Development of a Electromyographically-Controlled Virtual Arm for Post-Stroke Motor Rehabilitation

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(1) Background

Stroke is a leading cause of adult disability worldwide.

- Almost 800,000 people suffering a stroke each year in the US alone.[1]
- As many as 70% of stroke patients initially present with arm weakness,[2] of which only 20% regain full use of the limb.[3]
- In patients who initially present with severe arm weakness (Medical Research Council (MRC) muscle scale of 0/5, 1/5, and 2/5), over 90% will have some residual arm weakness and over 75% will have residual weakness that requires assistance in activities of daily life (ADLs).[2,3]

Rehabilitation interventions for patients with severe upper limb weakness are limited.

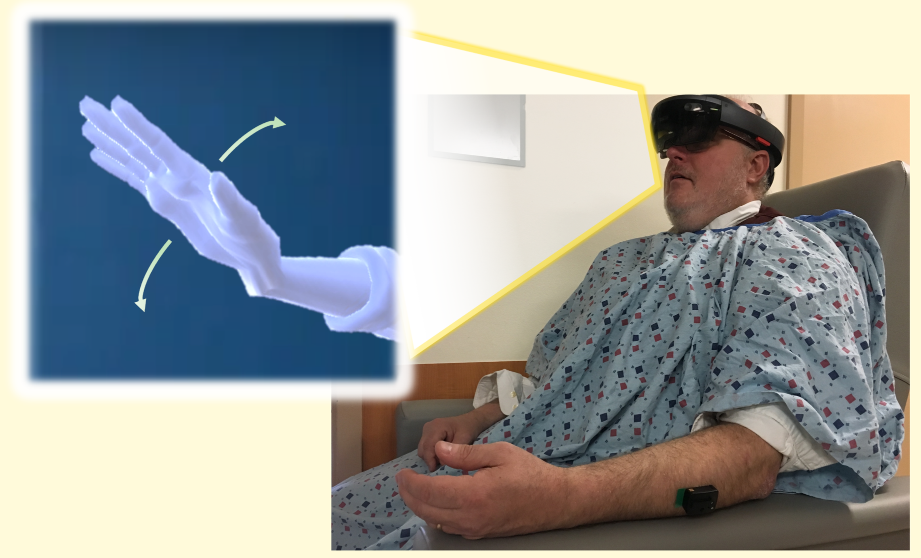
- Many traditional rehabilitation techniques (including Constraint Induced Movement Therapy) require at least some movement to engage with the rehabilitation therapy.
- Despite having larger functional deficits, patients with severe weakness are often triaged to Skilled Nursing Facilities where they receive lower doses of rehabilitation.

Previously described rehabilitation strategies which show promise for patients with severe arm weakness:

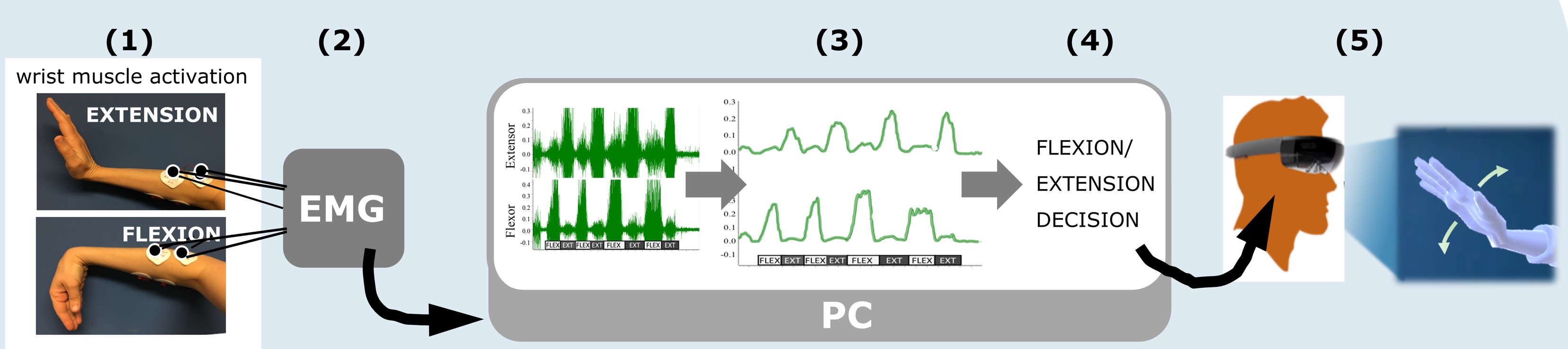
- **Biofeedback** - Patient is provided feedback (auditory, visual, or sensory) about their muscle activation to encourage further muscle activation. In recent years, there has been increased interest in using biofeedback to promote specific muscle patterns (such as encouraging independent activation of opposing muscles) and/or using EMG signals to control computer interfaces/computer games.[4,5]
- **Motor Imagery** - Patient is instructed to spend time imagining the paretic limb performing specific movements, Some studies report improved outcome when imagery is used in addition to standard care.[6]
- **Robotic devices** – Robotic interfaces, such as the InMotion Robot, promote repetitive activity-based therapies and many can provide support and facilitate movement, thus making it possible for patients with severe weakness to engage in high number of repetitive exercises.[7]

