Classification of Hand Preshaping in Persons with Stroke using Linear Discriminant Analysis*

Saumya Puthenveettil, Gerard Fluet, Ph.D, Qinyin Qiu, Ph.D, and Sergei Adamovich, Ph.D, Member, IEEE

Abstract—Objective: This study describes the analysis of hand preshaping using Linear Discriminant Analysis (LDA) to predict hand formation during reaching and grasping tasks of the hemiparetic hand, following a series of upper extremity motor intervention treatments. The purpose of this study is to use classification of hand posture as an additional tool for evaluating the effectiveness of therapies for upper extremity rehabilitation such as virtual reality (VR) therapy and conventional physical therapy. Classification error for discriminating between two objects during hand preshaping is obtained for the hemiparetic and unimpaired hands pre and post training. Methods: Eight subjects post stroke participated in a two-week training session consisting of upper extremity motor training. Four subjects trained with interactive VR computer games and four subjects trained with clinical physical therapy procedures of similar intensity. Subjects' finger joint angles were measured during a kinematic reach to grasp test using CyberGlove[®] and arm joint angles were measured using the trackSTAR[™] system prior to training and after training. Results: The unimpaired hand of subjects preshape into the target object with greater accuracy than the hemiparetic hand as indicated by lower classification errors. Hemiparetic hand improved in preshaping accuracy and time to reach minimum error. Conclusion: Classification of hand preshaping may provide insight into improvements in motor performance elicited by robotically facilitated virtually simulated training sessions or conventional physical therapy.

I. INTRODUCTION

The evolution of the human hand during transport (reaching) and prehension (grasping) has been studied extensively in order to determine the underlying neural mechanisms of motor planning. Hand preshaping consists of both an early phase and late phase. The early phase is a predictive phase where hand formation is selected while during the late phase, grasp on the object is optimized [1]. During a reaching and grasping task (Fig. 1), the fingers initially straighten and the grip aperture increases, and as the hand approaches the object, grip closes in order to match the size of the object [2]. During the transport phase, the posture of hand can be discriminated among various shaped

* This work was supported in part by NIH grant HD 58301 and by the National Institute on Disability and Rehabilitation Research RERC grant #H133E050011.

S. Puthenveettil is with the New Jersey Institute of Technology, Newark, NJ 07102 USA (e-mail: saumya.puthenveettil@gmail.com).

G. Fluet is with the University of Medicine and Dentistry of New Jersey, Newark, NJ 07107 USA (e-mail: fluetge@umdnj.edu).

Q. Qiu is with the New Jersey Institute of Technology, Newark, NJ 07102 USA (e-mail: qq4@njit.edu).

S.V. Adamovich is with the New Jersey Institute of Technology, Newark, NJ 07102 USA (corresponding author phone: 973-596-3413, fax: 973-596-5222; e-mail: sergei.adamovich@njit.edu). objects and gradually evolves [3]. Previous studies employed a reach to grasp experiment to measure finger joint angles of subjects with Parkinson's disease and stroke compared to normal subjects with results indicating significant differences in hand shaping abilities and kinematics [4,5,6].

Stroke can result in physical disabilities such as weakening of the limbs, decreased reaction times, and disordered movement [7]. Due to the complexity of sensorimotor control involved in reaching and grasping tasks, even slight impairment of this control can adversely affect performance of activities of daily living. Studies show that repetitive training can aid in neural reorganization in order to recover lost upper extremity (UE) motor functioning [7,8]. This approach to training has resulted in improvements in kinematic measurements of reaching and finger function along with improvements in clinical tests of UE function [9].

There are several ways to measures changes in motor function subsequent to upper extremity rehabilitation in persons with stroke. These include measurements of force generation, active range of motion, and performance Additionally, measurements of the ability to measures. coordinate or control multiple degrees of freedom of the hand may be a useful adjunct to these existing measurements due to the complex nature of hand function. The goal of this study is to examine the ability of persons with stroke to preshape the hand to conform to different shaped and sized objects as an indicator of the brain's ability to coordinate these multiple degrees of freedom. Validity of this approach will be tested using classification of hand posture, by examining changes in preshaping ability, demonstrated by a group of subjects subsequent to two weeks of intensive motor training.



Figure 1. Reach to grasp test schematic: Trial begins with hand at rest, placed in initial preset position. At cue, (1) subject reaches for the shape (centered), (2) places it on a 7.5 cm high target platform, (3) return to initial position. Trials are run for both hemiparetic and unimpaired hand.

