34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Directed Causality of the Human Electrocorticogram During Dexterous Movement

Heather L. Benz, *Student Member, IEEE,* Maxwell Collard, Charalampos Tsimpouris, Soumyadipta Acharya, Nathan E. Crone, Nitish V. Thakor, *Fellow, IEEE,* and Anastasios Bezerianos, *Senior Member, IEEE*

***Abstract*— While significant strides have been made in designing brain-machine interfaces for use in humans, efforts to decode truly dexterous movements in real time have been hindered by difficulty extracting detailed movement-related information from the most practical human neural interface, the electrocorticogram (ECoG). We explore a potentially rich, largely untapped source of movement-related information in the form of cortical connectivity computed with time-varying dynamic Bayesian networks (TV-DBN). We discover that measures of connectivity between ECoG electrodes derived from the local motor potential vary with dexterous movement in 65% of movement-related electrode pairs tested, and measures of connectivity derived from spectral features vary with dexterous movement in 76%. Due to the large number of features generated with connectivity methods, the TV-DBN a promising tool for dexterous decoding.**

I. Introduction

We aim to find movement-related information in the electrocorticogram (ECoG) to aid in studying and decoding highly dexterous movements. Human ECoG-based decoding has progressed since its first demonstration in 2004 [1], with some forays into dexterous decoding, including grasps [2]-[4]. Classification of contralateral and ispsilateral individual finger movement [5] and decoding the time course of individual finger tapping [6] have been demonstrated. However these offline dexterous decoding achievements have not been replicated in a real-time ECoG BMI, in which the challenges of asynchronous decoding will require much more information-rich signals than are currently available. We have demonstrated previously that directional connectivity, a description of directed connections between cortical areas, provides grasp-related information beyond what is present in standard decoding features [7], [8]. We now apply a dynamic directional connectivity technique, time-varying dynamic Bayesian networks (TV-DBN) [9], to ECoG data collected during individual finger flexion and extension. We hypothesize that cortical connectivity maps contain movement-related variation that may be relevant for dexterous decoding.

*The project was funded by the John S. Latsis Public Benefit Foundation, the Defense Advanced Research Projects Agency under Grant 19GM-1088724, and the National Institutes of Health under R01NS40596. The sole responsibility for the content lies with its authors.

H. L. Benz (phone: 443-424-2369; e-mail: benz@jhu.edu), M. Collard, S. Acharya, N.E. Crone, and N. V. Thakor are with the Johns Hopkins University, Baltimore, MD 21205 USA.

C. Tsimpouris and A. Bezerianos are with the University of Patras, Patras 26500 Greece.

II. Methods

A. Study Participants and Experimental Paradigm

Three subjects undergoing ECoG monitoring in the Johns Hopkins Hospital Epilepsy Monitoring Unit gave informed consent to participate in research under a protocol approved by the Johns Hopkins University Institutional Review Board. Subject details are given in Table I.

TABLE I. Study Participants

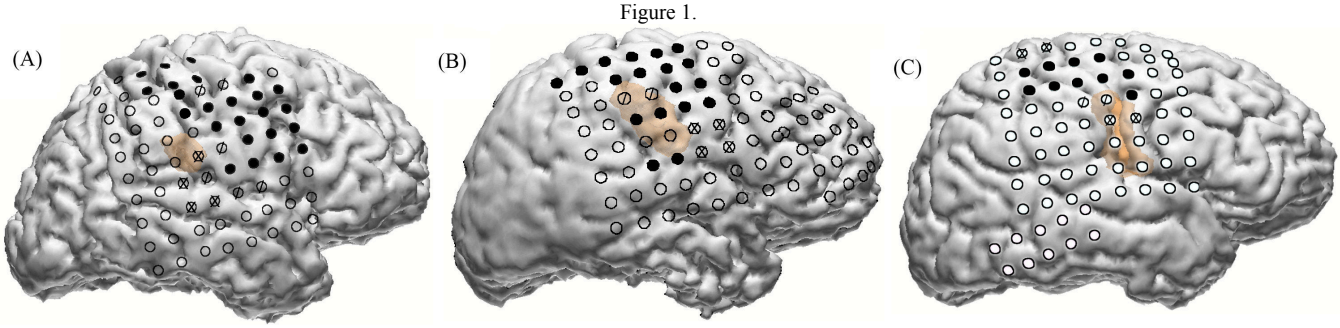
Subject	Gender, Age	ECoG Coverage, Pathology	CyberGlove Hand
A	Male, 55	Right frontal- parietal- temporal grid, right parietal operculum / cortical dysplasia	Left
B	Male, 12	Right frontal- parietal grid, right ventral peri-central encephalomalacia	Left
C	Female, 20	Right frontal- parietal- temporal grid, right frontal- parietal operculum / cortical dysplasia	Left