The sEMG-Virtual Arm Project:

__OBJECTIVE:__ To develop a surface-electromyography (sEMG) controlled augmented reality arm for early post-stroke upper extremity motor rehabilitation in patients with moderate to severe arm weakness.

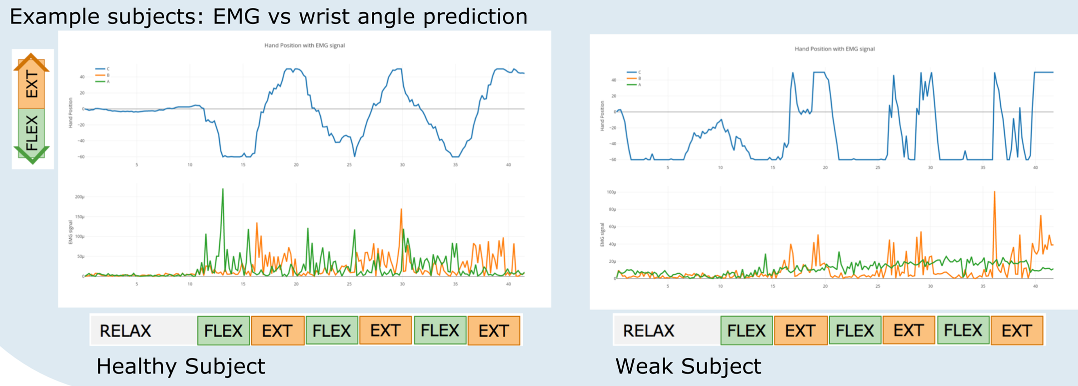


(2) Initial Prototype - "Winner Takes All" Strategy



(1) sEMG electrodes are placed over user's flexor and extensor muscle groups on the user's forearm
(2) Electrical signals are collected by the EMG machine (Delsys EMG system with Trigno wireless electrodes).
(3) These signals are then amplified, and raw EMG signal is rectified and smoothed.
(4) The relative intensity of the signal from the wrist flexor versus wrist extensor muscles controls the angle position of the virtual wrist in the arm model ("winner takes all" strategy)
(5) The arm model is displayed to the user with the Microsoft HoloLens, augmented reality goggles which inserts elements of virtual reality as holographic images onto the user's view of the real world.

Example subjects: EMG vs wrist angle prediction



→ This strategy resulted in model wrist movements with relatively long lag (poor responsiveness), as well as limited accuracy in prediction of direction of wrist movement (especially in weaker subjects)

(3) Improving the System Using Machine Learning Algorithm to Predict Wrist Angle

In order to create a system that portrays more realistic wrist movements in response to user's varying sEMG signals, we used a machine learning approach:

