31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

A Fuzzy Logic Model for Hand Posture Control Using Human Cortical Activity Recorded by Micro-ECoG Electrodes

R Vinjamuri, D J Weber, A D Degenhart, J L Collinger, G P Sudre, P D Adelson, D L Holder, M L Boninger, A B Schwartz, D J Crammond, E C Tyler-Kabara and W Wang

Abstract— **This paper presents a fuzzy logic model to decode the hand posture from electro-cortico graphic (ECoG) activity of the motor cortical areas. One subject was implanted with a micro-ECoG electrode array on the surface of the motor cortex. Neural signals were recorded from 14 electrodes on this array while Subject participated in three reach and grasp sessions. In each session, Subject reached and grasped a wooden toy hammer for five times. Optimal channels/electrodes which were active during the task were selected. Power spectral densities of optimal channels averaged over a time period of 1/2 second before the onset of the movement and 1 second after the onset of the movement were fed into a fuzzy logic model. This model decoded whether the posture of the hand is open or closed with 80% accuracy. Hand postures along the task time were decoded by using the output from the fuzzy logic model by two methods (i) velocity based decoding (ii) acceleration based decoding. The latter performed better when hand postures predicted by the model were compared to postures recorded by a data glove during the experiment. This fuzzy logic model was imported to MATLAB®SIMULINK to control a virtual hand.**

Manuscript received on April 7, 2009. This work was supported by the National Science Foundation under Cooperative Agreement EEC-0540865, Grant Number 5 UL1 RR024153 from the National Center for Research Resources (NCRR), a component of the National Institutes of Health (NIH) and NIH Roadmap for Medical Research, and a special grant from the Office of the Senior Vice Chancellor for the Health Sciences at University of Pittsburgh. This paper's contents are solely the responsibility of the authors and do not necessarily represent the official view of NCRR or NIH. Information on NCRR is available at http://www.ncrr.nih.gov/. Information on Re-engineering the Clinical Research Enterprise can be obtained from http://nihroadmap.nih.gov/clinicalresearch/overview-translational.asp. Additional funding support was provided by NIH grants from the NIBIB (1R01EB007749) and NINDS (1R21NS056136) and grant W81XWH-07-1-0716 from the US Army Medical Research and Material Command.

Ramana Vinjamuri is Post-doctoral Research Associate in Department of Physical Medicine & Rehabilitation, University of Pittsburgh.

Douglas J Weber is Assistant Professor in Departments of Physical Medicine & Rehabilitation and Bioengineering, University of Pittsburgh

Alan D Degenhart is a graduate student in Department of Bioengineering, University of Pittsburgh.

Jennifer L Collinger is Research Bioengineer in Department of Physical Medicine & Rehabilitation, University of Pittsburgh.

Gustavo P Sudre is a graduate student in Program in Neural Computation, Carnegie Mellon University.

P. David Adelson is Director of the Children's Neuroscience Institute and Chief of Pediatric Neurosurgery in Phoenix Children's Hospital.

Deborah L. Holder is Director of Epilepsy Monitoring Unit, Children's Hospital of Pittsburgh and Assistant Professor in Department of Pediatrics, University of Pittsburgh.

Michael L Boninger is Professor in Departments of Physical Medicine & Rehabilitation and Bioengineering, University of Pittsburgh.

Andrew B Schwartz is Professor in Departments of Neurobiology and Bioengineering, University of Pittsburgh.

Donald J Crammond is Assistant Professor in Department of Neurosurgery, University of Pittsburgh.

E C Tyler-Kabara is Assistant Professor in Departments of Neurosurgery and Bioengineering, University of Pittsburgh.

Wei Wang is Assistant Professor in Departments of Physical Medicine & Rehabilitation and Bioengineering, University of Pittsburgh.
(wangw4@upmc.edu, 412-648-6666).

I. Introduction

BRAIN-COMPUTER interface (BCI) or direct brain interface (DBI) in the near future is expected to be a promising technology in providing help to control assistive devices in people suffering with spinal cord injury (SCI), cerebral palsy, myodystrophy and other debilitating injuries. Recent advances in BCI relevant to this paper include controlling cursor movement on computer screen in one or more dimensions [1], moving a robotic arm [2], etc. Robotic or prosthetic hand control via neural signals is of vital importance in providing assistance for limb amputees who have lost most of the major muscles. Even for amputees with some muscles left intact, muscular control of actuator of a prosthetic hand faces challenges when extracting the control signal from noisy muscle activity. In this paper a fuzzy logic model is presented which decodes the human hand posture using neural/cortical activity.

