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14. ABSTRACT

The proposed project centers on developing and evaluating a novel set of control modes for modern prosthetic wrist/terminal device systems that provide a much simpler interface between the user and the devices. These semi-autonomous ‘‘smart control modes’’ aim to manage some of the complexity of coordinated multi-joint movement, as apparent in the human wrist during everyday manipulation tasks. Such tasks may be keeping a soup spoon level when eating, tilting a cup towards the mouth when drinking or simply coordinating the motion of biological and artificial arm joints when reaching.

15. SUBJECT TERMS

Upper Limb Prosthetics, Amputee, Assistive Technology, Motion Capture

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1. INTRODUCTION

This project centered on investigating the nature of upper limb prosthesis use in everyday tasks through both an in-home and lab-based study on upper-limb amputees and age and gender-matched normal subjects. For the in-home study we used an unobtrusive head-mounted camera to record and then later observe prosthesis/hand use during domestic tasks. In the lab study we used a motion capture studio and video cameras to record accurate and detailed upper body motion during a series of standardized tasks. These tasks are clinically validated measures of hand / arm function functional evaluation. By recording participant performance and examining prosthesis/hand use, we then identify shortcomings in current prosthetic terminal devices and implementations that will inform improvements to existing designs and inspire new classes of devices in the future.

2. KEYWORDS

Upper Limb Prosthetics, Amputee, Assistive Technology, Motion Capture

3. ACCOMPLISHMENTS

This reporting period covers the full four years of the project.

What were the major goals of the project?

The major goals of the project are to investigate more intuitive control of multi-DoF powered upper-limb wrist prosthesis to reduce cognitive burden and increase functional performance. This will be completed in a two-stage approach.

1. <u>To design, implement, and test the smart control modes based on human observation</u>
   - Record human subjects carrying out a variety of ADL (Activity of Daily Living) tasks in a motion capture studio.
   - Analyze the human motion data in order to find motion synergies
   - Determine the smart control modes (SCMs) based on synergistic motions and simple control inputs
   - Implement and verify the smart control mode (SCM) algorithms in software.
   - Establish whether SCMs may be accessed and controlled via the use of IMUs, (Inertial Measurement Units) or EMG's (electromyography) located on an amputee participant's limbs.

2. <u>To conduct human subjects evaluation of the control concepts</u>
   - Enable interaction of the smart control modes in software
   - Implement volitional control based on EMG PR and arm coordination
   - Compensate the effect of arm position change by using the sensor fusion method on IMUs data and EMG data.

What was accomplished under these goals?

In the **first year** we prepared measurement equipment and the necessary protocols to enter participants into our study. Preliminary analysis has additionally taken place. In particular the following achievements were made:

1. Experimental protocols were finalized: a set of activities of daily living (ADL) tasks were selected.
2. The protocol was approved by Yale's IRB and the DoD. Necessary human subjects training was also completed for relevant members of the study team.
3. Custom data processing scripts to extend the functionality of Vicon software to export skeletal angles have been created. These scripts have been written to match the guidelines of the international society of biomechanics (ISB).
4. Collection and setup of materials for the laboratory space. This includes a door handle on a bare beam and hinge (to simulate a full door) and various household items.
5. Accuracy of the Vicon motion capture system was verified using a goniometer modified with an encoder (Figure 1).

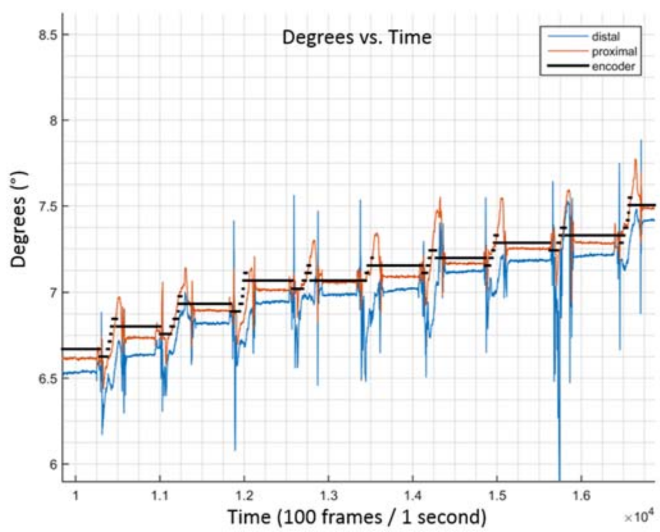

Figure 1: Verification of optical motion capture joint reconstruction (red and blue lines) via an encoder-sensorized goniometer (black line). The experiment verified that the Vicon system is capable of reliably recognizing <0.1° motions. The 'proximal' and 'distal' legend refers to two sets of markers used in reconstruction.

6. A number of pilot experiments were recorded to verify the forward kinematics and analytical algorithms.
7. Motion synergies have been proposed using the preliminary data and prior literature. The synergies were used to inform the experimental tasks and the evaluation of participants' motion.
8. A PCA (Principle Component Analysis) approach was used to decompose the recorded ADL motions into one or two dimensional components.

9. An initial ‘motion synergy graph’ was created to aid intuition when analyzing the motion data and attempting to agnostically identify motion categories.

In the **second year** of the project the following developments were made:

1. Recordings of arm motions were segmented into separate and distinguishable motions, such as reaching for an object on a table and transferring an object from one point to another. This was performed using different methods with manual segmentation providing the most reliable results.
2. Various time-series representations were explored to remove the time dependency of arm motions segments. These include various functions (B-splines, Beziers, polynomials), and phase plot histograms.
3. The segmented motion data was clustered using different unsupervised learning techniques (k-means, spectral, and hierarchical clustering). Hierarchical clustering appeared to perform the best.
4. A clustering performance metric was developed and calculated for every combination of motion segment representation technique, clustering method, and number of clusters. A combination that resulted in more consistent clustering would receive a higher score, i.e. we expect that all “reaching for a cup on the table” segments would belong to the same cluster.
5. T-Distributed Stochastic Neighbor Embedding (t-SNE) algorithm was explored to aid visualization and intuition of the results.
6. Cluster average algorithms were developed to obtain a set of representative motions. Forward kinematics simulation was created as well to visualize the resulting averages.
7. 3 additional pilot studies were conducted in preparation for the full 12 subject study. These assisted in identifying equipment and protocol shortcomings as well as aiding in motion capture camera recalibrations.
8. Participant recruitment began, with various advertisements placed around university campus and online.
9. Quantification of the effect of EMG variation due to upper extremity posture change on the 2-degrees of freedom (2-DoF) musculoskeletal model offline kinematic predictions was performed. The Model-Based EMG interface was reliable against upper limb posture changes (Figure 1-3).
10. A generic musculoskeletal model was developed by averaging the model parameter values derived from 6 able-bodied subjects across all subjects and all trials. Then, the generic model was tested with off-line experimental data from the 6 able-bodied subjects.
11. The generic model was tested on one able-bodied subject and one transradial amputee subject. The subjects were instructed to perform virtual hand/wrist posture matching tasks using the generic musculoskeletal model (Figure 4).