II. METHODS

A. Subjects and Motor Training Program

Eight subjects post stroke, average age 52, five males and three females with hemiparesis were recruited for this study. Time since stroke varies from 10 months to 140 months. Five subjects have cortical lesions, 3 subjects have subcortical lesions. Average Chedoke McMaster (CM) Arm Impairment Inventory score is 5.2 and average CM Hand Impairement Inventory score is 5.3. Wolf Motor Function Test (WMFT) [10] and Jebsen Test of Hand Function (JTHF) [11] measurements were taken for each subject. Average WMFT pre training score was 86 and average JTHF pre training score was 112. Force measurements and wrist and finger joint angle measurements during reach to grasp tests were acquired pre and post training. Four subjects trained their hemiparetic hand with interactive virtual reality (VR) computer games and four subjects trained their hemiparetic hand with a program of non-automated repetitive task practice (RTP). For both groups, each subject's total duration was 2.5 hours per session.

B. Data Capture

Subjects sat in front of a flat table and were presented objects of five different shapes and dimensions. Objects shapes and dimensions are as follows: small circle (diameter d=3.2cm), small cube (l=9.5cm, w=3.2), big circle (d=5.7cm), big cube (l=6.7cm, w=5.7cm), huge circle (d=10 cm), and a spray bottle (d=3.81 cm, height=10.8 cm). Position of joints and rotation of the subjects' arms were recorded using four electromagnetic sensors (trackSTARTM system, Ascension Technologies, Inc.) attached with adhesive tape to the shoulder, elbow, wrist, and trunk. Flexion and extension of finger joints were measured using resistive bend sensors in a glove (CyberGlove[®], Immersion, Inc.) worn on both hands. The flexion/extension of the metacarpophalangeal (MCP), proximal interphalangeal (PIP), and distal interphalangeal (DIP) joints of all five fingers were included in this study as well as abduction/adduction joints of all five fingers. A six-axis force/torque sensor system (Nano17[™], ATI Industrial Automation) was mounted below the object to measure the time at which the object was lifted. All three devices were programmed using MATLAB and merged using C++. Devices were synchronized to capture data at 100Hz.

C. Procedure

The CyberGlove[®] sensors were individually calibrated for both hands for each subject during pre and post training sessions. Calibration measurements were obtained with hand position corresponding to zero degrees, 90 degrees, and 20 degrees by directing subjects to flatten their hand on a table with fingers together, make a fist, and keep hand flat on surface with fingers stretched apart respectively. At the beginning of each trial, the subject's hand is in a preset initial position. When cued, the subject is asked to reach to and grasp the object at a comfortable speed. Once the object is grasped, it is lifted by the subject and placed on a 7.5 cm high platform on the table surface (Fig. 1). Trials were run for both impaired and unimpaired hands. Total trials per experiment were 120 (6 shapes x 2 hands x 10 trials). If an object was not grasped successfully, another trial was run to replace it.

D. Analysis

Data from CyberGlove[®] is stored in a matrix of twenty columns that correspond to twenty of the twenty-two joint angle sensors. Rows of the matrix correspond to total samples of data collection. All glove data were transformed into degrees such that the angle for each sensor at every moment in time is a fraction of the original calibration angles for each sensor. Wrist trajectories and force sensor data were examined in order to determine movement onset and offset times. Onset and offset times from force sensor data and wrist kinematics were used to determine a window of time for preshaping of the hand for each subject.

Movement onset 1 is the time that movement first begins, offset 1 is the time the hand reaches the object, and onset 2 is the time of object lift. Onset 1 is measured as 5% of peak velocity between onset 1 and offset 1. Fig. 2 is a kinematic profile of the entire movement sequence of the proximal interphalangeal joint beginning with initial resting position and corresponding velocity profile. Phase 1 refers to the initial resting position upon hearing the bell. Phase 2 begins movement and corresponds to the reaching phase where hand preshapes to the object's shape. Phase 3 begins when the hand reaches the object and the subject is struggling to pick up the object. Phase 4 begins with hand picking up object and transporting the object to the platform. Phase 5 refers to the time when the object is placed on the platform. Phase 6 refers to when the hand returns to the initial resting position. Phase 7 is the end of movement where hand is resting. Fig. 3 shows kinematic profiles of both the impaired and unimpaired hands for index PIJ.