Subjects performed motor trials in a seated or semi-prone position in a bed or comfortable chair. The wrist was supported with a pillow or table in a comfortable position, and the hand was unsupported and free-moving. Trials lasted between two and five minutes, with a brief rest between trials. Each subject performed one or two trials of the repeated flexion and extension task used for this analysis. During the trials, subjects flexed and extended each finger several times before moving to the next, in a random order. They repeated these multiple flexion and extensions between 10 and 35 times per trial. Subjects were either self-paced, vocally cued, or visually cued. In some cases, subjects viewed a virtual representation of a prosthetic hand in the MSMS virtual environment [10] moving in synchrony with their own hand on a computer screen.

B. Data Collection and Pre-Processing

Subjects had been implanted for clinical purposes with ECoG electrode arrays (Ad-Tech Medical Instrument Corp., Racine, WI) with between 64 and 128 platinum electrodes, 4 mm in diameter and spaced 10 mm apart. Electrode locations are shown in Fig. 1. ECoG was recorded on Stellate (Stellate Systems, Inc., Montreal) and Neuroscan (Compumedics, Charlotte, NC) amplifiers at 1000 Hz.

Figure 1.



Reconstructions of cortex and electrode locations for all subjects. Electrodes for which electrical stimulation mapping (ESM) caused motor responses are filled black, electrodes for which ESM caused sensory responses are marked with an "X", and electrodes for which ESM cased both motor and sensory responses are marked with a "/". ESM is a commonly-used tool for identifying brain functional areas.

Subjects wore a glove (CyberGlove Systems, LLC, San Jose, CA) on the hand contralateral to the brain hemisphere to track 18-22 joint angles at 25 Hz, including all finger and thumb joint angles. ECoG and kinematic signals were synchronized by writing time stamps and events to both.

All ECoG channels were screened, and noisy channels were excluded from subsequent analysis. Remaining ECoG channels were common average referenced (CAR) to remove information such as artifacts and noise that were common to all channels. ECoG data were then band pass filtered from 0.1 to 250 Hz.

C. Feature Extraction

Both temporal and spectral features were used in the analysis. The temporal feature was the local motor potential (LMP), which has been used in a number of brain-computer interface kinematic decoders [11], computed with a window size of 500 ms. The LMP is the ECoG smoothed with a moving average window and was found using:

$$LMP(t)_n = \frac{1}{T}\int_{t-\tau}^{t} X(t)_n dt \,, \tag{1}$$

where T is the window size, t is the time, and $X(t)_n$ is the ECoG data from one channel, n.

Spectral features were average power in the delta (0-4 Hz), theta (4-8 Hz), mu (8-13 Hz), beta (14-30 Hz), low gamma (31-50 Hz), and high gamma (70-110 Hz) bands. Spectral power was calculated in 1 Hz bins with an autoregressive model using the Burg method of order 20 on windows of 1 s.