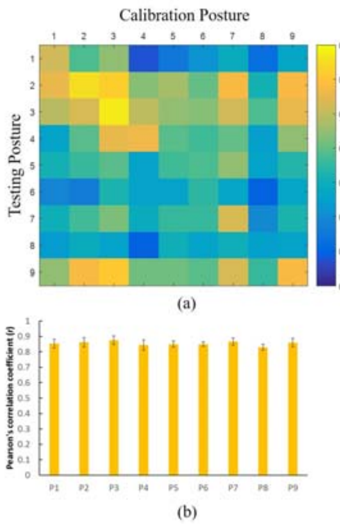

Figure 2: (a) Confusion matrix of Pearson's correlation coefficient (r) between measured and estimated joint angles averaged across all AB subjects and all movements; (b) Pearson's correlation coefficient (r) between measured and estimated joint angles in each Specific Model averaged across all AB subjects, all movements, and all testing postures.

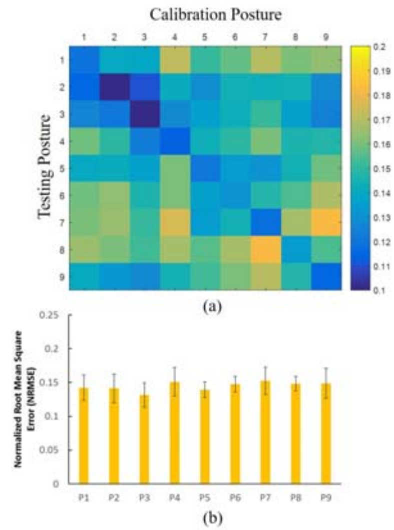

Figure 2: (a) Confusion matrix of NRMSE between measured and estimated joint angles averaged across all AB subjects and all movements; (b) NRMSE between measured and estimated joint angles in each Specific Model averaged across all AB subjects, all movements, and all testing postures.

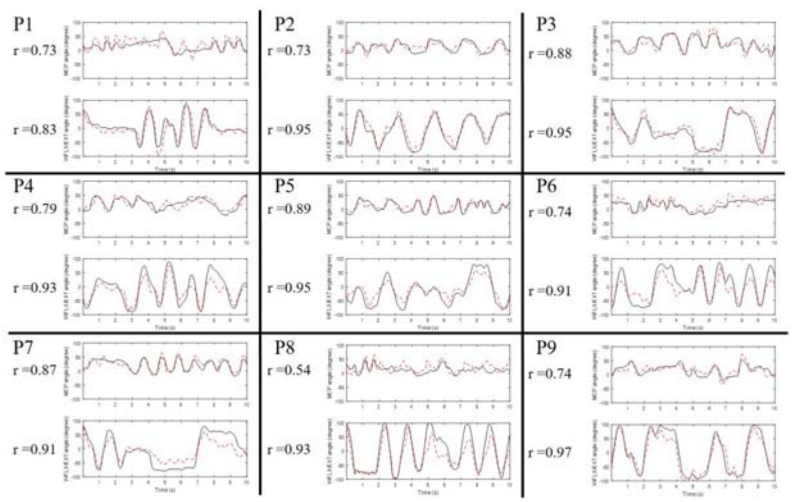

Figure 3: Representative estimation performance during simultaneous 2-DoF random movements of the cross-posture test on M3 in 9 different postures for AB subject 2. Measured and estimated joint angles are shown by the solid black line and dashed red line, respectively.

In the **third year** of the project the methods previously developed were refined leading to publication/dissemination. More specifically:

1. All 12 planned subjects have completed the experiment. The motions from 5 of the subjects were processed to obtain preliminary results. The steps to process the data from the 5 subjects includes motion segmentation, averaging, and clustering.

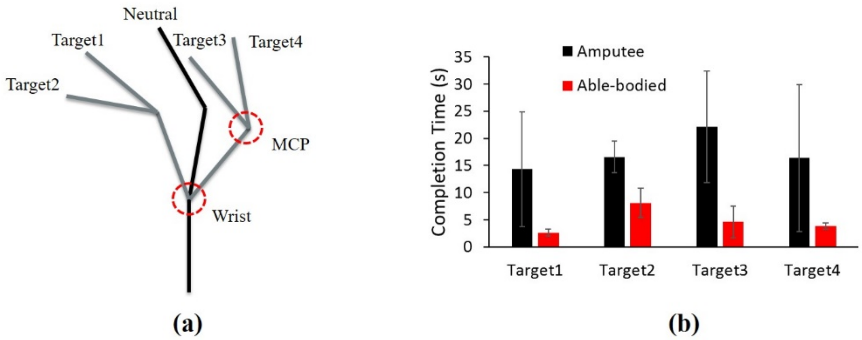

Figure 4: (a) Neutral posture and 4 target postures; (b) Average completion time across 4 trials of each target for amputee and able-bodied subjects.

2. The analysis pipeline was updated by averaging repetitions and using a more accurate divergence measure between motions for clustering. The updated choices were verified against alternative approaches using the cluster quality as the metric.
3. Inter- and intra- cluster variation analysis was added, which helped intuit the results.
4. Preliminary findings identified 6 clusters for the full arm (7 degree of freedom) joint angle model, seemingly grouped based on start and end locations of the hand. The findings were accepted as a full paper with poster presentation at the IEEE International Conference on Robotics and Automation in Montreal, Canada.
5. Tools were developed to quantify and describe the amount of variation around an arm motion trajectory average.
6. Analysis pipeline was tested on hand Cartesian locations to obtain preliminary corroboration of the joint angle trajectory results.
7. A search for a 3D platform was performed and Unity was selected to develop a virtual testing bed for proposed prosthesis control schemes.
8. We tested the generic forearm-wrist model on seven AB subjects, four of whom were newly recruited, and one transradial amputee subject. Subjects performed a virtual hand/wrist posture matching task with different upper-limb postures. The calibration procedure only involved capturing maximal voluntary muscle contraction for all monitored muscles for individuals (Figure 5).
9. We proposed a control approach with combination of the generic model and the Kalman filter. The combination approach was tested on the previously acquired data from six able-bodied subjects in 9 different upper limb postures.
10. As some cases had significant jitter in the predicted path and overshooting of targets was common for the generic musculoskeletal model, we investigated the predictive accuracy for the musculoskeletal model as well as the kinematic model (using a Kalman filter) across different movement profiles, as described by the magnitude of the ratio of acceleration to velocity. The accuracy was tested on the previously acquired data from six able-bodied subjects in 9 different upper limb postures.
11. A musculoskeletal model based controller that utilized the surface EMG signal to drive prosthesis was developed to drive the wrist joint. Inertial measurement units (IMUs) were used to provide real-time insight into the limb kinematics, acceleration and orientation of gravity. The controlling parameters for specific subject was tunable in real time The

system had a real-time 3-dimentional graphic rendering interface that highly mimicked actual human movement (Figure 6 (A)) The prediction stability improved by incorporating the joint damping feature (Figure 6 (B)).

