the peripheral nervous system. Using electrodes attached to the skin of the subject, EMG recordings pick up the action potentials given off by the neuron that controls a specific bundle of muscle fibers. If the muscle is contracted for a long duration, the activated bundle of muscle fibers may recruit other nearby bundles, causing an intensified contraction and a noisier, more visible signal when recorded.

2.3.2 ECoG - Electrocorticography

EMG recording has been known and widely used for a number of years. However, a current active area of study is direct brain-computer interfacing where electrical recordings are taken directly from the brain. In a sense, EMG can be seen as a form of brain-computer interfacing because it is reading neurons in the peripheral nervous system that are commanded by the central nervous system and thus by the brain itself. A recent breakthrough in 2004 has allowed scientists to directly read from the cortical (outer) surface of the brain. This technique is called Electrocorticography (ECoG) [9].

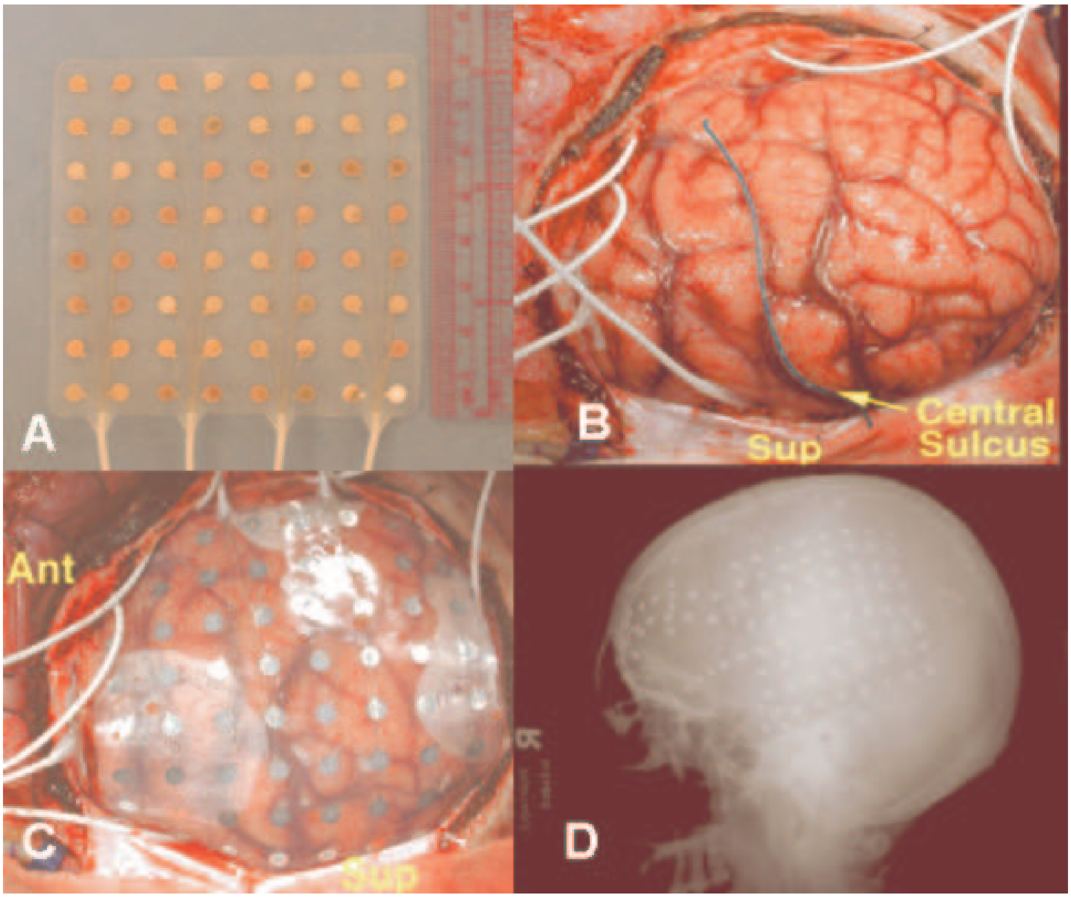

Figure2.2 A) An electrode array commonly used in Electrocorticography B) Example of the procedure necessary to implant the electrode array C) An array of electrodes has been placed onto the brain D) X-Ray showing the position of electrodes after closing the skull

ECoG recording is an invasive procedure that requires an electrode array to be placed underneath the scalp and skull, resting directly on top of the outer surface of the brain. The cortical section of the brain where all the high-level functions take place has two distinct structural parts to it: a layer of 'gray matter' along the outside surface of the brain and a section of 'white matter' connecting the inside surface of the gray matter to the lower level functions of the brain. The gray matter contains five distinct layers of cells, each connected to its neighbors in a myriad of ways. In a simplified description of brain function, all cognitive function and biological computation takes place in the 'gray matter' and the resulting signals are transmitted through via the white matter to other parts of the brain, spinal cord, and body.

