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High-density EEG and independent component analysis mixture models distinguish knee contractions from ankle contractions

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Abstract—**Decoding human motor tasks from single trial electroencephalography (EEG) signals can help scientists better understand cortical neurophysiology and may lead to brain computer interfaces (BCI) for motor augmentation. Spatial characteristics of EEG have been used to distinguish left from right hand motor imagery and motor action. We used independent component analysis (ICA) of EEG to distinguish right knee action from right ankle action. We recorded 264-channel EEG while 5 subjects performed a variety of knee and ankle exercises. An adaptive mixture independent component analysis (ICA) algorithm generated two distinct mixture models from a merged set of EEG signals (including both knee and ankle actions) without prior knowledge of the underlying exercise. The ICA mixture models parsed EEG signals into maximally independent component (IC) processes representing electrocortical sources, muscle sources, and artifacts. We calculated a spatially fixed equivalent current dipole for each IC using an inverse modeling approach. The fit of the models to the single trial EEG signals distinguished knee exercises from ankle exercise with 90% accuracy. For 3 of 5 subjects, accuracy was 100%. Electrocortical current dipole locations revealed significant differences in the knee and ankle mixture models that were consistent with the somatotopy of the tasks. These data demonstrate that EEG mixture models can distinguish motor tasks that have different somatotopic arrangements, even within the same brain hemisphere.**

I. Introduction

A BRAIN COMPUTER INTERFACE (BCI) enables command of an electronic device by brain activity modulation [1]. Originally, BCIs were intended to facilitate communication for people with severe motor disabilities [2]. However, there is an emerging consensus that BCIs could also be beneficial for neurorehabilitation [3],[4]. One focus of our laboratory is electromechanical devices for gait rehabilitation. Therefore, we are interested in the notion that a BCI, which supplements impaired descending motor commands during gait training, could increase treatment efficacy [4].

A common technology used for non-invasive BCI is electroencephalography (EEG). However, these signals are often considered to be too prone to movement artifact and to have too poor spatial resolution (due to the distance between the sensors and the cortex) for effective use in electrical neuroimaging and BCI applications. However, independent component analysis (ICA) can effectively parse underlying electrocortical sources from artifact contaminated EEG [5]-[11] even during walking [12]-[14]. ICA may be an effective tool for EEG-based BCI [15],[16], even in dynamic environments where movement artifact is likely.

When combined with an inverse modeling approach [8],[17],[18], ICA reveals the spatial distribution of electrocortical sources that collectively contribute to EEG signals on the scalp. Incorporating this spatial distribution with spectro-temporal properties of electrocortical sources can enhance BCI capabilities [15],[16],[19]-[22]. Spatial characteristics of EEG have been used to distinguish left from right hand motor imagery [19],[22],[23] and motor action [24],[25]. Here we use ICA of EEG to distinguish right knee action from right ankle action, a unique challenge given the close somatotopic arrangement of the knee and ankle within the primary motor cortex.

II. Methods

A. Tasks

Five healthy volunteers with no history of major lower-limb injury and no known neurological or locomotor deficits completed this study (all subjects were males, age range 21–31 years). Subjects were screened for right handedness. All subjects provided written informed consent prior to the experiment. All procedures were approved by the University of Michigan Internal Review Board and complied with the standards defined in the Declaration of Helsinki.

Subjects sat on a bench while performing isometric (contraction without limb movement) and isotonic (contraction with limb movement, concentric followed by eccentric) contractions about the knee and ankle. Two sets of 20 reps of each exercise were performed. Each contraction was performed over roughly 3 seconds. Timing queues were not provided, therefore exercise timing was approximate. Exercises were performed in flexion and extension; except for isotonic knee flexion, which could not be accommodated by the test apparatus. Isometric ankle exercises were performed at a neutral ankle angle and isometric knee exercises were performed at 45 degrees of flexion.