D. Electrode Selection

We used the electrode activation index (AI) to select a subset of electrodes for connectivity analysis. The AI is a measure of how much ECoG channel activity varies with movement. We found the cross-correlation coefficient [12] for all features between movement and rest states:

$$F = \left| \frac{(m-r)^3}{|m-r|\sigma^2_{m\cup r}} \frac{N_m N_r}{N^2_{m\cup r}} \right| \tag{2}$$

Here m is the mean feature value during movement, r is the mean feature value during rest, N is the number of samples in each state, and $\sigma^2_{m\cup r}$ is the variance across all states. Then the AI for an ECoG channel was the largest change across all features between movement and rest states. To also find features that varied prior to movement or after movement onset, AI was calculated for m windows shifted 25 samples (1 s) preceding and following movement onset. For subsequent analysis we used the ten ECoG channels with maximum AI.

E. Connectivity Calculation

Time-varying dynamic Bayesian networks (TV-DBNs) were used to map connectivity between ECoG channels, as in [7]. A TV-DBN's connectivity coefficient from channel i to j is high if activity in channel i at time t–1 can be used to model activity in channel j at time t. For each ECoG feature, amplitude in all N channels used for the analysis was represented at time t as a vector, $F^t = (f_1^t, f_2^t, \ldots, f_N^t)$, which could be modeled as a function of previous feature amplitude:

$$F^t = A^t F^{t-1} + \varepsilon \tag{3}$$

The matrix A^t contained the connectivity coefficients from each channel i to each channel j. To create a stable estimate of A^t, we used data from time 0 to t–1, weighted by a Gaussian RBF kernel so that data at t–1 was most heavily weighted and preceding data was weighted decreasingly in the model as it became more distant from t–1. Formally, we minimized the criterion:

$$\hat{A}_i^t = argmin_{A_i^t \in R^{1\times N}} \frac{1}{T}\sum_{\tau=1}^{t-1} w^t(\tau) f_i^\tau - A_i^t F^{\tau-1} + \lambda \|A_i^t\| \tag{4}$$

where N is the number of ECoG channels, the parameter λ is a regularization term to shrink A's spareness (λ=100 [9]), and the weight of an observation at time τ is given by the Gaussian RBF kernel $w^t(\tau)$:

$$w^t(\tau) = \frac{K_h(\tau - t)}{\sum_{\tau=1}^{t-1} K_h(\tau - t)}, \; where \; K_h(.) = e^{-t^2/h} \tag{5}$$

We used 5 for the kernel bandwidth, h [9].

We used TV-DBNs to explore cortical connectivity during dexterous movement in the three subjects tested. TV-