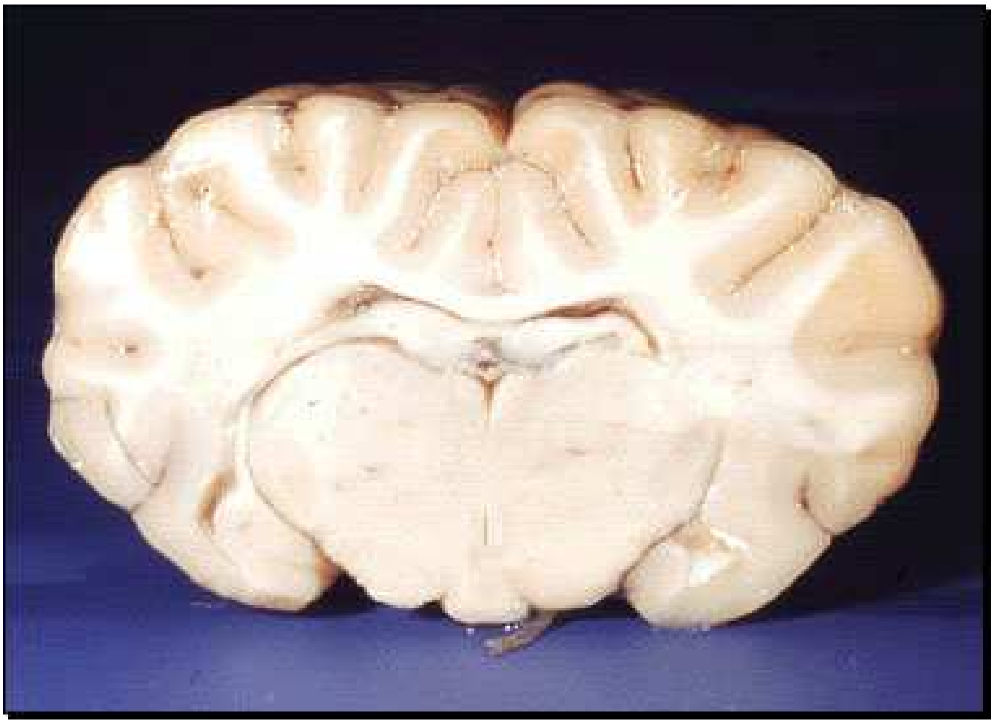

Figure2.3 Gray matter, the computational layer of the brain, can be seen surrounding the connecting white matter layer

Because nearly all cognitive processing is done in the outer five layers of gray matter, it is not necessary to sample from below the surface of the brain for our purposes.. While information from the innermost of the 5 layers may not be strong enough to make a large difference in the signal recorded by the electrode, information can be collected from the first two or three layers. In addition, because neurons in close proximity to one another do not usually fire independently, sampling of a small population of cells can provide detailed enough information to find spatial patterns on the cortical surface of the brain.

Previous research has shown that information can be collected from motor cortex neurons is possible in both monkeys[4] and rats[3]. Since the field of direct brain recording is still young, only a limited amount of information is currently extracted from the signals recorded through ECoG. As the field matures, and more sophisticated signal processing techniques are applied, we will be better able to extract more data from the signal. However, for the moment it falls into the same low dimensional input category as EMG and joystick input.

2.4 BCI2000

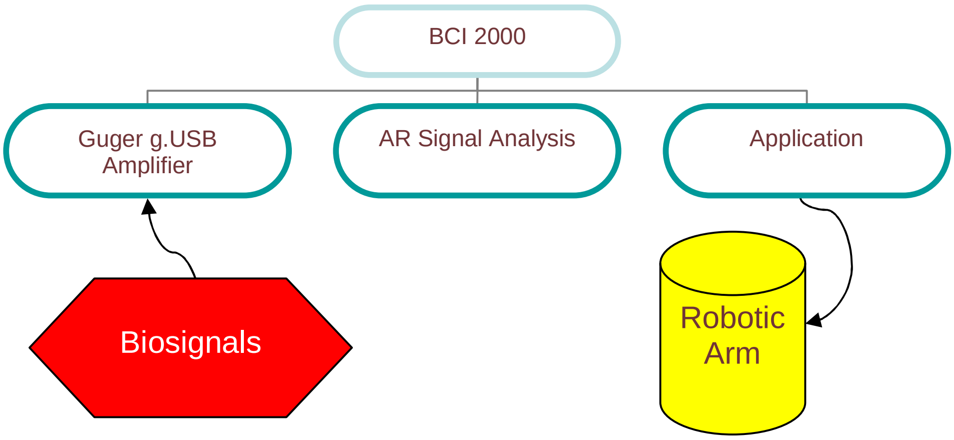

Figure2.4 Diagram of how BCI2000 is connected

Our acquisition and interpretation of the biosignals is done via an open source research platform called BCI2000[8]. The BCI2000 program suite is composed of four separate executables: an operator, a signal acquisition module, a signal analysis module and a client module. The operator executable is the communication hub between the three modules, linking them via a TCP/IP Socket. Because the TCP protocol is used, it is not required that each component is run on the same machine. Setups that require a large amount of computation can be distributed over up to four different machines, each running a separate module.

The system used in our experiments was implemented on one machine. All processes were connected locally, resulting in a minimal lag in the data transfer.

Chapter 3

Experimental Setup

We intended to determine if a user could control complex robotic systems with low dimensional input. The first step was to design a suitable task.

3.1 Task Design

The task was designed with two degrees of control freedom in mind. However, to accommodate failure to discern two separate biological control signals, it could also be accomplished with a single degree of control.

3.1.1 Object finding

With these considerations in mind, we decided to have the user move the arm in order to find an object. The arm faces a white posterboard that serves as a uniform background. Placed on the background are cutouts of different shapes of different, uniform colors. The user is tasked with moving the robotic arm's gripper around the posterboard to find a specific shape.

A webcam is placed between the jaws of the gripper and is pointed directly outward along the gripper. Video from the webcam is transferred and displayed directly to the computer in front of the subject, giving him both real-time feedback on progress and providing him with a goal area that the shape is to be centered in. When the arm is at rest, it will be in a position similar to figure 3.1. The shapes are placed randomly on the background, requiring the user to pan the arm around searching for the current shape. Because of the limitations of the arm, the left and right direction are rotational while the up and down were translational. With these limitations in mind, we designed a user interface that would abstract the user from these differences.