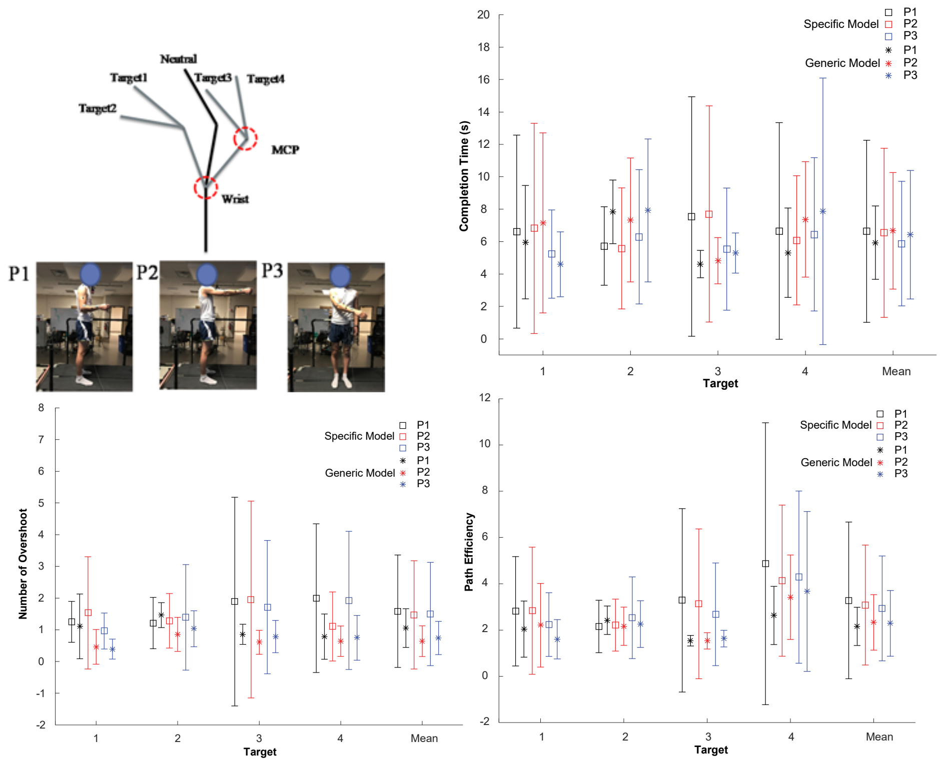

Figure 5: Average completion time, number of overshoots, and path efficiency for each target across trials for able-bodied subject. Error bars represent the standard deviations.

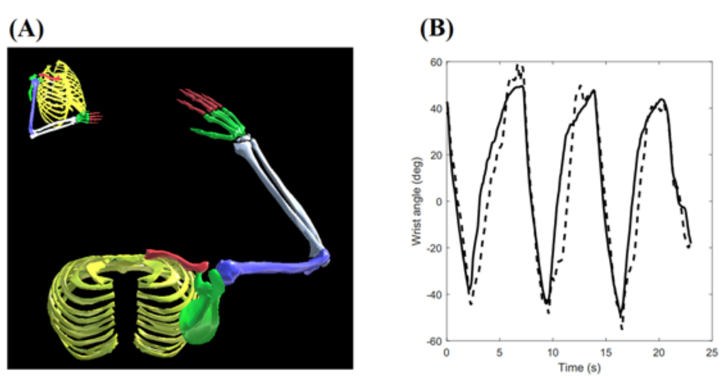

Figure 6: (A) Real-time 3-dimentional graphic rendering interface; (B) Model predicted wrist joint angle (dash line) and wrist joint angle measured by inertial measurement units (solid line).

In the **fourth year** the rest of the collected data was analyzed from able-bodied participants. Use of the external resources for grasping and manipulation was defined, explored, and published. More specifically:

1. The rest of the 12 subjects' data was processed: cleaned, segmented, and integrated into the analysis. The additional data corroborated and expanded previous results by adding the wrist, elbow-wrist, and shoulder-elbow joint angle motion trajectories to the analysis. Additional expansions included calculating subsets of motions for each of the arm models, obtaining the motion variation, and a data driven method was implemented to decide on the number of clusters. Figures 7-9 include the following results in order:
    a. Plots compare the proposed analysis pipeline against other popular alternatives for each of the joint angle models. The chosen method outperforms the alternatives at nearly every number of clusters.

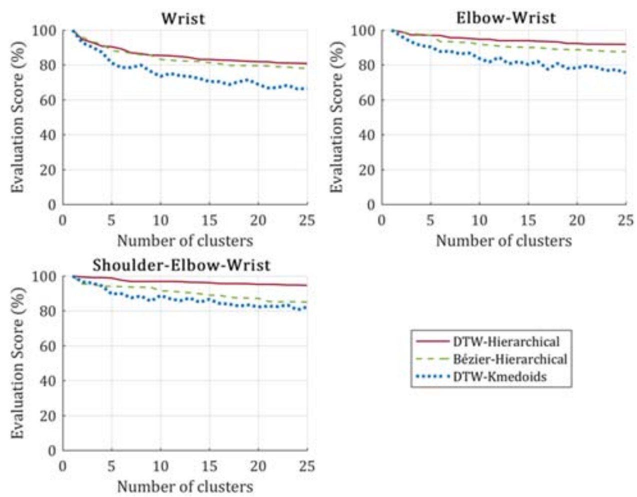

Figure 7: Quality of clustering for different divergence measures and clustering algorithms across a range of number of clusters. Scoring metric assessed how frequently repetitions clustered together.

    b. Cluster dendrograms of each of the joint angle models: wrist, elbow-wrist, shoulder-elbow-wrist, and shoulder-elbow. The first three correspond to respective amputation levels, while the fourth is presented to corroborate that the shoulder-elbow joint angle data dominates the wrist. The diagrams also depict the similarity relationship between each of the trajectories, offering a multi-level interpretation of our daily arm motions.
    c. A subset of motions was obtained by averaging each of the clusters. As an example, he full arm model for one of the motions is displayed along with the largest direction of variation.
2. Simulations of the subset of extracted motions were created using the KineMan simulation tool to visualize the wrist and the elbow-wrist joint angle trajectories. The shoulder-elbow-wrist joint angle trajectory was simulated using straight line links in Matlab.
3. Joint angle range of motions were compared across tasks and subjects.
4. A follow up analysis was conducted using the same subject data but decoupling the hand location and orientation. Groupings of motions and locations can be seen overlaid on top of a skeleton model in Figure 10.