Electro-corticography (ECoG) has been shown to be a promising modality in extracting neural signals with sufficient neural information useful in decoding movement related kinematics [1]. In ECoG, electrodes are placed on the surface of required areas of the brain for e.g. motor cortex, auditory cortex, etc. This study used a micro-ECoG electrode array as shown in Fig.1.

Power spectral densities of the selected channels/ electrodes in the high frequency range (60-120Hz) were fed into a fuzzy logic model to get an output which decodes the hand posture by scaling the opening of the hand (0—Open, 1—Closed). Fuzzy logic models are known to accommodate the fuzziness in the real world applications [3]. Fuzzy logic models can be generated by using two approaches—(i) Sugeno and (ii) Mamdani. In the current paper Sugeno approach was chosen as it is computationally efficient for optimization and adaptive techniques which makes it favorable for real time applications [3]. Fuzzy logic models can be easily implemented in hardware using micro controllers like Motorola HC12 [4].

II. Materials and Methods

A. Human subjects and the behavioral paradigm

This study was approved by the University of Pittsburgh Institutional Review Board and followed all guidelines for human subject research. The subject was a 17-year old righthanded female undergoing monitoring for intractable epilepsy with seizure foci in the left temporal lobe. At the beginning of each session, about one minute of baseline data were acquired when the subject relaxed with eyes open. During the task, upon a go cue, Subject was instructed to perform reach and grasp task for the wooden toy hammer placed about a distance of 15 cm from the resting position of the hand, and the BCI2000 [5] software was used to prompt the Subject to move. Finger movements of hand were recorded with a 14-sensor 5DT data glove. 10 of the sensors corresponding to proximal interphalangeal and metacarpal phalanageal joints were used in the analysis. Three sessions of five repetitions each, were conducted.

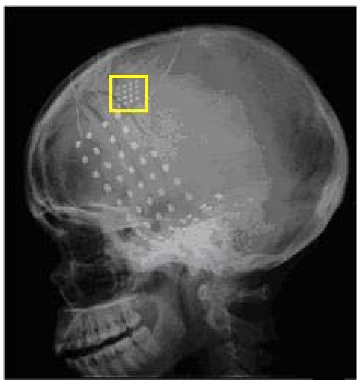

Fig. 1. Head x-ray of the Subject highlighting the 16-conatct micro-ECoG grid highlighted in the yellow Square.

B. ECoG recording

A regular clinical ECoG grid (Ad-Tech, Corp.) with 32 disc electrodes was implanted subdurally over the left temporal lobe and inferior frontal lobe for epilepsy seizure monitoring. In addition, an experimental micro-ECoG grid was implanted subdurally superior-posterior to the large ECoG grid and anterior to the central sulcus over the motor cortical area. The micro-ECoG grid (Ad-Tech, Corp.) consisted of 16 disc electrodes arranged in a 4-by-4 pattern (Fig. 1). Two corner electrodes were designated as reference electrodes. All ECoG signals were band-pass filtered between 0.1 to 200 Hz and sampled at 1200 Hz using g.USBamp (Guger Technologies, OEG) in conjunction with the BCI2000 software. Neural signals recorded from 14 electrodes in the micro-ECoG grid were used in the current paper.

C. Analysis

Neural signals recorded from the micro-electrode's 14 channels were band pass filtered 0.1—200Hz. Time-frequency analysis was performed on each of the channels for each task of reaching and grasping. A typical time-frequency plot of the neural activity is shown in Fig. 3 under Results. For all the channels strong activation in power was seen in high frequency range (60-120Hz) 0.5 seconds after the GO cue.