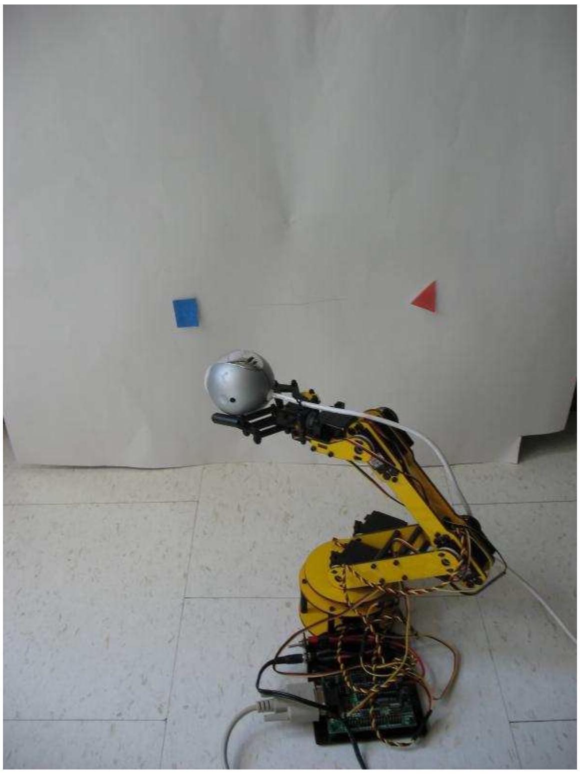

Figure3.1 Photograph of experiment setup

3.1.2 User Interface Design

The user interface is built on top of the 'client' module for BCI2000. Low-level communication and signal acquisition is taken care of by this lower level. Built on top of this level is the part of the program that will interact with the user and give real-time feedback. We have a separate window drawn using OpenGL that will display to the user exactly what the robot's camera is seeing and, thus, what the robotic arm is pointing at.

The BCI2000 interface level operates synchronously, meaning every signal that is acquired by the source module is passed to the signal module and then in turn to the client module. Since we sample at 1200 Hz, new information will be processed 1200 times per second. Though the signals will most likely be slightly different at each sample, it is too CPU intensive to redraw the user interface after every sample is received. We split the client process into two separate threads: one to process the signals, analyze the result, and update the internal state and another to update the screen at a constant, user-selectable, rate based upon the latest internal state.

3.1.3 Video Capture

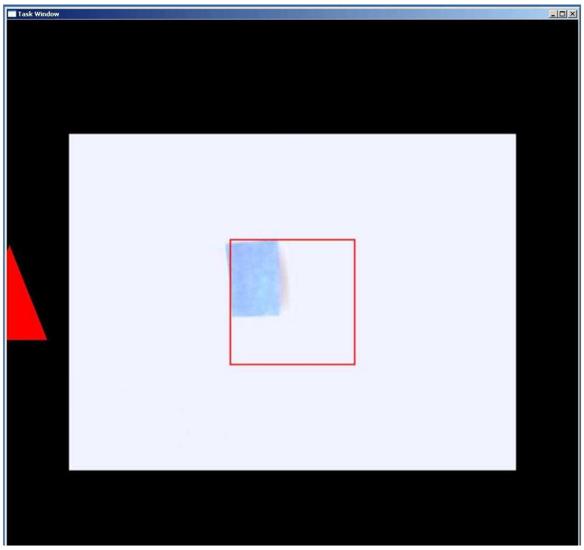

Figure3.2 Screen capture of user interface

Inside the display window of the user interface is a large rectangle centered in the screen that displays the live video from the camera. Because OpenGL does not offer support for acquisition of external images, we opted to use a subset of the Microsoft multimedia API DirectX called DirectShow. The webcam we used came with DirectShow drivers, which allowed us to quickly set up a 'video filter chain' using precompiled filters within DirectX. This filter chain took care of the acquisition, color space conversion, audio filtering, and memory management of the camera's images. At each refresh of the screen, we copy the processed memory from DirectX into an OpenGL texture that is mapped to the onscreen area. Combining the DirectShow filters and the OpenGL texture updates provides real-time video display, running up to 30 Hz.

3.1.4 Color Recognition

Recognition of the different shapes and their position on the screen was done via color thresholding. To allow the CPU to devote the majority of its computation towards signal acquisition and processing, we chose to do color recognition via simple thresholding. Before the image is copied from program memory to video memory, a color thresholding algorithm is run over every pixel in the image. Each pixel has an RGB triple of values between 0 and 255, inclusive. The criteria we used was

$$\left.\begin{array}{l} 2 \cdot blue < red \\ 1.5 \cdot green < red \\ blue < 140 \end{array}\right\} consider\ red$$
$$\left.\begin{array}{l} red < blue \\ green < blue \\ red < 90 \end{array}\right\} consider\ blue \tag{3.1}$$

Every pixel in the image is run through these criteria. If it fits one of the two color thresholds in equation 3.1, it is added to the total number of that color found. After all pixels have been classified as a color or discarded, the average of the color blobs is taken to find the geometric center of the object. Since the background is solid white, it can be assumed that the only colors seen through the camera will be one of the shapes. Each shape is a distinct color, which means each individual blob's geometric center will correspond to that shape's actual center.

3.2 Offline Analysis

Closed loop control via biosignals operates by looking for specific neuronal firing frequencies on certain electrodes. Frequencies are grouped into separate bins in 5hz increments using a Fast Fourier Transform[1]. In order to know what frequency bin to look for, screening and offline analysis is required prior to running the application closed-loop.

The screening task uses the same BCI2000 modules as the robotic arm task, with the exception of the client module. During the screening task, the screen is filled with a solid color. A word will appear at specific intervals during the screening task, dictating a certain action will be taken. In this setup, there were two words: "left" and "right". When a word appears, the subject tightens the forearm muscle corresponding to that side. As soon as the word disappears, the subject stops exerting the muscle. This action is repeated ten times per stimulus.

During a muscle contraction, a single neuron stimulates a number of muscle fibers (called a motor group) in the muscle. If more force is necessary or the muscle fibers begin to become fatigued, a phenomenon called 'recruitment' occurs; muscle fibers in close proximity to the motor group, yet not directly connected to the neuron begin to contract sporadically, adding additional force. Because these recruited muscle fibers are not connected to the motor, they fire independently and at different frequencies from the neuron controlling the original group.

Figure3.3 Experimental screening

After the screening task completes, offline analysis is required to bin the frequencies and detect a correlation between specific frequencies and the corresponding state the screening task was monitoring. After the analysis program bins the signal, it calculates the correlation of bin power during the 'right' stimulus, and shows the results in the form of a plot. The phenomena of recruitment causes many different frequencies to be picked up via EMG, showing a high correlation over many frequencies when the stimulus was shown.