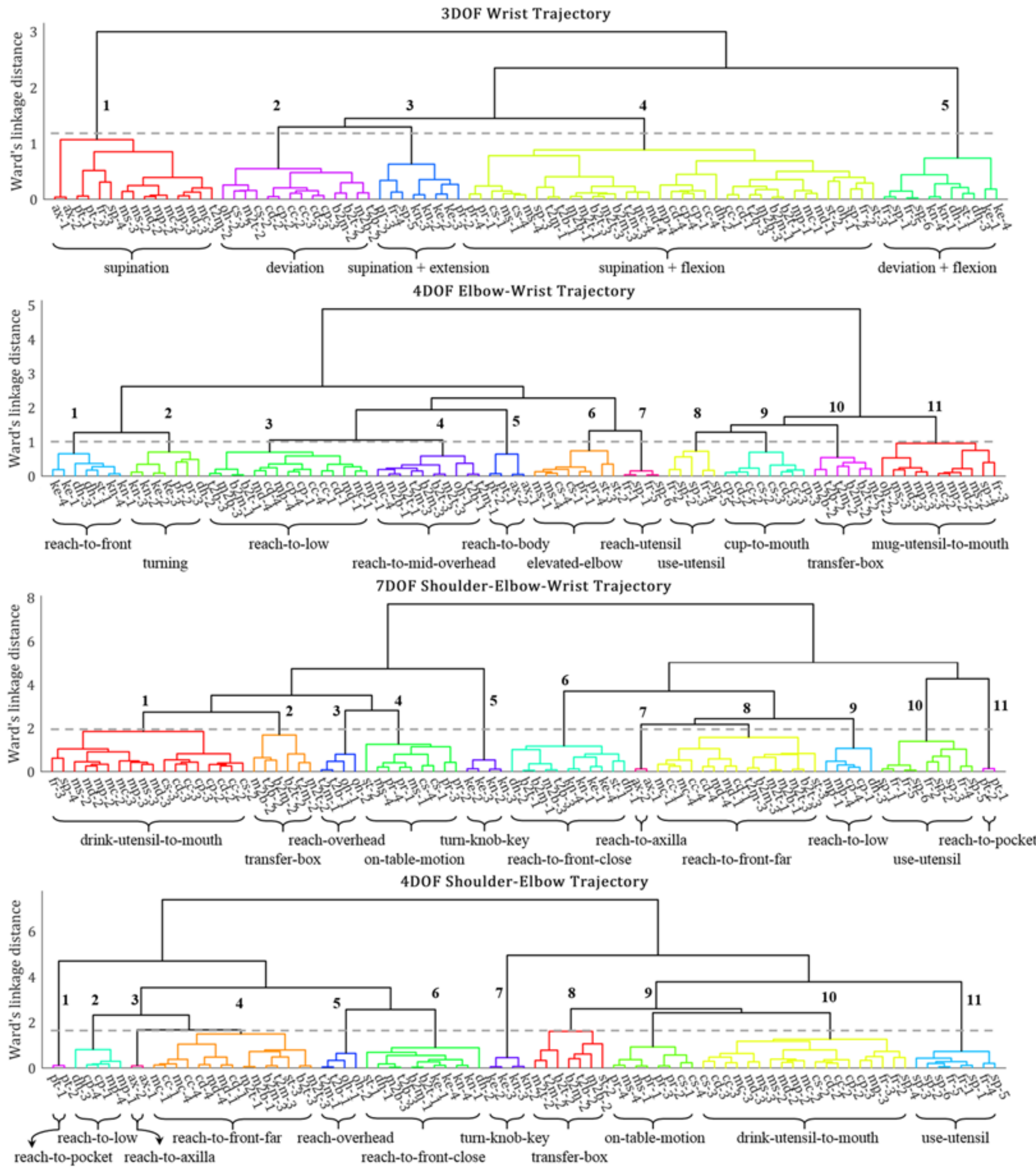

Figure 8: Dendrograms for the 3, 4, and 7 DOF models. Location of the horizontal cut (dashed line) was chosen using a data driven approach. An appropriate cluster name accompanies each of the clusters: major axes of wrist rotation for the 3 DOF model and generalized description of the motions for the 4 and 7 DOF models. Cluster colors are auto-generated and are unrelated between dendrograms.

5. The distributions of hand orientations between the Global, Torso, and Forearm reference frames were compared, Figure 11. Although Global and Torso have a lot of overlap, there are still a few notable differences that could be leveraged in prosthesis control.
6. The clusters obtained for hand locations were further analyzed to obtain a set of hand orientation. Although a variety of statistical techniques were explored, a custom metric was used to analyze distribution of orientations, see Figure 12. One discovery was that certain reference frames and cluster locations correlate with a single hand orientation, thus simplifying the proposed decoupled control. Each reference frame has its own advantages, and could be used interchangeably in a prosthetic wrist control.
7. The results in this section are in preparation for a joint journal submission: joint angle