Linear Discriminant Analysis (LDA) is used to compare how accurately hand posture during the preshaping phase can predict what the target shape is pre and post rehabilitative training. LDA creates a decision boundary between different classes of multidimensional data. In this classification study, the training data, or the two classes are hand postures for two different shapes at one instant of time across multiple trials. An observation is classified into one of the two classes by calculating the Mahalanobis distances between the hand posture to be classified and the hand posture for each class where S⁻¹ is the pooled covariance matrix, where x_i is a multidimensional observation, and μ_j is a multidimensional mean vector for the jth class [12].

$$D_{ij}^{2} = (x_{i} - \mu_{j})' S^{-1}(x_{i} - \mu_{j})$$
(1)

An observation is classified into one of two classes that has the minimum distance or maximum posterior probability which is a function of D_{ij}^2 . In order to compare hand postures using LDA, all movement data were synchronized such that onset 1 across trials occurred at the same time.



Figure 2. Index PIJ joint angle sensor from CyberGlove® plotted with velocity profile from wrist sensor. Seven phases of movement are involved in the reach to grasp test



Figure 3. Kinematic trajectories for subject's impaired and unimpaired hand (joint PIJ of index finger). Impaired hand shows more variability in movement and instability.

Data captured during the reaching phase was normalized to 100 data points. LDA was performed from times between onset 1 and offset1 to predict which of the two objects the hand posture belonged to. Sensors measuring PIP, MCP, and abduction angles, of the index through pinky fingers were analyzed to produce an eleven dimensional vector for two classes. For every moment of time the posterior probability of one observation belonging to one of the two classes was calculated and the higher posterior was awarded the observation. Misclassification rate at every time point across trials was tabulated in order to report classification errors.

III. RESULTS

All subjects show improvement in JTHF and WMFT scores subsequent to training suggesting that they may have made improvements in motor function. Finger joint angle classification errors indicate the percentage of misclassified observations from the true class. Results from all eight subjects show a decrease in error as movement progresses post UE motor training of the hemiparetic arm and hand (Table 1) indicating that during hand preshaping, the subjects' abilities to form and optimize hand shape improved. Subjects 2, 3, and 7 do not reach an error of zero pre and post training. However, throughout their movement, classification error post training is lower than that of pre

training. Data from Fig. 4 and Fig. 5 correspond to the preshaping phase which is epoch 2 in Fig. 2. Classification error rates were lower for the impaired hand post training (Fig. 6). Fig. 7 shows a classification error profile where the unimpaired hand performs at a higher accuracy than the impaired hand. These preshaping error rates correspond to Subject 6 to distinguish between two objects "spray bottle" and "small cube" for both impaired and unimpaired hands. Post training, Subject 6's impaired hand reaches a value of zero error earlier in time and more closely resembles the unimpaired hand. Post training, Subject 6 improves in the ability to keep hand in an identical resting position for both shapes (as indicated by higher classification error at 0% movement time).



Figure 4. Subject 4's Kinematic data obtained prior to training. Data is segmented at onset 1 and offset 1 to correspond to time when movement begins to time when hand touches object (preshaping phase).



Figure 5. Subject 4's Kinematic data obtained after training. Data is segmented at onset 1 and offset 1 to correspond to time when movement begins to time when hand touches object (preshaping phase).



Figure 6. Subject 4's Classification Error for Figures 4 and 5 to discriminate hand postures for shapes 'huge circle' and 'small cube'. A decrease in classification error for post treatment (Figure 5) illustrates the the subject's ability to effectively shape the hand during reaching.

Table I	. MINIMUM	ERROR	TIMES
---------	-----------	-------	-------

Minimum Cla	assification Erro	or of Hemiparetic	Hand: Normalized
-------------	-------------------	-------------------	------------------

Movement Time(%)				
	Pre-Training	Post-Training		
SUBJECT 1	74%	58%		
SUBJECT 2	100%	100%		
SUBJECT 3	100%	100%		
SUBJECT 4	71%	33%		
SUBJECT 5	72%	47%		
SUBJECT 6	64%	55%		
SUBJECT 7	100%	100%		
SUBJECT 8	100%	71%		



Figure 7. Subject 6's classification errors decrease as movement progresses. Classification error of unimpaired hand is less than impaired hand. Hand posture is distinguishable earliest in time for the unimpaired hand. After training, impaired hand more closely resembles unimpaired hand and reaches a minimum error earlier in time.