3.3 Electrode Placement

Our experiment was set up using two points of input: the left and right forearm. An electrode is placed near the flexor carpi radialis muscle in each forearm (See Figure 3.4), a muscle along the inside of the forearm that is stimulated when the fingers and wrist contract. Recording from these muscles is desirable because it is easy to consciously stimulate this muscle by making a tight fist and a mapping of left-arm-to-left-direction is natural for the user. The electrodes contain an electrical conducting jelly that touches the skin and a conductive button that attaches to a wire lead on the outer side.

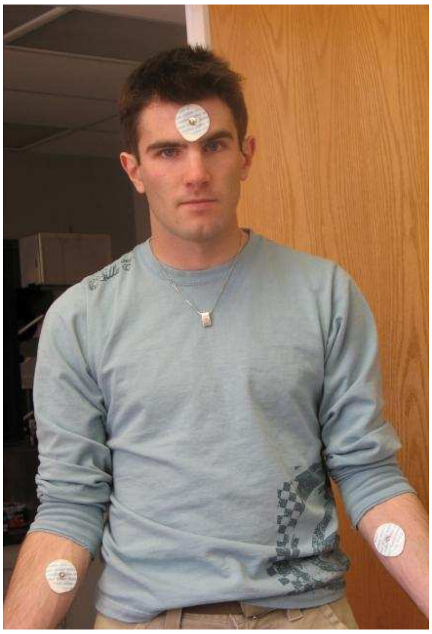

Figure3.4 Electrode placement

Because the body inherently possesses an electrical charge, a third electrode is necessary as a reference. This electrode is placed on the forehead, between and above the eyes.

This electrode allows the amplifier to determine whether a signal it received was due to a muscle contraction, or a natural flux in the body's resting voltage. Due to the lack of substantial subsurface muscles in the forehead and roughly equal proximity to each recording electrode, the forehead is the ideal location to observe the resting voltage of the body.

Chapter 4

Results

In this section we show that our system can be controlled effectively with two different forms of inputs, both of which have limited dimensional output.

4.1 Joystick Control

The first attempt to control the arm was done using a joystick. Translation of the signals from the joystick mapped naturally to the robotic arm. Left and right joystick movement corresponds to rotation of the base joint, while up and down corresponds to the arm raising and lowering vertically. However, due to the limited amount of input available via EMG, we have restricted the joystick task to one dimension in order to be able to make a comparison.

Table 4.1 Joystick Trial Data

Run	Time To Complete Task (Seconds)	Distance From Center (Pixels)
1	10.2925	10.0400
2	7.8667	24.5100
3	10.7467	24.5100
4	8.6667	30.8000
5	8.4800	22.0200
6	7.0400	5.8300
7	9.0933	27.1600

Seven timed runs were recorded. During each run, the desired shape was placed along the horizontal dimension of the arm. The robotic arm started off at zero degrees (straight forward) at the beginning of each run. The average time to reach the target across the runs was 8.88 seconds with a standard deviation of 1.30 seconds. In addition, the geometrical center of the shape was 19.534 pixels away form the center of the goal area on average, with a standard deviation of 9.21 pixels. There were no unsuccessful runs[2]. These results suggest that the user successfully gained control of the arm and completed the task.

4.2 EMG Control

Using our EMG control setup, only one dimension of output can be acquired. Since only one dimension of input is available to the robotic arm, we narrowed the scope of the object search to one dimension: left vs. right. To allow the user to manipulate the arm as naturally as possible, stimulation of the left forearm corresponded to the arm moving left with the right forearm controlling movement to the right.

4.2.1 Screening

Before testing could proceed, screening was necessary to determine what frequencies to look for during closed-loop control. One run of the screening task described in 3.2 was completed, and the result analyzed using the AR Signal Analysis program created by Gerwin Schalk[8].

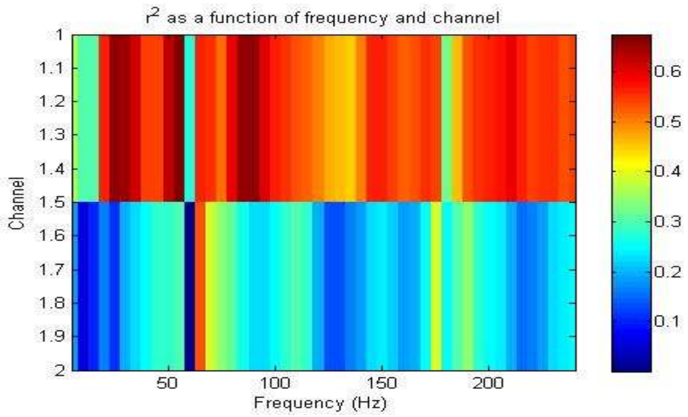

Figure4.1 A plot of signals corresponding to the stimulus "Right", illustrating a high correlation with the top array (electrode reading from right forearm)

Figure 4.1 shows a plot of the correlation values across many frequency bins during the "Right" stimulus. The signal coming from the electrode placed on the right forearm is

[2] An unsuccessful run is any run that the user did not complete the objective within sixty seconds.

shown as the upper array of values, while the signal from the left electrode is shown along the bottom. Because the body is never electrically stable, the noise recorded by the left electrode can correlate across a few frequencies. However, because we are only looking for the "move right" signal on the electrode connected to the right forearm, the upper line is the line we are interested in.

The x-axis represents the frequency of the electrical potential change recorded during the trial. The y-axis represents the signal recorded from each electrode. The color or z-axis represents the r^2 correlation value, or the percent of time that the 'right' stimulus was given that corresponded to a signal in a specific frequency bin, squared.

Bands can be seen along the 55-60hz and 175-180hz bins. These bands are due to software filtering of 60hz interference from the AC circuits surrounding the test setup. The alternating current in the wall induces a potential change in the unshielded wires. Since this 60hz noise is present in the data, it is removed via a notch filter. Bands seen at multiples of 60hz are the result of harmonics, where the a signal appears at integer multiples of its frequency.

