Using Big Data to Reanimate a Paralyzed Limb

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Speaker Introduction

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Conflict of Interest

Michael Schwemmer, Ph.D.

Salary: Salaried employee of Battelle
Agenda

- Learning Objectives
- An Introduction of How Benefits Were Realized for the Value of Health IT
- Introduction
- Study Overview
- Neural Bypass System Components
- Demonstrations of System Use
Learning Objectives

• Describe a system for bypassing a damaged spinal cord by using large amounts of data collected from a cortical implant to control a muscle stimulation system which moves a paralyzed limb controlled by the subject's thoughts
• Examine an example of using big data to create a model that is personalized for individuals to interpret intracortically recorded brain data and translate it into movement
• Discuss the potential and some of the pitfalls of using big data to inform a brain computer interface and how these lessons can be applied more broadly
An Introduction of How Benefits Were Realized for the Value of Health IT

• The value steps impacted were: Treatment/Clinical

Movement Possible
Paralyzed person can control hand movements with thoughts
Paralysis – Facts and Figures

• Estimated ~5.6 million people living with some form of paralysis in the United States

• Spinal cord injury (SCI) is the second leading cause of paralysis, affecting ~1.3 million individuals

• There are ~17,000 new SCI cases each year

• SCI cases alone cost the health care system ~40.5 billion annually

Signal Pathway From Brain to Movement

Primary Motor Cortex

Image credit: https://en.wikipedia.org
Signal Pathway From Brain to Movement

- SCI disrupts this pathway, but, in many cases, both the motor cortex and the limb muscles that it controls remain intact
Bypassing the Disrupted Pathway

Primary Motor Cortex

• Idea is to bypass the disrupted pathway and use the intact brain signals to control electrical stimulation of limb muscles

Image credit: https://en.wikipedia.org
Challenges

• Getting approval to perform the study
• Finding the right patient
• Constructing the muscle stimulation system
• Dealing with a massive amount of neural data
  – System produces millions of data points every second
  – Data processing and muscle stimulation must occur quickly in order for movements to appear natural
Study Overview

• Collaboration between Battelle and The Ohio State University Wexner Medical Center
• FDA- and IRB-approved clinical IDE study
• Investigate the effectiveness of a cortically controlled neuromuscular stimulation system to restore movement in a paralyzed person
• Study participant is a 26-yr old male who suffered a complete C5/C6 spinal cord injury from a diving accident
Surgical Procedure

• Surgery performed at the Ohio State University Wexner Medical Center ~2 years ago
• fMRI was used to map the patients’ motor cortex prior to surgery
• A microelectrode array (MEA) was implanted in the patients’ primary motor cortex
System Overview

BRAIN IMPLANT
A 96-channel Utah array is implanted in the motor cortex of the participant.

DECODING
Machine learning based algorithms decode user intent.

NON-INVASIVE STIMULATION
A high-definition neuromuscular stimulation system can provide control of individual muscle stimulation.
Neural Data

- Neurons communicate through large changes in their electrical activity called action potentials or spikes.

- The implanted microelectrode array (MEA) simultaneously records the electrical activity of neurons in a 0.15 in x 0.15 in region of primary motor cortex.

Image credits:
- https://en.wikipedia.org
- https://www.codeproject.com/KB/recipes/NeuralNetwork_1/BrainNeuronSpike.png
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• Big raw data can be more useful when converted to smaller more concise data
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• Big raw data can be more useful when converted to smaller more concise data

• Overall system requires that the data be extracted, filtered, isolated, decoded and used to trigger the muscle stimulation in 0.1 sec
Filtering and Compressing the Data

• Filters were constructed to remove the artifact induced by the muscle stimulation
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• Wavelet decomposition was then applied to the data in order to simultaneously compress the data and construct informative features
Wavelet Decomposition

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- The raw signal is represented using a wavelet function basis

\[ \text{Wavelet function: } \psi(t) \]


http://www.aticourses.com/blog/index.php/tag/continuous-wavelet-transform/
Wavelet Decomposition