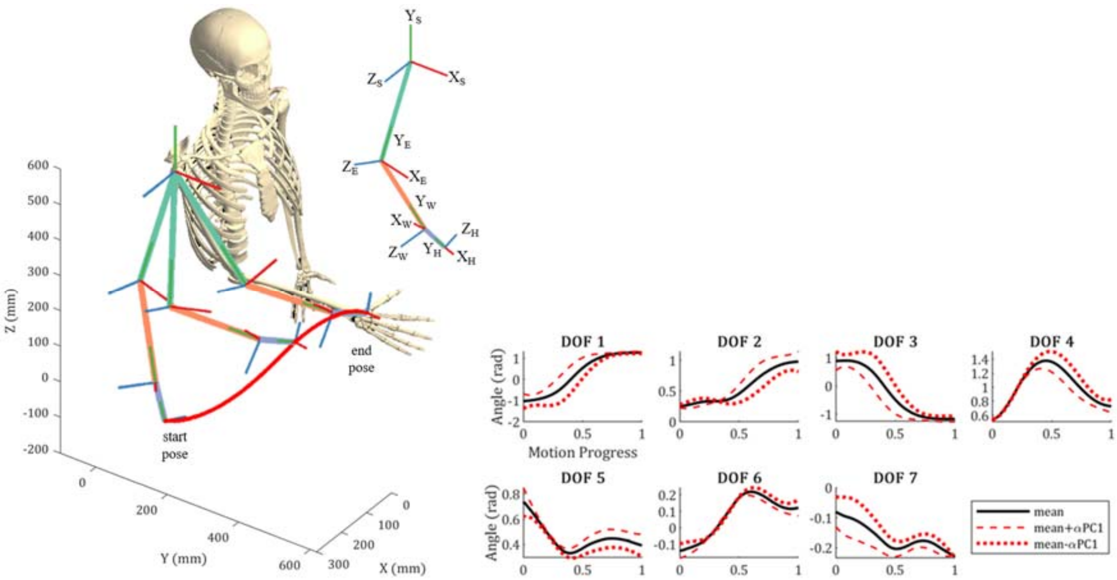

Figure 9: Forward kinematics are used to display the average motion of the 8th cluster for the 7 DOF model, reach-to-front-far. Three reference frames are displayed with X, Y, and Z axis using subscripts S, E, W, and H for shoulder, elbow, wrist, and hand, respectively. The shoulder coordinate frame is fixed throughout the motion. Humerus, forearm, and hand lengths correspond to an average adult. DOF angle correspond, respectively, to humeral elevation, plane of elevation, internal rotation, elbow flexion, wrist supination, wrist, flexion, and wrist deviation. Individual joint angle trajectories are displayed along with the first principal component. α was set to equal the proportion of total variation explained by that component.

trajectory analysis, and decoupled location and orientation analysis.

8. Since testing the subsets of motions is infeasible given the current state of prosthetic technology, we have begun development of a virtual reality test bed where users can control a simulated prosthesis. Vicon inputs are used to track the subjects' location and orientation in the virtual space while EMG's placed on the arm will be used to move the simulated prosthesis.
9. We developed and validated an inverse of the musculoskeletal model (mapping kinematics to muscle activations) for use as the measurement mapping function in the Unscented Kalman Filter (UKF) algorithm.
10. We developed a motor decoding algorithm using the UKF to combine the predictions of the musculoskeletal model and a kinematic model. This algorithm was tested for accuracy of prediction of wrist and metacarpophalangeal (MCP) joint kinematics for 6 able-bodied subjects in 9 postures. Reduction in root mean square error (RMSE) for the MCP joint was observed with this algorithm when compared to the musculoskeletal model alone (Figure 13).
11. We compared the musculoskeletal model (MM) performance to linear regression (LR) and artificial neural network (ANN) motor decoders. The MM was found to have better performance (higher correlation and lower RMSE) on average across all subjects, postures, and motion types (Figure 14).
12. We developed another implementation of the UKF algorithm to fuse the MM with a data-driven approach. In this formulation (Figure 15) the MM is used to forward predict the kinematic state, while an ANN is trained to act as the measurement mapping function

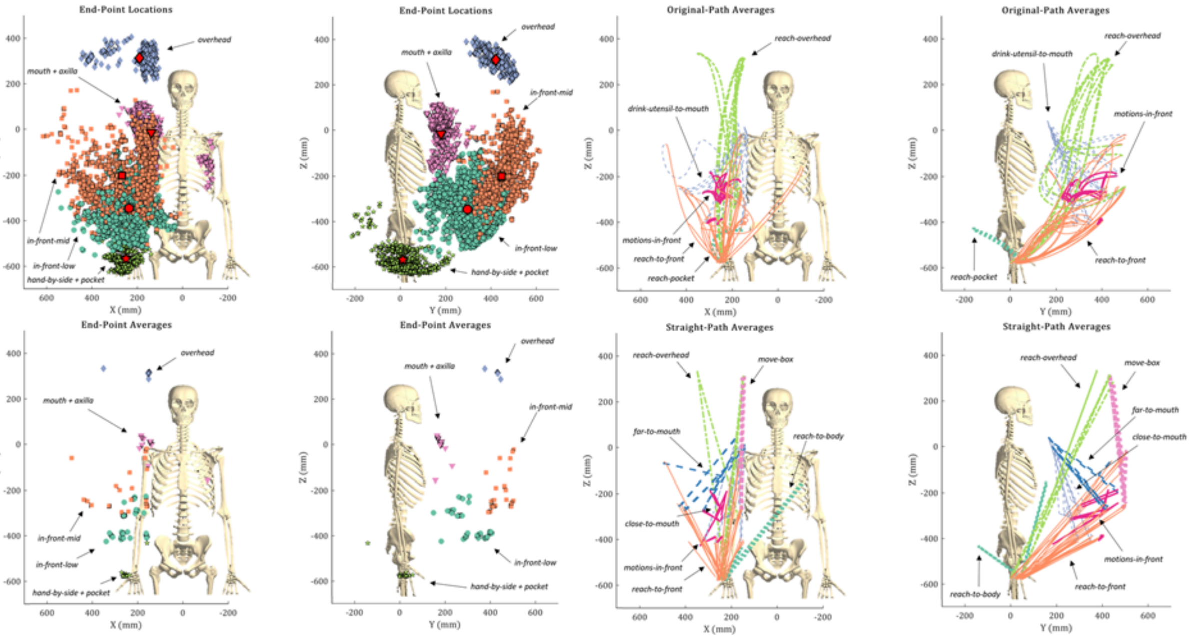

Figure 10: Visual representations of the end-point locations (top left), the location averages (bottom left), original-path trajectories (top right), and straight-path trajectories (bottom right). The end-point locations of the un-averaged repetitions are classified according to average results. Centroids (red) are included in the top-left results. The origin is located halfway between markers placed on the C8 spinal segment and at the top of the sternum. Clusters are identified with unique line patterns and colors. Cluster labels are additionally included.

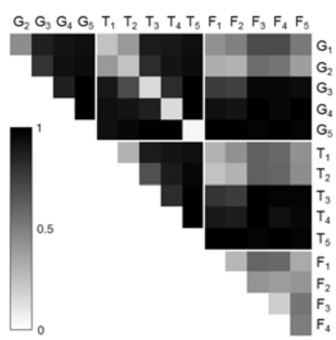

Figure 11: Relative similarity between hand orientation distributions across clusters and reference frames. Reference frames are indicated by G, T, and F, for global, torso, and forearm respectively.

relating kinematics to muscle activations. The UKF algorithm leads to improvement in the trajectory prediction performance as shown in Figure 16.

