From "MEC '08 Measuring Success in Upper Limb Prosthetics," Proceedings of the 2008 MyoElectric Controls/Powered Prosthetics Symposium, held in Fredericton, New Brunswick, Canada, August 13–15, 2008.

SOFTWARE UNDERACTUACTION FOR REDUCED INPUT CONTROL OF LARGE DEGREE OF FREEDOM STRUCTURES: DEVELOPMENT OF A HAND CONTROL STRATEGY FOR ADVANCED UPPER EXTREMITY PROSTHETICS

J. Kuniholm and R.L. Clark

Center for Biologically Inspired Materials and Materials Systems, Duke University

ABSTRACT

Pattern recognition strategies have been explored for prosthetic hand control for over 20 years, but have not been commercially implemented. [1] Articulated research hands now rival human hand articulation, presenting new control challenges. Because no methods of processing signals of any source (cortical, peripheral nerve or myoelectric) are currently capable of delivering joint angle intent, the information content of user intent must be expanded. Control information for the 15 to 20 joints of a highly articulated hand must be derived from a single variable of grasp information. Two strategies are proposed for augmenting intent to control these hands. First, an array of grasp endpoints composed of the joint angles desired is created for each grasp, and the linear path to the desired endpoint constantly updated. Finger collisions are supervised by the user. Second, a larger set of grasp control parameters are explored. Using additional parameters allows more precise control of the arrangement of the fingers than whole hand grasps, a greater degree of intuitive control over the arrangement of the fingers, and the possibility of dextrous manipulation.

BACKGROUND

Grasping, Manipulation and Control

Most studies of hand use have focused on grasping: static prehensile or enclosing postures. Equally important are non-prehensile postures, as well as the movements used to generate a hand posture. Beyond strategies based on the taxonomies of grasping, truly advanced prosthetic control will depend on intuitive inputs to usefully manipulate objects. A well-designed control strategy will allow the creation of hand postures appropriate to every task, and to the manipulation of objects once in contact with the hand.

The variety of grasp taxonomies developed speaks to the complexity of simple grasping tasks, not to mention manipulation. Classifications based on purpose, which digits are used and the roles they play have been developed by Napier, Cutkosky and Kamakura. [2–5] Kamakura, Kang and Iberall further classify grasps using the non-finger contact areas of the hand. [6, 7] Such classification is interesting for prosthetic control to the extent that it could inform control inputs. In terms of effective control, it may be that the identification of the lateral pinch by name will prove less useful than the control goals for sensory inputs such as the force vectors resulting from contact, and the ability to pre-shape the hand for contact.

Postural Synergies

Neurologically inspired investigations into how hand postures are administrated during grasping have identified little difference among the discrete postures named by researchers in other disciplines. Santello *et al* found that the joint angles of the hand did not vary independently during the performance of distinct static grasps, and that two principal components can account for more than 80 per cent of the variance in joint angles. They propose that finer thumb and finger positioning represent the less significant components that serve to further refine postures. Mason *et al* extended this work to dynamic reach to grasp, finding a higher contribution of two principal components to hand pre-shaping in reach to grasp, albeit for a limited scope of objects all representing power grasps. [8,9] Thakur *et al* performed a similar experiment, extending the interaction to manipulative exploration, finding seven principal components responsible for 90 per cent of joint angle variance. [10] These synergies were not found evident in EMG signals by Weiss and Flanders. [11] This does not mean, however, that EMG could not be used to control the principal components as method of supervisory control for prosthetic positioning.

Experimental Setup

This research is being developed in the Johns Hopkins Applied Physics Lab (JHU-APL) Virtual Integration Environment (VIE), part of the DARPA Revolutionizing Prosthetics 2009 program (RP2009). The VIE allows components of the limb control system to be quickly prototyped and tested on the modular Matlab-based platform. Input is provided through a variety of means to either the prosthetic limb or to a sensor array connected to the VIE. Thus far, skin surface electromyographical signals (EMG) have been used for all patient use. Data is collected with Duotrodes, or from a socket constructed for the P2 Intrinsic Hand, using traditional myoelectric construction with 16 pairs of LTI small dome electrodes.

Within the VIE, user interface and control algorithms can be tested. A representation of either of the arms designed by the program can be controlled in real time. Object interaction in the VIE is a planned feature, but is not yet sufficient for verification of control strategies. While prototypes of both hands have been built and demonstrated, they have not been developed into platforms that can be used to test grasping or manipulatory control. In order to verify the effectiveness of the grasp strategies designed to date, testing on articulated hand hardware needs to be done. Testing is planned using the NASA Robonaut platform at NASA Johnson Space Center in Houston, with the JHU-APL VIE system controlling the Robonaut through ethernet commands. While having three fewer degrees of freedom, the Robonaut has been under development for some time and represents a reliable test bed.