B. Recording EEG

We recorded EEG at 512 Hz using an ActiveTwo amplifier and a 264-channel active electrode array (BioSemi, Amsterdam, The Netherlands). We measured the location of the electrode head cap with respect to anatomic head

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reference points, as well as the location of 8 electrodes that were external to the head cap, using a digitizer (Polhemus, Colchester, VT, USA). Before data collection, electrode gel was used to bring electrode impedance below 25 kΩ.

After data collection, we applied a zero phase lag 1 Hz high-pass Butterworth filter to the EEG signals to remove drift. EEG signals exhibiting substantial noise throughout the collection were removed from the data in a manner similar to [12],[13]. Channels with std. dev. ≥1000 µV were removed. Next, any channel whose kurtosis was more than 3 std. dev. from the mean was removed. Then, channels that were uncorrelated ($r \leq 0.4$) with nearby channels for more than 0.1% of the time-samples were removed. On average, 197 channels were retained for analysis (range: 134–240; sd.: 43.9). The remaining channel signals were re-referenced to an average reference. All analysis was performed in MATLAB (The Mathworks, Natick, MA) using scripts based on EEGLAB, an open source MATLAB toolbox [8].

C. Independent Component Analysis

For each subject, EEG signals from all movement conditions were merged into a continuous dataset. These data were submitted to an adaptive mixture ICA algorithm [AMICA] [26],[27] that generalizes infomax [28],[29] and multiple mixture [30],[31] ICA approaches. We allowed AMICA to identify two distinct mixture models. Each mixture model linearly transformed the EEG channel signals into a set of maximally independent component (IC) processes. AMICA had no prior knowledge of the underlying exercises (i.e., timeframes of the merged dataset were not differentiated by exercise type). We computed the log-likelihoods for each model at each time-point. Log-likelihood is a measure of the goodness-of-fit of the model to the recorded EEG. The average log-likelihood was used to identify the mixture models that best fit the data collected during knee and ankle exercises; we therefore refer to the *knee model* and the *ankle model*, respectively. For all subjects, one of the two models best fit the data for knee exercises and the other model best fit the data for ankle exercises. Next, single trial data (i.e., one exercise repetition) were categorized as *knee* or *ankle* based on the fit of the respective ICA model to the data for that trial.

DIPFIT functions within EEGLAB [18] computed an equivalent current dipole model that best explained the scalp topography of each IC using a boundary element head model based on the Montreal Neurological Institute (MNI) template (the average of 152 MRI scans from healthy subjects) and a non-linear optimization technique [33]. We excluded ICs if the projection of the equivalent current dipole to the scalp accounted for less than 85% of the scalp map variance, or if the topography, time-course, and spectra of the IC was reflective of eye movement or electromyographic artifact [6],[7]. The remaining ICs reflected electrocortical sources. These sources were clustered across subjects using EEGLAB routines that implemented k-means clustering on vectors jointly coding differences in equivalent dipole locations and the topography of the dipole projection to the scalp. Prior to clustering, scalp topography was reduced to 10 principal dimensions using principal component analysis. To account for differences in the dimensions of the dipole locations compared to the scalp topography, dipole locations were given a weight of 3 and topography principle components were given a weight of 1 prior to clustering (as in [12],[13]).

Clusters of electrocortical sources containing ICs from at least 4 of the 5 subjects were paired across mixture models by minimizing the Euclidian distance between cluster centroids, such that each cluster pair contained one cluster from the knee model and one cluster from the ankle model. For example a cluster pair might include a right motor cortex cluster from the ankle model and a right motor cortex cluster from the knee model.

A multivariate analysis of variance tested for differences between the paired clusters (e.g., the right motor cortex cluster for the knee model was compared to the right motor cortex cluster for the ankle model). The inputs to the analysis of variance were the vectors representing the ICs in the multi-dimensional principle component space that was used for clustering.

III. Results

The knee and ankle ICA mixture models parsed an average of 23.2 and 26.2 electrocortical sources from the EEG signals, respectively (Fig. 1). The number of electrocortical sources per subject was not significantly different between the two models (ANOVA, $p = 0.67$).