Nearly all of the frequency bins showed a correlation, from the 0-5hz bin up to and above 160hz. Of the many frequency bins that showed correlations of $r^2 \geq .5$, three were chosen for closed-loop control: 20-25hz, 26-30hz, and 31-35hz. Most of the information encoded in neuronal firing does not occur in high frequencies, meaning lower frequencies have a better chance of being detected. Multiple channels were chosen for redundancy in the signal and to increase the probability that the muscle stimulation would be registered.

4.2.2 Testing

The EMG results were gathered under the same circumstances as the joystick task. The target shapes were placed at random along the horizontal dimension along the backdrop, allowing completion of the task using only one dimension.

Table 4.2 EMG Trial data

Run	Time To Complete Task (Seconds)	Distance From Center (Pixels)
1	9.2792	7.0700
2	10.5067	32.7500
3	9.3333	8.6000
4	10.9333	22.3600
5	10.3467	129.5400
6	13.9467	25.0700
7	9.8400	42.2000

Seven timed runs were recorded. The average time to reach the target across the runs was 10.598 seconds with a standard deviation of 1.60 seconds. The geometrical center of the shape was 54.8 pixels away form the center of the goal area on average, with a standard deviation of 42.14 pixels. There were zero unsuccessful runs. These results suggest that the user successfully gained control of the arm and completed the task.

4.2.3 Comparison

The task was completed successfully every time for both inputs, with a difference of 1.718 seconds between the mean run times. Comparison of the two via a T-Test results in a p-value of 0.048 for time and 0.303 for distance.

Table 4.3 Statistical Comparison

	Time		Distance	
Control	**Joystick**	**EMG**	**Joystick**	**EMG**
Mean	8.88	10.60	20.70	38.23
Std. Dev	1.30	1.60	9.21	42.14
P-Value	0.048		0.303	

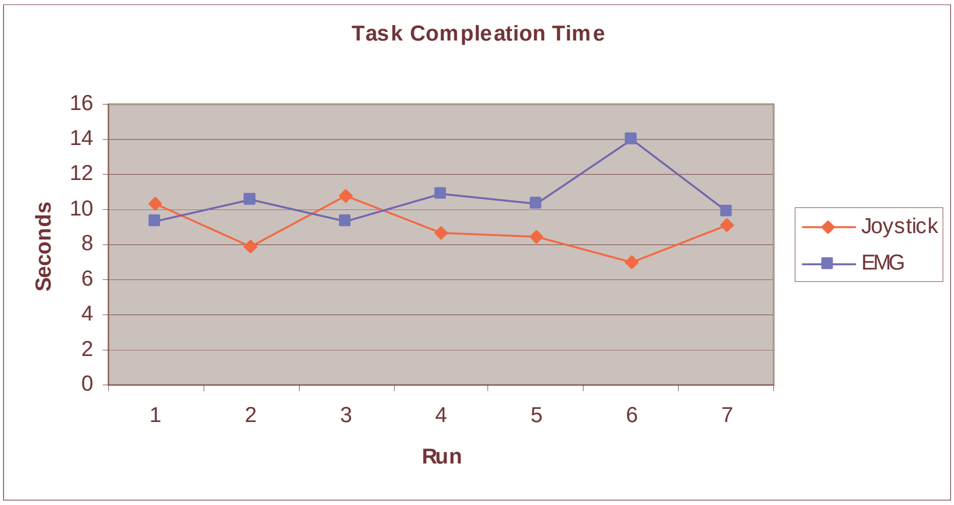

Figure 4.2 Graphical comparison of joystick and EMG trials

Because the p-value is above the 95% confidence interval, we believe that control of the robotic arm was attained with both forms of low dimensional input: a joystick and EMG with respect to time-to-complete. However, accuracy of the runs via biosignals is not comparable to conventional control.

Chapter 5

Extension to Electrocorticography

We have shown that different forms of low dimensional input can control a robotic arm. We would like to explore the possibility of using another, more complicated form of biosignals using our experiment. If control is attained via another form of biosignals, it is possible to state that this system could be extended to other forms of biosignals.

5.1 Patient Availability

ECoG research requires invasive and severe surgery to place the electrodes directly onto the surface of the brain. Currently, the risks involved in the long surgery outweigh any possible advantages gained in implanting it in a healthy human. However, directly recording brain signals is useful in the medical field, specifically in diagnosing and localizing epileptic seizures in patients suffering from epilepsy.

Epileptic seizures are electrical storms in the brain that are started by over-activation of a small group of neurons. The high potentials created affect surrounding groups of neurons, creating a cascade of neuronal firings inside the brain. In order to treat the group of cells that is misfiring, it is necessary to localize the epileptic seizure's starting location. Patients requiring this type of treatment undergo a surgery that involves opening the scalp, removing a part of the skull, placing electrodes on the brain, and closing the skull and scalp.

Barnes Jewish Hospital, in association with the Washington University School of Medicine, presently performs this surgery during epilepsy monitoring and treatment. We were given permission to record data alongside the monitoring unit during the experiment. Note that patient names have been changed to protect privacy, and are not associated with their 4-letter code.