- 12 healthy volunteers were asked to flex/extend their wrists over 1 minute
- During this time, EMG signals from wrist flexor and extensor muscle groups were measured
- At the same time, "Ground truth" wrist angle was recorded using the Cyberglove I (a glove with flexible wire sensors designed to measure joint angle).
- EMG data was processed using FFT to remove low frequency noise, and Cyberglove wrist angle data was binned (into 5 wrist positions)
- This data set was then used to generate models using several machine learning approaches (Support Vector Machine (SVM), Multivariate Linear Regression, Decision Tree, Naive Bayes)
- 10-cross validation was used to identify the algorithm with best ability to predict actual wrist angle from EMG data
- By decreasing the EMG interval size (used for wrist angle prediction), responsiveness of system in real-time was improved (decreased lag) without substantially decreasing accuracy

Algorithm	Accuracy (using different EMG interval times)		
	1s	0.5s	0.1s
SVM	93.125	92.125	89.875
Decision Tree	87.875	90.125	87.125
Linear Regression	85.875	83.5	83.125
Naive Bayes	92.125	90.125	87.875

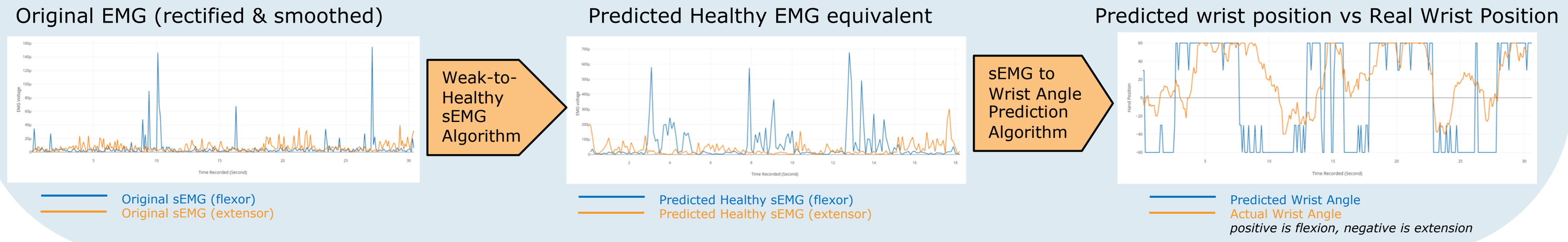
Example of EMG-to-Predicted Wrist Angle In Healthy Subject:

(4) Adapting EMG Signals from Weak Patients

- In our updated system, EMG data from weak subjects is first translated into a predicted healthy sEMG signal (using a machine learning model made from EMG and Cyberglove wrist angle data from 7 subjects with moderate weakness (MRC scale 3/5 or 4/5)), then translated to wrist angle
- This system also shows improved accuracy from original prototype
- However, using 2 machine learning algorithms (first translation of weak EMG to predicted healthy sEMG signal, then translation to predicted wrist movement) adds substantial processing burden
- We are currently re-structuring the design of our system to implement parallel processing and decrease lag due to multiple scripts/processing time.

Algorithm	Accuracy (EMG interval times)		
	1s	0.5s	0.1s
SVM	92.75	89.5	88.75
Decision Tree	87.5	87.25	85
Linear Regression	89.25	88.75	86.25
Naive Bayes	87.5	87	83.85

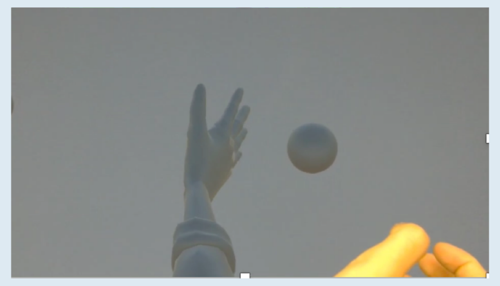
Example of EMG processing from weak subject (MRC scale of 3 out of 5):



(5) Ongoing Work/Future Directions

Addition of game interface and iterative improvements based on patient feedback

- Simple game using wrist movement to push ball, knock bowling pin over, etc., to stimulate interest/effort
- Iterative improvements of system design based on small-group patient feedback
- Goal of developing system which patient will use for at least 15min per session



3. Pilot trial to gather further data for future efficacy trial

- RCT using acute and subacute patients
- 5 sessions / week, x 2 weeks
- Primary outcome: time spent with device
- Secondary outcomes: Adverse events / tolerability, number of muscle activations/repetitions and relative flexor/extensor co-activation, improvement over time

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