IV. DISCUSSION

As a group, subjects tend to begin with larger error rates since during the resting position finger joint angles show little differences between objects, and minimum error rates at the end of movement since object has been grasped to form the contours of the shape. When movement begins (transport), the hand shape gradually evolves in order to optimize grasping and lifting of the target shape [3]. Improvement in classification errors or decrease in error during post training sessions may indicate improvement in an ability to coordinate finger motion. Since the classification error results consider eleven finger joint angles from the index to pinky fingers, this analysis may provide insight into improvement in coordination of multiple degrees of freedom to preshape the hand to the object shape. Since reaching and grasping involve different neural mechanisms, patients with neurological difficulty such as stroke subjects may be able to reach efficiently but have difficulty grasping and vice versa [13]. Fig. 3 above demonstrates a smooth and consistent joint angle trajectory of the unimpaired hand and the hemiparetic hand trajectory which shows disruptions in coordination and an inability to maintain stability. It is this

variance in the trajectory of the joint angles of the hemiparetic hand that is hypothesized to have varied post treatment. In addition, there is an improved ability to position fingers with precision at time zero (Fig. 5).

V. CONCLUSION

Classification of finger joint angles may be beneficial in assessing improvement in hand preshaping and motor control. Virtual reality training and conventional physical therapy of the hemiparetic arm and hand can improve stroke subjects' abilities to reach for objects and grasp them. Improvement in hand preshaping accuracy following training can be used as an additional measurement for assessing the effectiveness of upper extremity rehabilitation.

ACKNOWLEDGMENT

Authors thank the University of Medicine and Dentistry of New Jersey and JFK Rehabilitation Center for their support during data collection and the motor training phase of this study.

REFERENCES

- L.F. Schettino, S. V. Adamovich, and H. Poizner, "Effects of object shape and visual feedback on hand configuration during grasping," *Exp Brain Res*, vol. 151(2), pp. 158-166, 2003
- [2] U. Castiello,"The neuroscience of grasping," *Nature reviews*. *Neuroscience* vol. 6(9), pp.726-736, 2005
- [3] M. Santello and J.F. Soechting,"Gradual molding of the hand to object contours." J Neurophysiol, vol. 79(3), pp. 1307-1320, 1998
- [4] L.F. Schettino, V. Rajaraman, D. Jack, S.V. Adamovich, J. Sage, and H. Poizner, "Deficits in the evolution of hand preshaping in Parkinson's disease," *Neuropsychologia*, vol. 42(1), pp.82-94, 2000.
- [5] P. Raghavan, M. Santello, A.M. Gordon, and J.W. Krakauer,"Compensatory Motor Control After Stroke: An alternative Joint Strategy for Object-Dependent Shaping of Hand Posture," J Neurophysiol, vol.103, pp.3034-3043, 2010
- [6] P.M.VanVliet and M.R. Sheridan, "Coordination Between Reaching and Grasping in Patients With Hemiparesis and Healthy Subjects," *Arch Phys Med Rehabil*, vol.88, pp.1325-31,2007
- [7] R. Boian *et al.* (2002) "Virtual reality-based post-stroke hand rehabilitation." *Studies in health technology and informatics* vol. 5,pp. 64-70, 2002
- [8] A.S. Merians, H. Poizner, R. Boian, G. Burdea, and S.V. Adamovich, "Sensorimotor training in a virtual reality environment: does it improve functional recovery poststroke?" *Neurorehabil Neural Repair*, vol. 20(2), pp. 252-267, 2006
- [9] A.S. Merians et al., "Robotically facilitated virtual rehabilitation of arm transport integrated with finger movement in persons with hemiparesis." J Neuroeng Rehabil, vol.8(27), 2011.
- [10] S.L.Wolf *et al.*, "Assessing Wolf motor function test as outcome measure for research in patients after stroke," Stroke, vol. 32, pp. 1635-1639, 2001
- [11] R.H. Jebsen, N. Taylor, R.B. Trieschmann, M.J. Trotter, and L.A. Howard, "An objective and standardized test of hand function," *Arch Phys Med Rehabil*, vol. 50(6), pp. 311-9, 1969
- [12] G.A. Marcoulides and S.L. Hershberger, *Multivariate Statistical Methods: A First Course*. Mahwah, New Jersey: Lawrence Erlbaum Associates, Inc., 1997. ch. 5.
- [13] A. Shumway-Cook and M.H. Woollacott, *Motor Control: Translating Research into Clinical Practice, Third Edition*. Philadelphia, Pennsylvania: Lippincott Williams & Wilkins, 2007. ch. 18.