5.2 Neurology and Task Setup

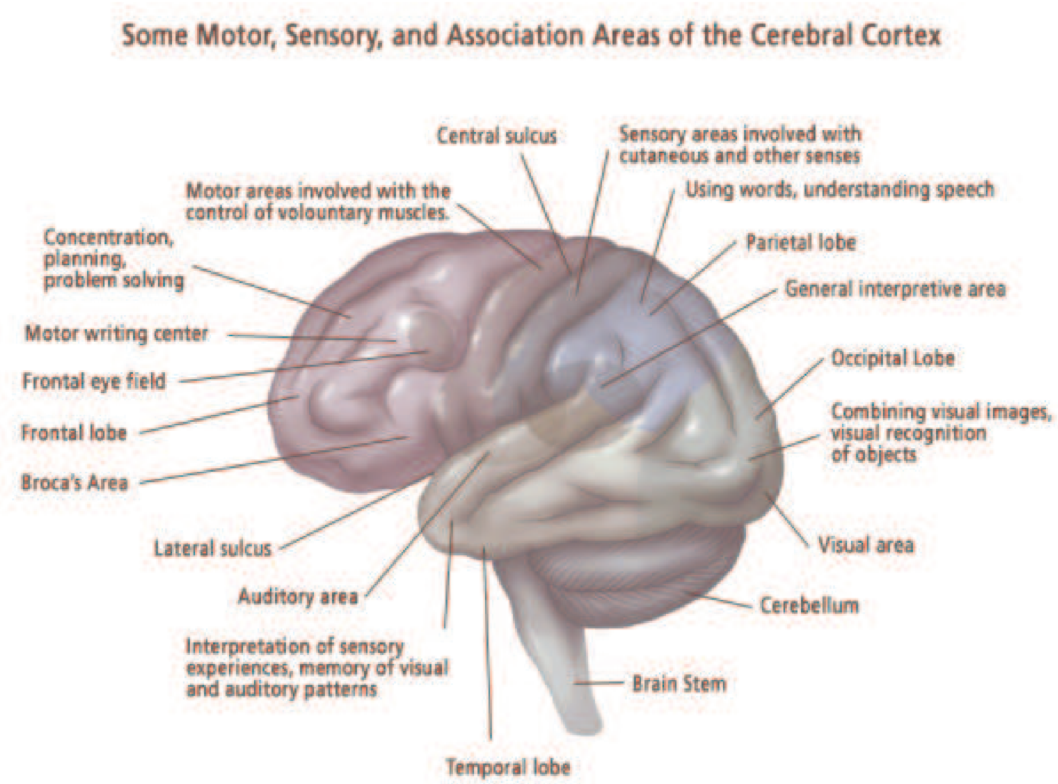

Figure 5.1 Mapping and function of the different areas of the human brain [6]

In many patients, the electrode grids are placed directly over the central groove of the brain, also known as the 'central sulcus'. The posterior (rear) side of the sulcus contains neurons whose function is mainly to interpret sensory input, while the anterior (forward) side of the sulcus contains neurons that control voluntary motor movement. Because this motor cortex is involved in controlling voluntary movement, it produces a large, signal when the patient consciously moves any muscle groups.

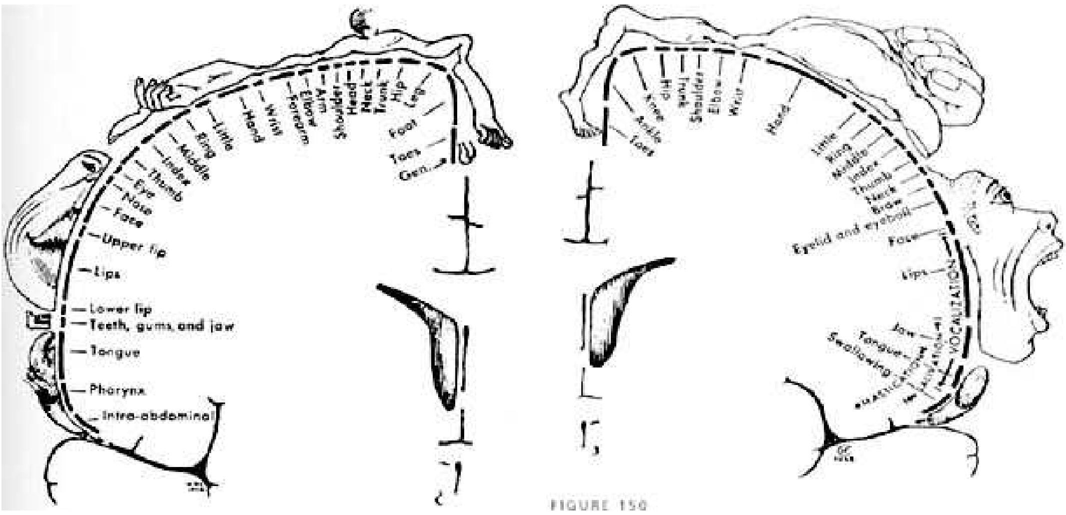

Figure 5.2 Graphic representation of the homunculus – or little man – areas along the motor cortex. Notice the large areas given to hands and face.

Many patients are implanted with grids directly over the motor cortex. According to previous studies[6], the motor cortex produces localized responses to conscious movements. This provides an excellent target signal for BCI applications to look for, since the signals are both repeatable and limited to a small area. Previous experiments using this area of the brain for BCI have proven successful[7].

Because the patients are continuously monitored for their seizures and thus remain connected to the recording system, it is necessary to perform the task in the patient's room. All the equipment for our system is placed on a mobile cart that we can move into the patient's room and connect to the patient's grid. Once the BCI system was connected, the patient was run through the screening task to screen for frequencies in covered areas.

Due to the arrangement of the interconnecting neurons in human brain, information from one side of the brain controls and responds to sensory information from the opposite side of the body. Depending on the side of the brain the electrodes were surgically implanted in, the screening task requires the subject to move muscles on the opposite side of the body in order to allow the electrodes to record activation.

Instead of moving the left or right forearm as the user would in the EMG task, the patients were instructed to move their tongue or hand corresponding to the left or right signal respectively. After the screening task was complete and frequency bins selected after analysis, the robotic arm was placed on the floor in close proximity to the recording computer out of sight of the patient.

5.3 Results

During the initial runs, the patient's brain was monitored for signals according to those determined from the screening task to ensure the electrodes had not moved and that the signal did not change in frequency. Since the screening technique only find the frequency bins of interest, discovering the mean signal power between resting and stimulation occurred iteratively during the initial runs of the trial. Though these initial trials were generally not successful, the later tasks across all three patients showed a high percentage of successful tests after the mean power was discerned.

All patients' fine control and direction changing of the arm was not as accurate as the joystick or EMG trials, though successful completion of the task was achieved for all three. The mean time to find the target across successful runs was 21.2 seconds fro TTES, 26.04 seconds for TOTS and 47.13 seconds for TOFS, with standard deviations of 12.31, 48.38, and 13.21. The average deviation from the center of the target area was 45.84, 49.79, and 52.81 pixels, with standard deviations of 42.15, 7.52, and 26.84. Note that runs 3 and 4 for TOFS were unsuccessful runs included in offline analysis.