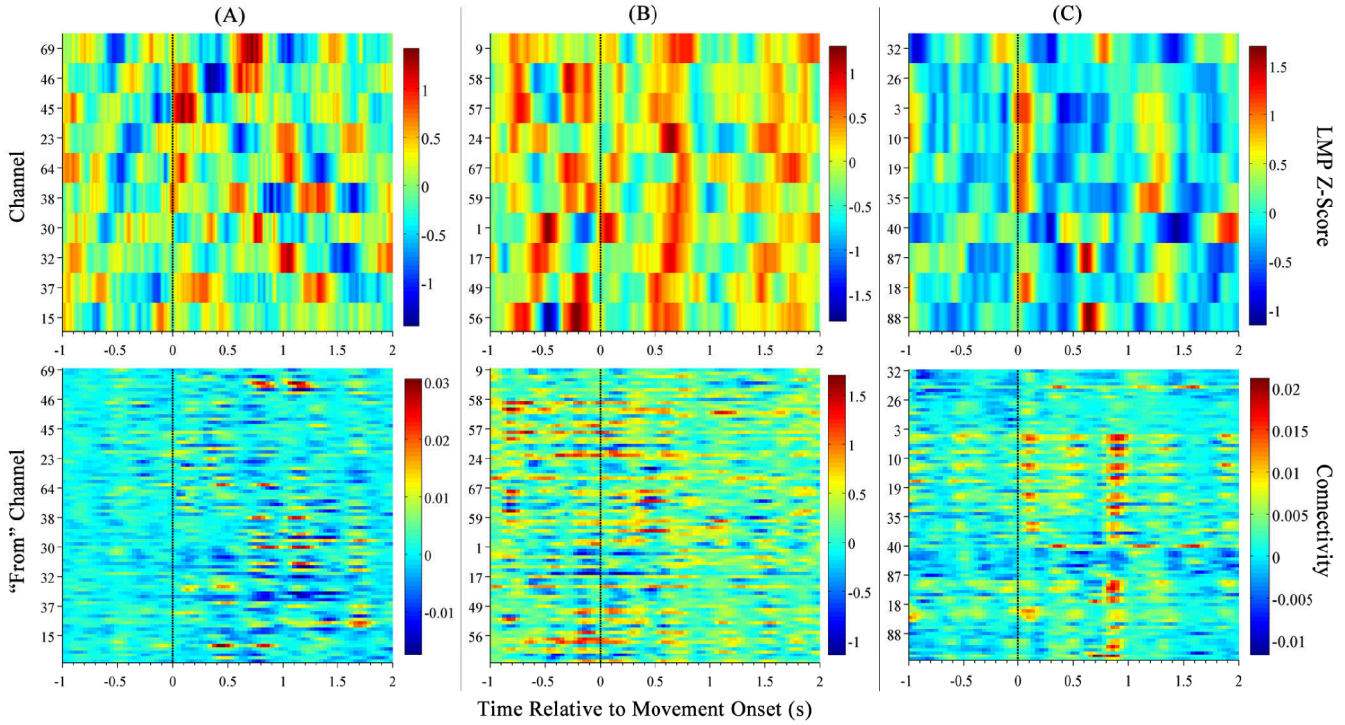


Figure 2. Trial-averaged LMP (upper row) and trial-averaged TV-DBN calculated from LMP (lower row) for one trial each for subjects A, B, and C. Plots are channels vs. time. Movement onset occurs at 0 s and is indicated with a dashed line. Movement-related LMP changes are difficult to distinguish, with the exception of subject C. Movement-related changes in TV-DBN coefficients, however, are evident in all subjects.

DBN maps were constructed with the LMP and all spectral features.

III. Results

A. Local Motor Potential and Connectivity

We have previously found a relationship between LMP-based connectivity and grasp during a slow hand open and close task [7], [8]. Fig. 2 demonstrates that LMP-based connectivity also changes with more rapid individual finger flexions and extensions. In two subjects the TV-DBN connectivity fluctuated in an oscillatory pattern. Across the three subjects, the LMP distribution changed statistically significantly between movement and baseline (Wilcoxon rank sum test with Bonferroni correction, $p < 0.05$) in 126 electrodes, or 54% of all electrodes, whereas the LMP-based TV-DBN connectivity changed statistically significantly from baseline in 176 channel-channel connectivity pairs, or 65% of the 270 channel pairs tested. This large number of movement-related features may help to inform a decoder for dexterous movement. This is a small fraction of the 53,130 total channel pairs that could have been explored with TV-DBN across all three subjects; we limited our selection to ensure we obtained results that are relevant to real-time decoding, which will require rapid computation that is only possible when analyzing a few channels with TV-DBN.

B. Spectral Features and Connectivity

One group has previously studied the response of TV-DBN connectivity coefficients constructed from activity in the alpha band of EEG activity during movement imagery [9]. TV-DBN connectivity has not been explored in other frequency bands. Fig. 3 shows the average spectrograms for subjects A and B, who had exemplary movement-related changes in spectral connectivity, as well as plots of average connectivity changes in the delta bands (A and B) and gamma band (A). Eighty-two percent of all spectral features on all channels included in the analysis changed from baseline to movement (Wilcoxon rank sum test with Bonferroni correction, $p < 0.05$). The number of channel-channel connectivity pairs whose connectivity changed statistically significantly relative to baseline ranged from 69-82% for individual features. Beta, low gamma, and high gamma-based connectivity features changed relative to baseline more often than lower frequency features. While the ratio of TV-DBN features changing was not higher than that of spectral features, with only ten electrodes we found between 357 and 494 modulating TV-DBN features per subject.