PROSTHETIC CONTROL STRATEGIES

Pattern Recognition

While intuitive user control of each joint in a hand movement is ideal, it is unlikely that it can be accomplished successfully in the near future, regardless of the signal source. Pattern recognition has been used with success in upper arm movement coordination (with the DARPA RP2009 P1 limb, for example), but extension into the hand has been more difficult. While pattern recognition for the upper arm joints provides intent data at the joint level, hand intent is currently available only as a single grasp type, classifying grasps according to the taxonomies described. These approaches have focused on classification accuracy as a measure of success rather than useability in a physical environment, and have only rarely been used to control actual hand prostheses in a clinical environment.

Multifunction Hands

Clinical use of pattern recognition within the hand has been limited to one or two grasp types, at least in part because of the mechanical capabilities of available hands. The ES and

SVEN, Swedish 'multifunction hands', in fact had two wrist degrees of freedom and only one hand degree of freedom. [12] The MARCUS multifunction hand had a precision and power grasp mechanically selected using sensors detecting object contact with the palm, but was controlled using conventional myoelectric control. [13] Farry *et al* used a pattern recognition classifier to differentiate between two grasps, controling the highly capable NASA Robonaut hand, with 12 intrinsic degrees of freedom. Once one of the grasps was identified, the robot controller would send the hand to the pre-defined position, along a trajectory called a "macro". Any change in classification engages the "open" macro. Although with more grasps and three more degrees of freedom, this is how the RP2009 P2 Intrinsic Hand was demonstrated. While the hand itself is an impressive feat of mechatronic packaging, this control strategy is almost animatronic, and is better looking than it is useful for grasping and manipulating objects. As real time virtual environments have developed, the grasp classifications have been paired with magnitude information, and been used to control animations of fixed trajectories between open and closed endpoints of a particular grasp, also referred to as macros, but different from those previously described. The user can modulate velocity with the strength of the contraction, and can stop and reverse direction. The RP2009 P1 hand, Otto Bock's Michelangelo, has a more limited grasp set, but was controlled using this approach. Changing to a new grasp involves going to a universal open position, or making an arbitrary movement to a nearby point on the new trajectory when grasps are changed. These strategies are shown in Figure 1.

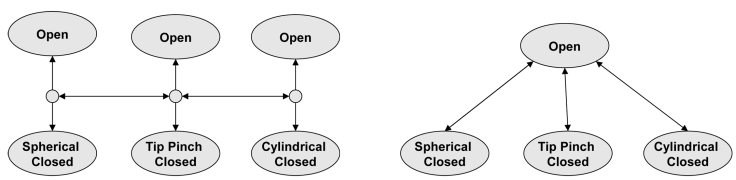

Figure 1: Traditional Macro-based Grasp Trajectories

Beyond Grasp Macros: Real-Time Shifting Endpoint Trajectories

For the greatest short term increase in prosthetic control capability, the already demonstrated capabilities of pattern recognition should be extended to the greatest effect. Because pattern recognition really represents a static endpoint goal (a closed grasp), we propose using those endpoints as control inputs for real-time arrangement of the hand. Based on a modulated macro strategy, a shifting endpoint strategy adds the capability to define new macros on the fly. The algorithm linearly interpolates the trajectory between the current hand position and the desired endpoint, whatever the state of the hand. Figure 2 illustrates an example. Beginning in an open position, the user selects a spherical grasp, and the hand begins to move toward the spherical grasp close endpoint. The figure shows that at any point along the way, the user can select another grasp, a tip pinch, for example, and the controller will interpolate a linear trajectory from the current position to the new desired endpoint. The software allows the definition of a distinct open position for each grasp, sending the hand to the particular open position appropriate for the last close command when a generic grasp open is selected. The obvious drawback of this strategy is that it is possible for the fingers to collide. Without proprioceptive feedback, the user must look at the hand to prevent collisions. This is exactly the method that users of traditional myoelectric prostheses use to modulate grip strength and monitor object contact, which, although imperfect, works in practice reasonably well. Although as yet untried in hardware, this approach is promising in simulation.