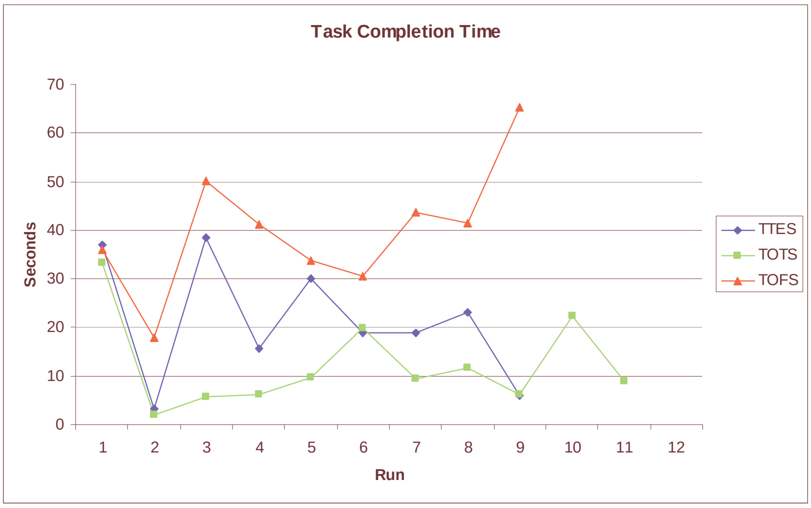

Figure 5.3 Graphical display of patient performance

Table 5.1 ECoG task results across four patients

Patient	Run	Time To Complete Task (Seconds)	Distance From Center (Pixels)
TTES	1	36.88	27.01
	2	3.33	155.2
	3	38.37	40.79
	4	15.6	31.06
	5	30.11	18.02
	6	18.91	23.85
	7	18.96	40.19
	8	23.17	49.4
	9	6.08	27.01
TOTS	1	33.36	60.87
	2	2.00	61.52
	3	5.71	54.40
	4	6.32	41.61
	5	9.71	51.22
	6	19.87	40.36
	7	9.49	40.22
	8	11.55	42.01
	9	6.16	48.02
	10	22.29	54.23
	11	8.91	50.53
TOFS	1	36.00	86.57
	2	17.97	41.76
	5	50.19	28.79
	6	41.17	64.35
	7	33.79	47.42
	8	30.48	42.54
	9	43.65	35.60
	10	41.44	36.40
	11	65.39	108.70

5.4 Offline Signal Analysis

Because all ECoG runs are recorded and saved, offline and post-experimental analysis can be performed and the results compared to previous knowledge from other tasks. We were interested in seeing if there was a correlation between movement in one direction and a specific frequency or location on the brain. The arm task was not looking for such a signal during closed-loop control, so in the ideal if a signal corresponding to direction was discovered, the patient may not need to move a muscle and instead only think about moving the arm to the target.

Using the ECoG signals recorded during the movement of the arm, we attempted to correlate the direction of arm movement with any specific signal pattern that may exist. Across all three patients, there appeared to be small correlations between the direction of movement and frequency such that a group of neurons being observed by an electrode fired at a specific frequency when the arm was moving to the right.

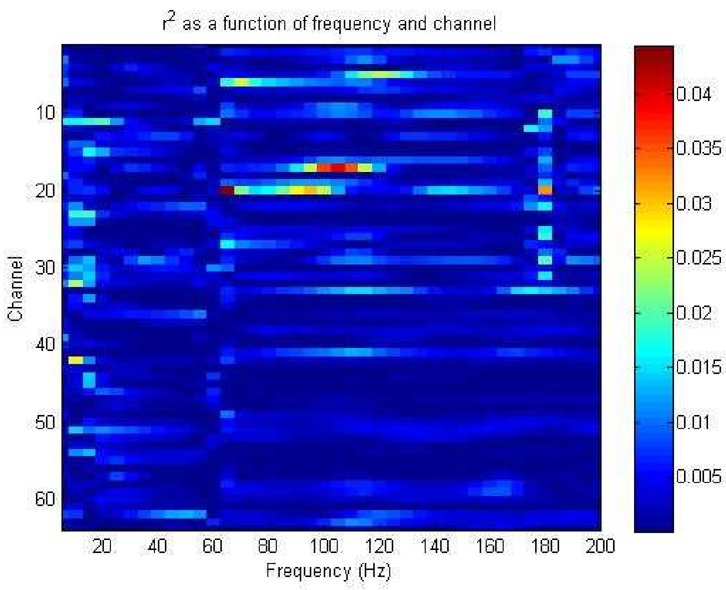

Figure 5.4 Correlation between frequency of neuron firing when the arm is moving right for patient TTES

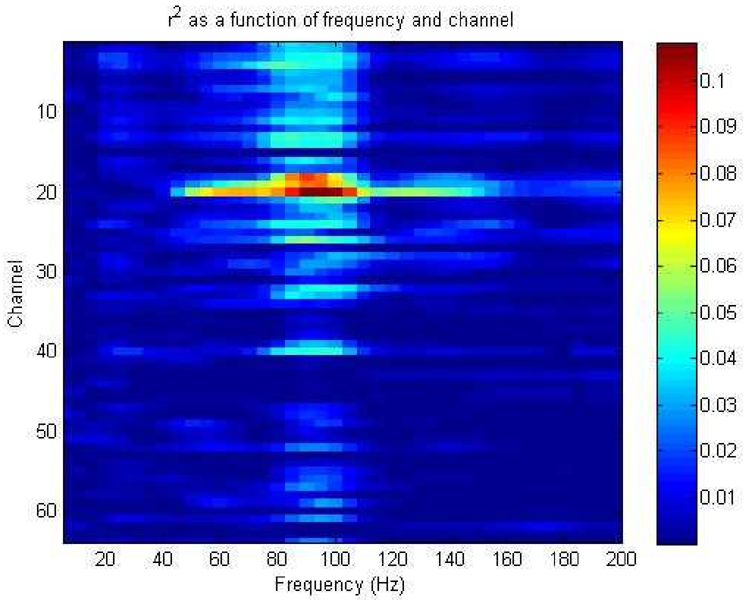

Figure 5.5 Correlation between frequency of neuron firing when the arm is moving right for patient TOTS. Note the similar band of correlation to the previous patient