D. Fuzzy Logic Model

Power spectral densities (PSDs) of the best channels averaged over a time period of 0.5 seconds before the movement onset and 1 second after the movement onset were used to train the fuzzy logic model. For each channel, PSD before movement onset corresponded to open hand posture (an output value of 0) and PSD after movement onset corresponded to flexed or closed hand posture when grasping the toy hammer (an output value of 1). Among the three sessions of data collected, two were used for training and one was used for testing the model. Four membership functions of type *gbellmf* (generalized bell-shaped membership function) were used in generating this model. Sugeno method was used in generating this model using *anfisedit* in MATLAB®.

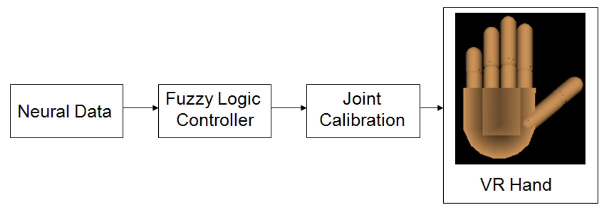

Fig. 2. SIMULINK model: Neural data is fed into fuzzy logic controller. The output of the controller is fed into joint calibration module and calibrated joints move the virtual hand.

E. Simulation in MATLAB®SIMULINK

Fuzzy logic model thus generated was imported as a block into MATLAB®SIMULINK as shown in Fig.2. Here the neural data fed is PSD of high frequency band (60-120Hz) during the task time (0.5 sec before movement onset to 1 sec after movement onset). When the simulation is executed, fuzzy logic model/controller closes or flexes the hand as task time progresses. The output from the fuzzy logic controller is used to predict of flexion of joints which are used to move the hand in virtual reality (VR) environment in real time. The neural signals can possibly encode position, velocity and acceleration in hand kinematics. Joint prediction was either velocity based decoding or acceleration based decoding. For velocity based decoding the output from the model is integrated once to obtain joint positions. Similarly, for acceleration based decoding the output from the model is integrated twice to obtain the joint positions. Predicted joint positions are stored and compared against the recorded joint positions from 5DT data glove.

III. RESULTS

Time-frequency analysis performed over one of the channels is illustrated in Fig.3. The black line (Time 0) represents the moment at which the "GO" cue was given. As it is evident, after about 0.5s from "GO" cue the high frequency band shows significant increase in power, demonstrating task-related modulation.

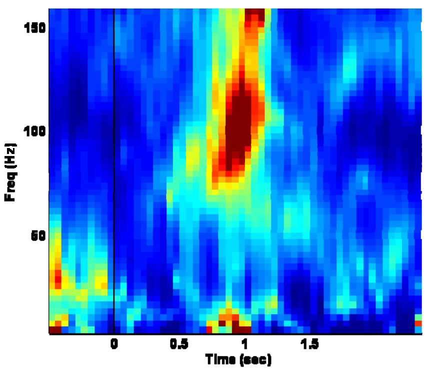

Fig. 3. Time frequency analysis showing strong activation in high frequency range (60-120Hz) between 0.5s—1.5s. 0s corresponds to "GO" cue.

Fig. 4 shows the results obtained from the fuzzy logic model also known as fuzzy inference system (FIS). Fig.4 Top depicts the input-output relationship between the power spectral density of a channel and the hand posture (0—open, 1—closed). Bottom two plots in Fig.4 show the training and the testing errors respectively. A training error of 0.205 and a testing error of 0.213 were obtained from the model. This means in predicting the open or close (0 or 1) of the posture there can be an average error of 0.2. In other words, model prediction is 80% accurate.

Fuzzy logic model was used to predict the hand postures across the time of the task using SIMULINK. Only one task modulated channel was used here. As discussed in Methods, fuzzy logic model output was used to decode (i) velocity (ii) acceleration of the joints. For velocity based decoding the output from the model is integrated once to obtain joint position. Similarly for acceleration based decoding the output from the model is integrated twice to obtain the joint position. Figures 5 and 6 illustrate the comparison between model-predicted hand postures, and the hand postures recorded by the data glove during the experiment. Please note that although the hand considered here includes 10 individual joints the model output which ranges from 0 to 1 is used as universal scale to all the joints. In Fig.5 red curve corresponds to the position predicted by the model when velocity encoding was used. Error bars indicate variability across five trials. The blue curve corresponds to the mean of positions across all joints across five trials recorded by the data glove. In Fig.6 black curve corresponds to the position predicted by the model when acceleration encoding was used. Error bars indicate variability across five trials. The blue curve corresponds to the mean of positions across all joints across five trials recorded by the data glove.