What opportunities for training and professional development has the project provided?

The project provided the opportunity for familiarization with literature on prosthetics, motion capture and functional outcome measures. Attendance at the ICRA (International Conference on Robotics and Automation) conference has greatly contributed to the staff's familiarization with the field of upper limb prosthetics.

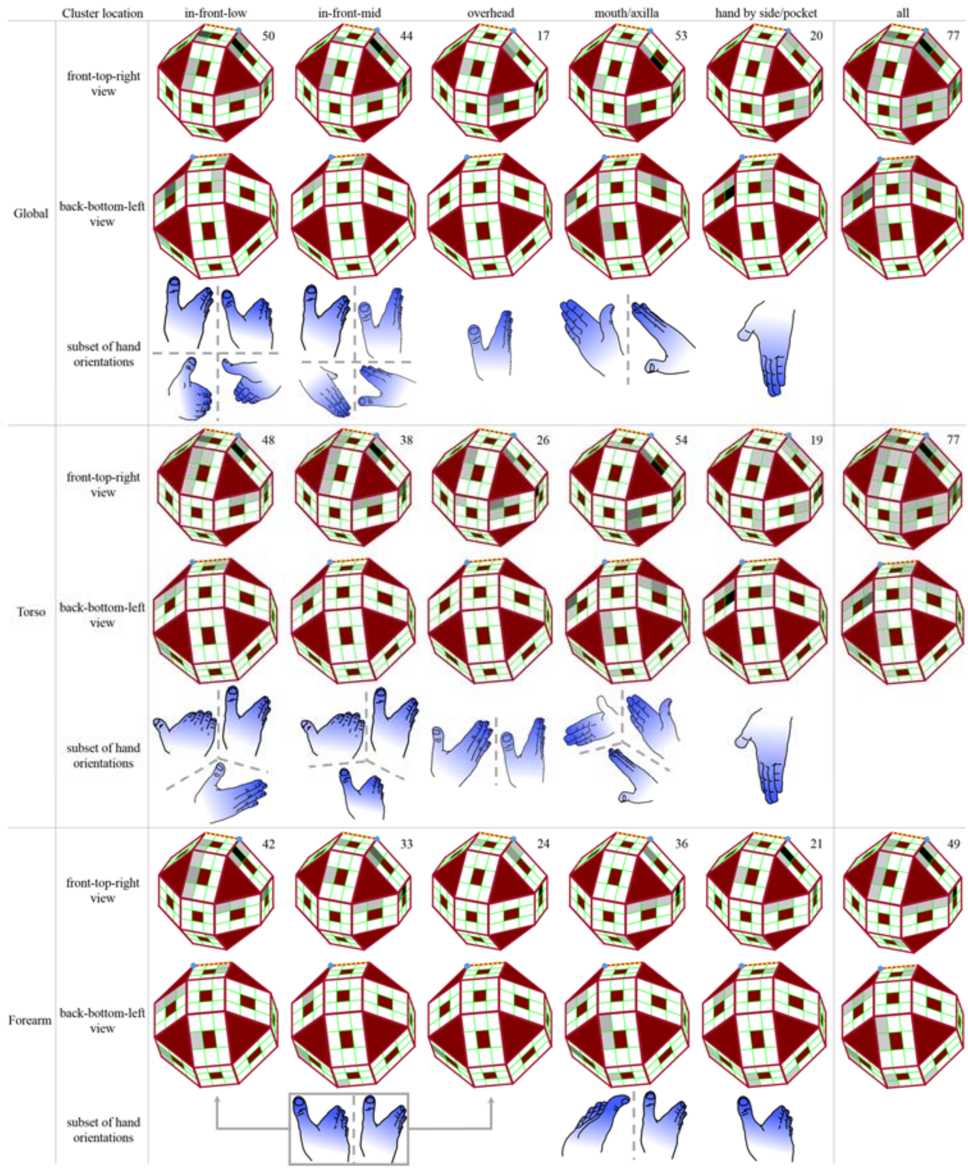

Figure 12: Distributions of the hand orientations are shown in each of the three reference frames (right column), as well as within each end-point location cluster. Subsets of the distribution, found by re-clustering, are shown below each respective distribution. Some subsets are identical across distributions, as is seen for three of the clusters in the forearm reference frame. Dispersion values are displayed at the top right of each distribution.

Technical training was completed by Yuri Gloumakov and Dr. Adam Spiers on the Vicon motion capture system. Training was also completed by Yuri Gloumakov Dr. Spiers on protocols and policies regarding human experiments. Yuri Gloumakov has subsequently trained two undergraduate students in how to use the motion capture system and both he and Dr. Spiers have written a guide for Vicon use in the lab.

Two undergraduate students and another graduate student has been trained in Vicon data processing.

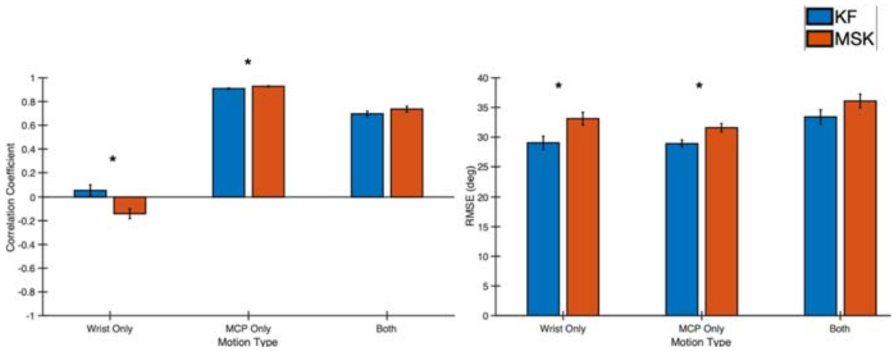

Figure 13: Comparison of correlation (left) and RMSE (right) of the UKF algorithm (blue) and MM (orange) for MCP joint motion prediction. The UKF algorithm causes a significant decrease in RMSE and a slight, but significant decrease in correlation as well.