IV. Conclusions

We have described changes in cortical connectivity related to dexterous movement. In connectivity computed from the LMP, oscillatory movement-related activity was observed. Connectivity computed from spectral features varied, and included both peri-movement increases in delta and high gamma connectivity in one subject, and decreases in delta connectivity following movement in a separate subject.

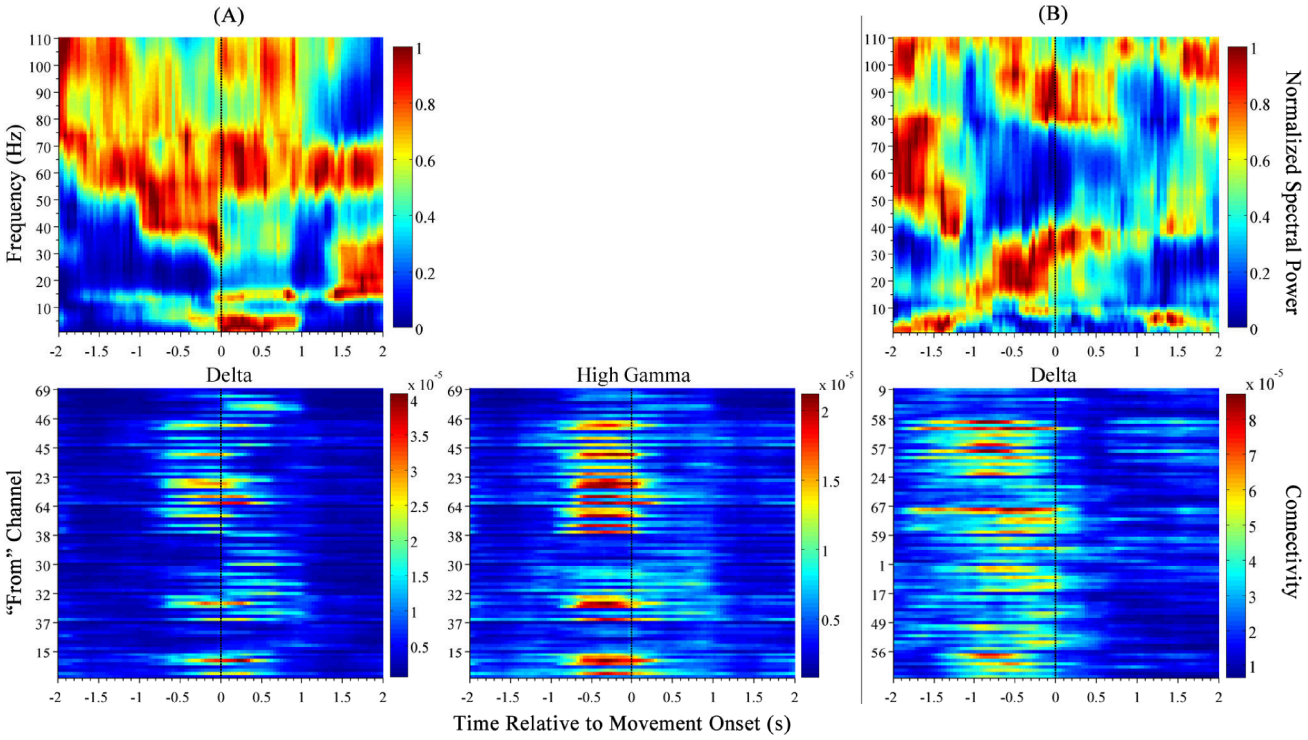


Figure 3. Selected average spectral (upper row) and spectral connectivity (lower row) features. Spectrograms are frequency vs. time for channel with the highest AI. Connectivity plots are channels vs. time. Movement onset occurs at 0 s and is indicated with a dashed line. (A) For Subject A, spectral-based connectivity in both the delta band (left) and high gamma band (right) changed visibly in many channel pairs before and during movement. (B) For Subject B, spectral-based connectivity in the delta band dropped following movement onset, a phenomenon observed in [7].