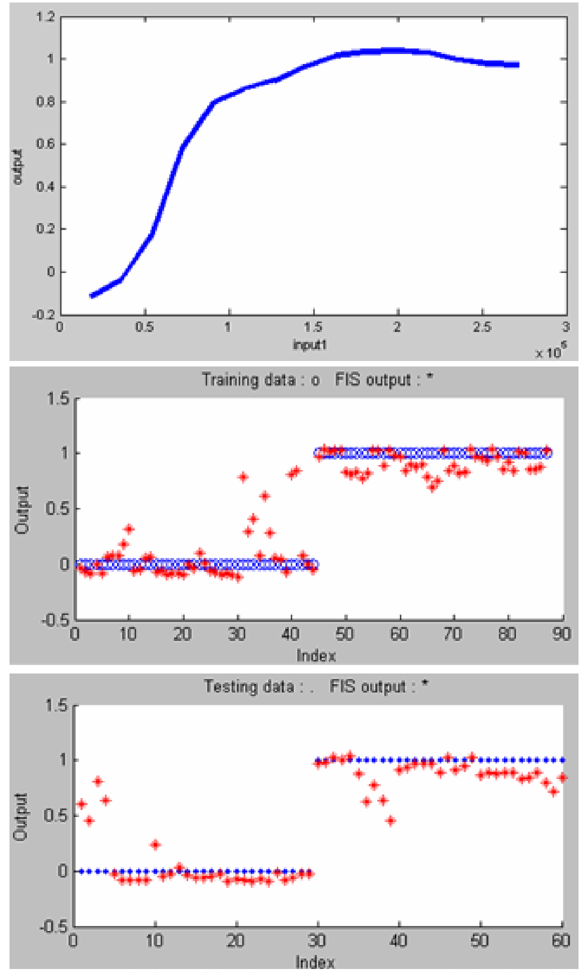

Fig. 4. Top: Flexion of hand vs. the power spectral density of the channel averaged over the high frequency range (60-120Hz). Middle: Training data (o) and Fuzzy logic model output (+). Bottom: Testing data (·) and Fuzzy logic model output (+)

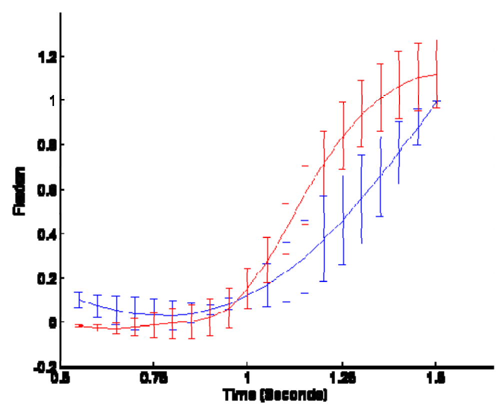

Fig. 5. A Comparison between model-predicted postures when velocity encoding was used and actual postures recorded by the data glove. Red curve corresponds to the position predicted by the model when velocity encoding was used. Error bars indicate variability across five trials. The blue curve corresponds to the mean of positions across all joints across five trials recorded by the data glove.

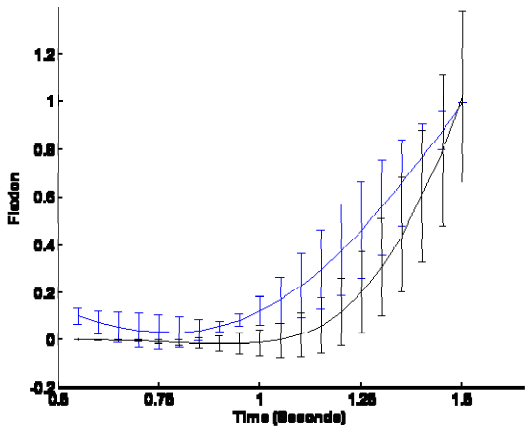

Fig. 6. A Comparison between model-predicted postures when velocity encoding was used and actual postures recorded by the data glove. Black curve corresponds to the position predicted by the model when acceleration encoding was used. Error bars indicate variability across five trials. The blue curve corresponds to the mean of positions across all joints across five trials recorded by the data glove.