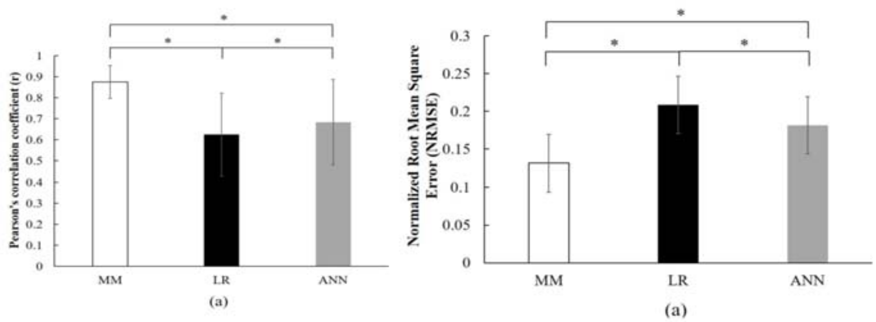

Figure 14: A comparison of correlation (a) and normalized RMSE (b) for the musculoskeletal model (MM), linear regression (LR), and artificial neural network (ANN) for all subjects, postures, joints, and motion types. The MM has higher correlation and lower normalized RMSE compared to the other approaches.

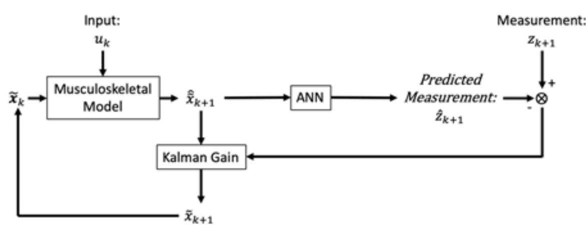

Figure 15: A block diagram of the new implementation of the UKF algorithm fusing the MM prediction with a data driven (ANN) prediction. The performance of this system is being analyzed currently.

How were the results disseminated to communities of interest?

Results have been presented extensively within our lab group.

A regular paper was accepted for ICRA 2019 (International Conference on Robotics and Automation) and a poster presentation given at the event.

Posters have been presented at both 2018 and 2019 NEMS (New England Manipulation Symposium)

Approximately 6 additional papers are currently in preparation for submission in the near future.

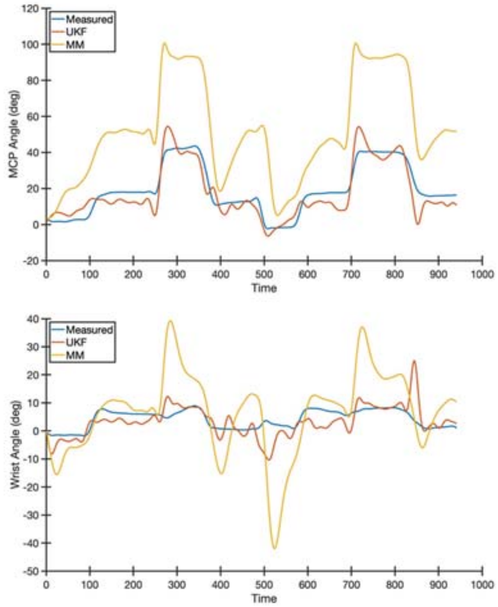

Figure 16: An example comparing the new UKF design to the musculoskeletal model. The UKF algorithm reduced MCP joint prediction (top) RMSE by 56% compared to the musculoskeletal model. However, the UKF design (R = 0.91) shows a slight reduction in correlation compared to the musculoskeletal model (R = 0.95) for the MCP joint. A similar effect is seen in the wrist joint prediction (bottom). The UKF design reduced RMSE by 18% compared to the musculoskeletal model with a slight decrease in correlation (UKF: R = 0.57, MM: R = 0.63).

IMPACT

What was the impact on the development of the principal discipline(s) of the project?

Describe how findings, results, techniques that were developed or extended, or other products from the project made an impact or are likely to make an impact on the base of knowledge, theory, and research in the principal disciplinary field(s) of the project. Summarize using language that an intelligent lay audience can understand (Scientific American style).

The human wrist has been previously shown by to be as important to successfully grasping and completing tasks in our daily lives as are the fingers. However, much of the prosthetic community has been focusing on improving finger control and varying the types of grasps that can be accomplished. This is in part due to the control complexity associated with rotating a wrist along three different directions. We began our analysis with looking for ways to extract “smart control modes” (or rather, subsets of important motions) from healthy motion in the human wrist by identifying which multi degree of freedom trajectories should be implemented in a wrist device. Due to overlap in content, the analysis has additionally been expanded to elbow-wrist and whole arm models corresponding to various levels of arm amputation, offering a unique, yet simple, solution to controlling a range of complex prosthetic devices.

The majority of the effort was focused on processing the data and identifying the correct machine learning tools to analyze the time-series joint angle data. The results from whole arm motion (simultaneous joint angle trajectories of the shoulder, elbow, and wrist) were the easiest to intuit and therefore used to select the appropriate analysis pipeline used in the rest of the analysis. Although our work was extended to various joint angle trajectories of the human arm, the analysis can be easily implemented in a wide range of applications dealing time-series data looking to identify cluster relationships.

We applied the same analysis pipeline to the human hand locations. The decoupling of location and orientation has led to a discretization of the human hand workspace and identification of conditions where some reference frames outperform others. Results from this work are useful in a variety of domains, such as rehabilitation and wheel-chair mounted robotic arms, and could be an alternative approach to controlling a prosthetic device.

Results from each of the joint angle models can be readily implemented in prosthetic devices. However, due to limitations in commercial availability, we look to demonstrate their practicality in virtual reality. The virtual reality testbed is itself a remarkable tool offering short turnarounds of novel prosthetic controls testing. We believe that a demonstrable improvement to prosthesis control will be encouraging for commercial development of complex multi-degree of freedom prosthetic systems.

What was the impact on other disciplines?

As described above, many of the results from this study have applications in the broader field of upper-limb rehabilitation, such as stroke rehabilitation. Furthermore, there are applications within robotics, especially as it relates to controlling multi-degree of freedom kinematic chains in a human environment, such a wheel-chair mounted robotic arm.

What was the impact on technology transfer?

We have identified unique simplified strategies for controlling multi-degree of freedom prosthetic devices that will inform control design. However, proof of concept is difficult given the lack of commercial devices, and we therefore are exploring testing in virtual reality. We expect these to eventually make it into commercial systems.

What was the impact on society beyond science and technology?

Nothing to report

5. CHANGES/PROBLEMS:

Changes in approach and reasons for change

Nothing to report

Actual or anticipated problems or delays and actions or plans to resolve them

Year 1 - Training, setup and familiarization of with the motion capture system added delays to the project compared to the original forecast. However we believe the quality and impact of the resulting data will be much higher as a result of this new measurement tool and the time taken to learn how to use it.