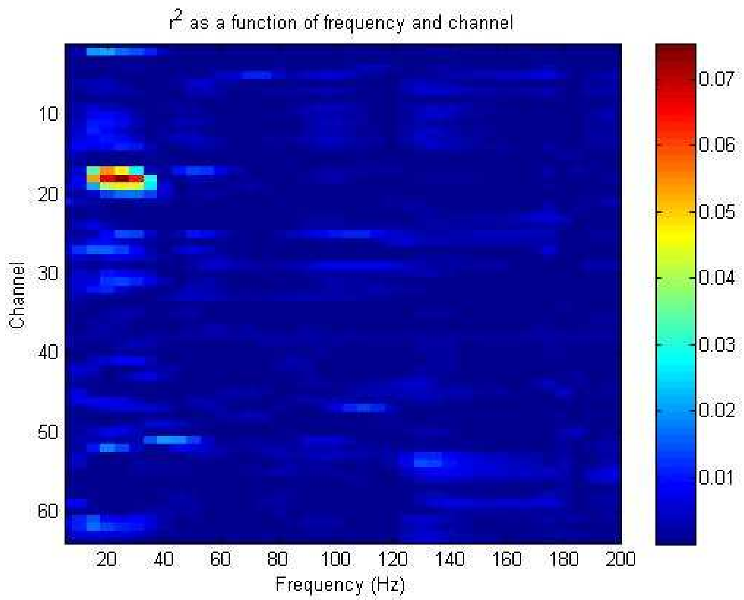

Figure 5.6 Correlation between for patient TOFS

Figures 5.3 through 5.5 show a graph of the correlations. Figures 5.3 and 5.4 show a similar band of activated frequencies near 90 to 100hz, while figure 5.5 shows a high correlation along lower frequencies between 15 and 35hz. Because each patient had the electrode grid implanted in different areas of the brain, the channel of the electrode does not necessarily correspond to the same location on the brain. It is helpful to visualize these data mapped onto a template brain[3], as shown in figure 5.6.

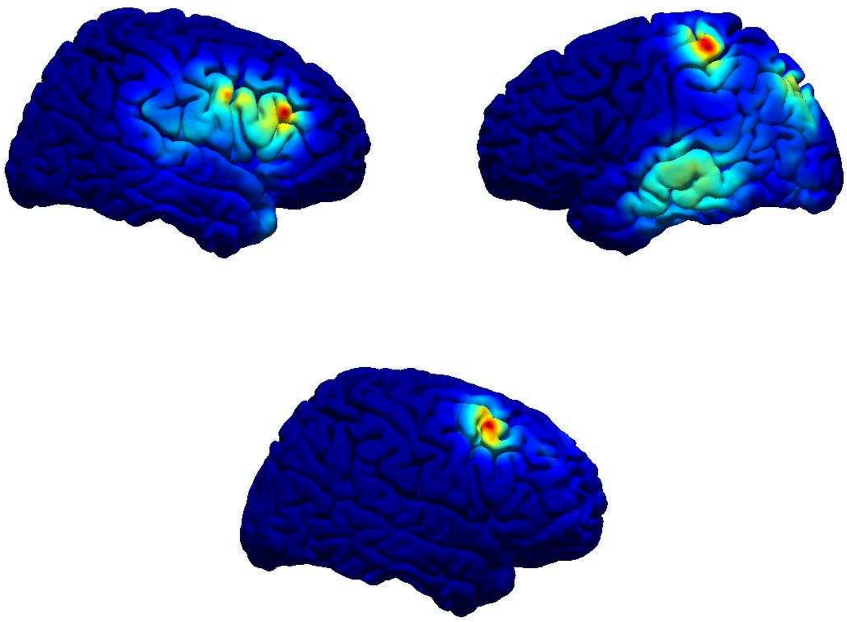

Figure 5.7 A spatial representation of the correlation mapped onto a template brain
Left: TTES Right: TOTS Bottom: TOFS

The correlation problem is interesting from a neuroscience perspective, since it allows inquiry into whether the brain is encoding information regarding left/right direction in addition to motor signals. Further analysis can be performed to increase correlation and localization of frequency.

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[3] A general brain representation, not indicative of the patient's actual brain shape

Chapter 6

Summary and Future Applications

We have shown that our system has been successfully applied to different forms of low-dimensional input: a joystick, EMG and ECoG biosignals. We have also shown that two different forms of low-dimensional biosignals can be successfully used with our system: EMG and ECoG. It is reasonable to assume that if control of an application that is connected to the output of our system can be achieved through joystick and EMG control, it is also controllable via direct brain recording using ECoG.

Because the field of biofeedback is somewhat new and an open research area, the amount of usable information gained through current analysis techniques is enough to only provide a few scalar outputs. Using this low-dimensional input to control high degree of freedom systems is an interesting open problem.

As mentioned in section 1.4, control of a mobile robot using low dimensional signals in a field of ongoing research. After the experiments with the arm were completed, we were interested to see if it was possible to control a simulated robot through the Multi-Robot Interface using biosignals. Though no quantitative tasks or experiments were designed, subjectively it seemed intuitive control of a mobile robot was attained by the user and further improved upon by the MRI's use of a sliding autonomy scale. Future goals include comparing the amount of time it takes an autonomous robot to map a world to the time it takes a robot supervised by biosignals. Further research and experiments in this area are viable and interesting from both a robotics and neuroscience perspective.

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"A Supervisory Control Interface for Large Mobile Robot Teams"
http://students.cec.wustl.edu/~tmb1/icra2007a.pdf

May 2007

Short Title: Robot Control via EMG and ECoG Signals Blakely, M.S. 2007