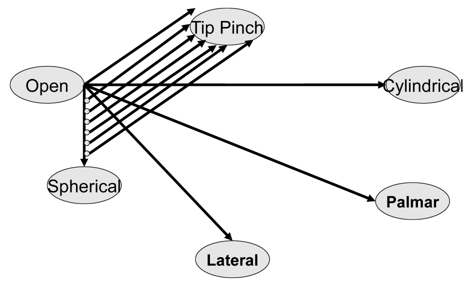

Figure 2: Real-Time Shifting Endpoint Trajectories (only some possibilities shown)

Simultaneous Endpoints: Postural Synergies as a Path to Manipulation

To extend the shifting endpoint strategy to mimic the postural synergies described by Santello and Thakur, we propose a simultaneous endpoint strategy. Simultaneous pattern recognition classifiers allow more than one degree of freedom to operate at a time, a big improvement over sequential movement where only a single degree of freedom can be operated at a time. If simultaneous classifiers are given shared control over joints, perhaps the user can usefully arrange the hand by requesting endpoints expressing multiple intent. For example, Figure 3 shows a user simultaneously requesting hand abduction and finger flexion, the combination of which could compose a spherical grasp. In this manner, the user can, rather than selecting an arbitrarily designed spherical grasp, add the appropriate amount of finger abduction, and stop, while continuing to close the hand around the desired object. As with the previous strategy, testing in actual hardware is the only way that we will know if current signal processing techniques can be married with newly capable articulated hands for truly multifunction capability.

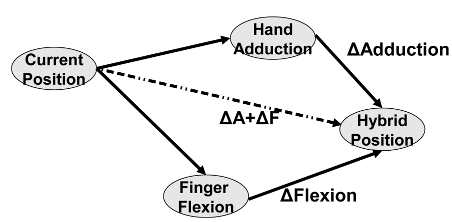

Figure 3: Simultaneous Endpoint Strategy

ACKNOWLEDGEMENTS

This research has been supported through the DARPA Revolutionizing Prosthetics Program, DARPA contract N66001-06-C8005, as well as by NSF grant DGE-0221632.

REFERENCES

1. R. W. Wirta, D. R. Taylor, and F. R. Finley. Pattern-recognition arm prosthesis: a historical perspective a nal report. Bull Prosthet Res, 8:35, 1978.
2. J. R. Napier. The prehensile movements of the human hand. Journal of Bone and Joint Surgery, 38(4):902-913, 1956.
3. M. Cutkosky and P.Wright. Modeling manufacturing grips and correlations with the design of robotic hands. Robotics and Automation. Proceedings. 1986 IEEE International Conference on, 3, 1986.
4. M. R. Cutkosky. On grasp choice, grasp models, and the design of hands formanufacturing tasks. Robotics and Automation, IEEE Transactions on, 5(3):269-279, 1989.
5. N. Kamakura, M. Matsuo, H. Ishii, F. Mitsuboshi, and Y. Miura. Patterns of static prehension in normal hands. Am J Occup Ther, 34(7):437-45, 1980.
6. S. B. Kang and K. Ikeuchi. Toward automatic robot instruction from perceptionmapping human grasps to manipulator grasps. Robotics and Automation, IEEE Transactions on, 13(1):81-95, 1997.
7. T. Iberall, G. S. Sukhatme, D. Beattie, and G. A. Bekey. On the development of emg control for a prosthesis using a robotic hand. Robotics and Automation, 1994. Proceedings., 1994 IEEE International Conference on, pages 1753-1758, 1994.
8. M. Santello, M. Flanders, and J. F. Soechting. Postural hand synergies for tool use. Journal of Neuroscience, 18(23):10105-10115, 1998.
9. C. R. Mason, J. E. Gomez, and T. J. Ebner. Hand synergies during reach-to-grasp. Journal of Neurophysiology, 86(6):2896-2910, 2001.
10. P. H. Thakur, A. J. Bastian, and S. S. Hsiao. Multidigit movement synergies of the human hand in an unconstrained haptic exploration task. Journal of Neuroscience, 28(6):1271, 2008.
11. E. J. Weiss and M. Flanders. Muscular and postural synergies of the human hand. Journal of Neurophysiology.
12. C. Almstrom, P. Herberts, and L. Korner. Experience with Swedish multifunctional prosthetic hands controlled by pattern recognition of multiple myoelectric signals. International Orthopaedics, 5(1):15-21, 1981.
13. P. J. Kyberd, O. E. Holland, P. H. Chappell, S. Smith, R. Tregidgo, P. J. Bagwell, and M. Snaith. Marcus: a two degree of freedom hand prosthesis with hierarchicalgrip control. Rehabilitation Engineering, IEEE Transactions on see also IEEE Trans. on Neural Systems and Rehabilitation., 3(1):70-76, 1995.