Year 2 – A lack of analysis tools that are able to deal with time-series data required that we explore as many options as possible and alter existing algorithms to deal with it. Although this gap in technology was unanticipated, this lead to a richer contribution.

Year 3 – Given the wide range of motions that we decided to analyze, processing the motion capture data turned out to take much longer than anticipated. This was alleviated by training additional undergraduates on the Vicon system and identifying quicker ways to process the data.

Year 4 – Due to the amount of data that was being processed, algorithms would take a long time to compute, lengthening the time it took to debug and analyze the data. The use of an external cluster was later implemented to perform the final calculations.

We have additional work on the project that we are still finishing up and will complete in the near future. .

Changes that had a significant impact on expenditures

We re-budgeted early on to purchase the motion capture system used in the in-lab studies.

Significant changes in use or care of human subjects, vertebrate animals, biohazards, and/or select agents

Nothing to report

6. PRODUCTS:

Publications, conference papers, and presentations

Poster presented at NEMS 2019: Y. Gloumakov, AJ Spiers, and AM Dollar, "Representative Cartesian Locations and Path Trajectories of the Hand Performing Activities of Daily Living".

Y. Gloumakov, AJ Spiers, and AM Dollar, "A Clustering Approach to Categorizing 7 Degree-of-Freedom Arm Motions during Activities of Daily Living", *IEEE International Conference on Robotics and Automation (ICRA)*, May 2019

R. Hinson and H. Huang. "Combining data-driven and modeling-based approaches to improve myoelectric motor decoding." *2019 Society for Neuroscience Annual Meeting*, Chicago, IL, 2019.

L. Pan, D. Crouch, H. Huang, "Comparing EMG-based human-machine interfaces for estimating continuous, coordinated movements", *IEEE Transactions on Neural System and Rehabilitation Engineering*, 2019.

L. Pan, DL Crouch, H. Huang, "Myoelectric Control Based on A Generic Musculoskeletal Model: Towards A Multi-User Neural-Machine Interface", *IEEE Transactions on Neural System and Rehabilitation*, 2018, 26(7):1435-1442.

L. Pan, D. Crouch, and H. Huang, "Can One EMG-based Neural-Machine Interface Fit All?" 2017 Society for Neuroscience Annual Meeting, Washington D.C., 2017

DL Crouch, L. Pan, H. Huang., "Musculoskeletal Model-Based Control Performance is Consistent Across Static Upper Limb Postures". The 42nd Annual Meeting of the American Society of Biomechanics, Rochester, MN, 2018, accepted.

L. Pan, D. Crouch, and H. Huang, "Can One EMG-based Neural-Machine Interface Fit All? Peer-reviewed abstract at the 47th annual meeting of Society for Neuroscience 06/21/2017, accepted.

L. Pan, D. Crouch, and H. Huang, "Reliable Musculoskeletal-Model-Based EMG Interface against Upper Limb Posture Changes," IEEE Trans. Neural Syst. Rehabil. Eng., 2017, under review.

Website(s) or other Internet site(s)

Recruitment Page

https://www.facebook.com/YaleGrabLab/

Technologies or techniques

Motion capture marker sets and processing techniques associated have been developed. These will accompany future publications as appendices.

The analysis pipeline has been demonstrated to work on a variety of multi-dimensional time-series data, and can be readily extended to other types of data.

Identified motion segments can be implemented in complex multi-degree of freedom prosthetic upper-limb devices. Additional proof of concept will be performed in virtual reality.

The virtual reality testbed for prosthesis use will be published following its completion.

The human arm motion dendrograms can implemented in various classification techniques that will be applicable to general analysis of upper limb use.

Inventions, patent applications, and/or licenses

Nothing to report

Other Products

Nothing to report

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

What individuals have worked on the project?

Name:	Aaron Dollar
Project Role:	PI
Researcher Identifier (e.g. ORCID ID):	Aaron.dollar@yale.edu
Nearest person month worked:	4
Contribution to Project:	**Expert on human hand functional use and robot / prosthetic hand development. Contributed to Protocol development, measurement equipment selection and setup.**
Funding Support:	This award.

Name:	Linda Resnik
Project Role:	Co-PI
Researcher Identifier (e.g. ORCID ID):	linda_resnik@brown.edu
Nearest person month worked:	4
Contribution to Project:	**Expert on upper limb prosthetics**

	and measures of upper limb functionality and rehabilitation outcomes. Contributed to protocol development.
Funding Support:	This award

Name:	Helen Huang
Project Role:	Co-PI
Researcher Identifier (e.g. ORCID ID):	hhuang11@ncsu.edu
Nearest person month worked:	4
Contribution to Project:	**An expert on myoelectric control. Contributed to protocol development.**
Funding Support:	This award

Name:	Adam Spiers
Project Role:	Postdoctoral Associate
Researcher Identifier (e.g. ORCID ID):	adam.spiers@yale.edu
Nearest person month worked:	8
Contribution to Project:	**Postdoc researcher responsible for running at-home and in-lab studies. Contributed to protocol development, IRB submission (Yale only), equipment selection, setup, customization and familiarization.**
Funding Support:	This award.

Name:	Yuri Gloumakov
Project Role:	Graduate Student
Researcher Identifier (e.g. ORCID ID):	yuri.gloumakov@yale.edu
Nearest person month worked:	48
Contribution to Project:	**Natural human arm motion analysis. Prosthetic wrist software and smart control modes development.**
Funding Support:	This award.

Name:	Kate Barnabe
Project Role:	Administrative Lead
Researcher Identifier (e.g. ORCID ID):	Kate.Barnabe@va.gov
Nearest person month worked:	4
Contribution to Project:	**Protocol development. IRB submissions (all institutions and DOD). Project administration.**
Funding Support:	This award

Name:	Ting Zhang
Project Role:	Postdoctoral Associate
Researcher Identifier (e.g. ORCID ID):	tzhang13@ncsu.edu
Nearest person month worked:	25
Contribution to Project:	**Protocol development, IRB preparation and submission,**
Funding Support:	This award

Name:	Lizhi Pan
Project Role:	Postdoctoral Associate
Researcher Identifier (e.g. ORCID ID):	lpan3@ncsu.edu
Nearest person month worked:	5
Contribution to Project:	**Algorithm development for myoelectric control**
Funding Support:	This award

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?

Nothing to report

What other organizations were involved as partners?

Nothing to report

8. SPECIAL REPORTING REQUIREMENTS

A Quad Chart accompanies this report.

9. APPENDICIES

None