We explored only ten electrodes per subject in order to draw conclusions relevant for online motor decoding, which is feasible with TV-DBN calculations for ten electrode pairs but not for an entire ECoG grid. However with only these ten electrode pairs per subject we discovered hundreds of movement-related connectivity features. Future work will probe the correlation of information contained in these features, with an aim to identify large feature sets with highly independent information content. Such information-rich feature sets may permit dexterous decoding to advance beyond simple grasps to individual finger movements.

References

[1] E.C. Leuthardt, G. Schalk, J.R. Wolpaw, J.G. Ojemann, and D.W. Moran, "A brain computer interface using electrocorticographic signals in humans," *J. Neural Eng.*, vol. 1, 2004, pp. 63-71.

[2] S. Acharya, M.S. Fifer, H.L. Benz, N.E. Crone, and N.V. Thakor, "Electrocorticographic amplitude predicts finger positions during slow grasping motions of the hand," J. Neural Eng., vol. 7, May. 2010, p. 046002.

[3] M.S. Fifer, M. Mollazadeh, S. Acharya, N.V. Thakor, and N.E. Crone, "Asynchronous decoding of grasp aperture from human ECoG during a reach-to-grasp task," *Conf. Proc. IEEE Eng. Med. Biol. Soc.,* 2011, pp. 4584-7.

[4] T. Yanagisawa, M. Hirata, Y Saitoh, T. Goto, H. Kishima, R. Fukuma, H. Yokoi, Y. Kamitani, and T. Yoshimine, "Real-time control of a prosthetic hand using human electrocorticography signals," *J Neurosurg.,* vol. 114, Jun. 2011, pp. 1715-22.

[5] R. Scherer, S.P. Zanos, K.J. Miller, R.P.N. Rao, and J.G. Ojemann, "Classification of contralateral and ipsilateral finger movements for electrocorticographic brain-computer interfaces," *Neurosurg. Focus*, vol. 27, Jul. 2009, p. E12.

[6] J. Kubánek, K.J. Miller, J.G. Ojemann, J.R. Wolpaw, and G. Schalk, "Decoding flexion of individual fingers using electrocorticographic signals in humans," *J. Neural Eng.*, vol. 6, Dec. 2009, p. 066001.

[7] H.L. Benz H. Zhang, A. Bezerianos, S. Acharya, N.E. Crone, X. Zheng, and N.V. Thakor, "Connectivity analysis as a novel approach to motor decoding for prosthesis control," *IEEE TNSRE*., 2011, DOI: 10.1109/TNSRE.2011.2175309.

[8] H. Zhang, H.L. Benz, A. Bezerianos, S. Acharya, N.E. Crone, A. Maybhate, X. Zheng, and N.V. Thakor, "Connectivity mapping of the human ECoG during a motor task with a time-varying dynamic Bayesian network," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, 2010, pp. 130-3.

[9] L. Song, M. Kolar, and E. Xing, "Time-Varying Dynamic Bayesian Networks," *Adv. Neural Inf. Process. Syst*., vol. 22, 2009, pp. 1732-1740.

[10] M. Hauschild, R. Davoodi, G.E. Loeb, "A virtual reality environment for designing and fitting neural prosthetic limbs," *IEEE TNSRE,* vol. 15, 2007, pp. 9-15.

[11] G. Schalk, J. Kubánek, K.J. Miller, N.R. Anderson, E.C. Leuthardt, J.G. Ojemann, D. Limbrick, D.W. Moran, L.A. Gerhardt, and J.R. Wolpaw, "Decoding two-dimensional movement trajectories using electrocorticographic signals in humans," *J. Neural Eng*., vol. 4, Sep. 2007, pp. 264-75.

[12] K.J. Miller, E.C. Leuthardt, G. Schalk, R.P.N. Rao, N.R. Anderson, D.W. Moran, J.W. Miller, and J.G. Ojemann, "Spectral changes in cortical surface potentials during motor movement," *J. Neurosci.*, vol. 27, Feb. 2007, pp. 2424-32.