IV. Discussion

This paper adapted a fuzzy logic approach to demonstrate the control of virtual hand directly using the human motor cortical activity. Although the model has single output which decodes whether the hand posture is closed or open, it is capable of estimating the variation of intermediate postures along the task time. Fuzzy logic models exploiting multiple membership functions are proved to be skilled in representing the fuzziness in the real world applications [3]. Thus the model results in a smooth movement across joints of the hand, unlike a binary switch which results in abrupt movements. Decoding the hand posture by itself is a complex optimization problem including more than 27 dimensions or Degrees of Freedom (DoF) due to the versatile architecture of the hands. In this paper, the problem was simplified by limiting the decoding of hand posture as one single unit or dimension. The biomechanical constraints of the human hand [6] pose restrictions to the independence of individual digits/fingers. In particular, in movements such as reaching and grasping, similarity between angular velocity profiles across the joints have been observed previously in [7]. Although the current model is not capable of decoding a virtual hand performing complex movements involving coordinated movements among multiple fingers, such as playing a piano, it serves as a sufficient decoder for smooth transformation of the hand posture across task time.

Several parameters of hand kinematics are represented in the motor cortex, cerebellum, basal ganglia, etc. These parameters are velocity, acceleration and position [8]. For decoding the hand postures across time two methods were used—velocity based decoding and acceleration based decoding. Position based decoding was not considered here as it led to abrupt movements of virtual hand. As shown in the results velocity and acceleration decoding led to better prediction of the posture across the task time.

Conclusion

This paper demonstrated the feasibility of controlling opening and closing of a virtual hand directly using human cortical activity recorded with micro-ECoG electrodes. One limitation to neural network or fuzzy logic type of models is the training time of the model. But once the fuzzy logic model, such as one presented here, is trained it can be used in real time control of a virtual hand. The model is to be extended to control kinematics of a real prosthetic hand. The model and methods presented in this paper are to be substantiated over more number of subjects. We view these as future scope.

Acknowledgment

We would like to thank the participant, all the clinical staff at the epilepsy monitoring unit at the Children's Hospital of Pittsburgh, who kindly made it possible for us to perform this study. We also like to acknowledge Patricia Lordeon and Clinton Young for technical support for this study. We thank Dr. Gerwin Schalk for helpful discussions regarding ECoG recording and BCI2000 software.

References

[1] E. C. Leuthardt, G. Shalk, J. R. Wolpaw, J. G. Ojemann, D. W. Moran, "A brain-computer interface using electrocorticographic signals in humans," *Journal of Neural Engineering*, vol. 1, pp. 63–67, 2004.

[2] A. B. Schwartz, X. T. Cui, D. J. Weber, D. W. Moran, "Brain-controlled interfaces: movement restoration with neural prosthetics," *Neuron*, vol. 52, pp. 205–220, 2006.

[3] B. Kosko, *Fuzzy Engineering* , New York: Prentic Hall, 1996.

[4] P. Singh, R. Vinjamuri, X. Wang and D. Reisner, "Design and implementation of a fuzzy logic based state-of-charge meter for Li-ion batteries used in portable defibrillators," *Journal of Power Sources*, vol. 162, pp. 829–836, 2006.

[5] G. Schalk, D.J. McFarland, T. Hinterberger, N. Birbaumer, and J.R. Wolpaw, "BCI2000: a general-purpose brain-computer interface (BCI) system," *IEEE Trans Biomed Eng,* vol. 51, pp. 1034-1043, 2004.

[6] T. E. Jerde, J. F. Soechting, and M. Flanders, "Biological constraints simplify the recognition of hand shapes," *IEEE Trans Biomed Eng,* vol. 50, pp. 4846-4849, 2003.

[7] R. Vinjamuri, ZH Mao, R. J. Sclabassi, and M. Sun., "Time-varying synergies in velocity profiles of finger joints of the hand during reach and grasp," *Conf Proc IEEE Eng Med Biol Soc*, France, pp. 4846—4849, 2007.

[8] V. Brooks, *The neural basis of motor control*, New York: Oxford, 1986.