- Wavelet decomposition has been shown to be an effective way to process raw neural signals for brain computer interface-related applications\(^1\)
- The raw signal is represented using a wavelet function basis
- The coefficients of the wavelet basis functions can then be used to represent the signal


Filtering and Compressing the Data

- Data was binned into 100 msec bins (288,000 data points) and wavelet coefficients for selected scales were extracted and averaged across time and then averaged together to yield 96 data points per bin.
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2.88 million data points/sec → 960 data points/sec

• This feature engineering step makes it possible to process the big data in real-time with standard hardware.
Decoding: Translating the Neural Data into Movement Commands

• The compressed 96-dimensional signal is then input into our decoding (aka classification) algorithms

• These algorithms translate brain activity to imagined movement

• Training data is acquired by having the subject imagine the movements of an animated hand he is seeing on a screen

• The decoding algorithms are trained and then used to control muscle stimulation
Decoding: Translating the Neural Data into Movement Commands

- We use a custom regularized Support Vector Machine (SVM) decoding algorithm (Humber et al., 2012)

http://www.med.nyu.edu/chibi/sites/default/files/chibi/Final.pdf
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Decoding: Translating the Neural Data into Movement Commands

- Individual decoders were trained for each movement tested (one against all others)
- The decoder with the highest output score above zero was used to drive the stimulator
Muscle Stimulation

• Electrode sleeve around the participants forearm allows for different patterns of muscle stimulation corresponding to different desired movements.
Overall System

Recording from the Brain

Channel 1

Channel 96

Wavelets

Mean wavelet power

Scale 1
Scale 2
Scale 3
Scale 4
Scale 5
Scale 6
Scale 11

Decoder output

- wrist flexion
- wrist extension
- hand open
- thumb flexion
- thumb extension
- middle flexion

Stimulator

Evoked hand movement
Individual Movement Task
Individual Movement Task

- Participant was able to perform 6 different movements with an overall accuracy of ~70%

Functional Improvements
The participant was able to successfully complete the grasp-pour-and-stir task 3 out of 5 times in 10 minutes with a completion time of 42 ± 10 s.
GRASSP Clinical Assessment
(Graded and Redefined Assessment of Strength, Sensibility, and Prehension)

- The GRASSP\(^1\) is a standardized test with excellent inter-rater and test-retest reliability developed to assess sensorimotor impairment of cervical SCI patients


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Motor impairment improved from the fifth and the sixth cervical (C5–C6) to the seventh cervical to first thoracic (C7–T1) level unilaterally, conferring on him the critical abilities to grasp, manipulate, and release objects.


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- Motor impairment improved from the fifth and the sixth cervical (C5–C6) to the seventh cervical to first thoracic (C7–T1) level unilaterally, conferring on him the critical abilities to grasp, manipulate, and release objects
- These findings quantify the reduction in functional motor impairments possible with the system for patients with cervical SCI

Credit Card Task
Keeping the Participant Engaged
Keeping the Participant Engaged
Summary and Additional Challenges

• Discussed the construction of our neural bypass system and the big data challenges we encountered

• Demonstrated that SCI can be bypassed in order to allow a paralyzed individual to regain hand and wrist usage

• Neural signals are nonstationary which force the decoding algorithms to be retrained every session in order to maintain similar performance levels

• Stimulation sleeve requires recalibration

• The system has a lot of large components which currently prohibits home usage
Future Directions

• Developing robust decoding algorithms that do not require daily retraining
  – Deep learning methods
• Developing a new stimulation sleeve that easier to put on/take off, contains more electrodes, and will also keep track of the users’ hand position
• Shrinking the size of various components of the system
  – Stimulator
• Recruiting the next patient and performing a new study
  – Leverage and build upon the framework developed with the first patient
Benefits Realized for the Value of Health IT

• The value steps impacted were: Treatment/Clinical

Movement
Possible
Paralyzed person can control hand movements with thoughts
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Questions

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The Business of Innovation

• Please complete the online session evaluation