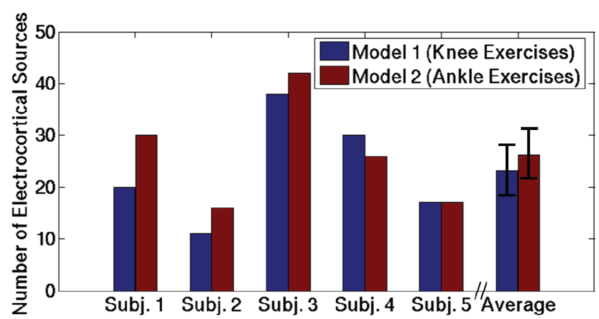

Fig. 1. Number of electrocortical sources for each subject and independent component analysis model. The average sources per subject was not significantly different by model ($p = 0.67$).

For each exercise repetition (i.e., a single trial), the average log-likelihood for all time-points within the trial was computed for both ICA mixture models. Each repetition was categorized as *knee* or *ankle* based on the ICA model that best fit the data for the individual trial. On average, 90% of trials were correctly categorized. For Subjects 1, 3, and 4, 100% accuracy was achieved. For Subject 2, 100% accuracy was achieved except for isotonic ankle exercises, which were categorized correctly 33% of the time. For Subject 5, all isometric repetitions were classified correctly and all isotonic repetitions were classified incorrectly (Fig. 2).

Clusters of electrocortical sources containing ICs from at least 4 of 5 subjects were localized to the anterior cingulate, posterior cingulate, visual, medial left motor, lateral left motor, and lateral right motor cortices. All of these clusters were present in both the knee and ankle ICA models (Fig. 3).

Electrocortical sources were clustered in a 13-dimensional principle component space (3 dimensions represented dipole location and 10 dimensions represented the topography of the dipole projection to the scalp). A multivariate analysis of variance, using these 13 principle dimensions as input, found the left medial motor, left lateral motor, visual, and posterior parietal cortex clusters to be significantly different between the knee and ankle ICA models ($\alpha = 0.05$). The anterior cingulate and right motor cortex clusters were not significantly different across ICA models.

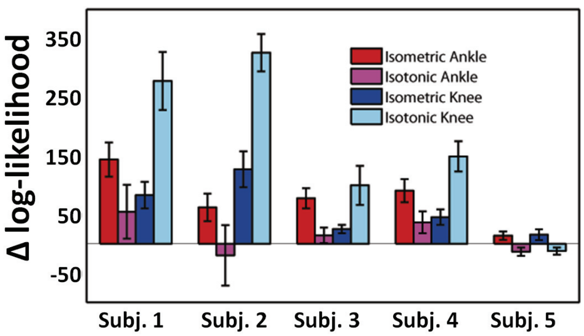

Fig. 2. Independent component analysis (ICA) models were assigned to categories *ankle* or *knee* based on which model best fit the EEG channel signals recorded during ankle and knee exercises, respectively. The average difference in the likelihood between the two models for each subject and each exercise type is shown. A positive difference indicates that the ICA model was able to correctly differentiate ankle exercises from knee exercises. Error bars represent ± 1 standard deviation. For all subjects and conditions, the likelihood of the respective ICA models correctly predicted the joint exercised, except for Subject 2 isotonic ankle exercises and Subject 5 isotonic knee and ankle exercises. In these cases, the average difference in the likelihood was negative, indicating incorrect predictions.

IV. Discussion

In this study, an adaptive mixture ICA algorithm was applied to EEG collected during knee and ankle contractions. Two distinct mixture models were generated *without prior knowledge of the underlying exercises*. Each model represented a spatially fixed distribution of source signals. For all subjects, one of the two ICA mixture models best fit the EEG signals collected during ankle exercises and the other best fit the EEG collected during knee exercises. Therefore, we called these models the *ankle model* and the *knee model*, respectively.

For 3 of 5 subjects, exercise repetitions (on a single trial basis) were categorized as *knee* or *ankle* with 100% accuracy. For the remaining subjects, isometric exercises were accurately categorized but some isotonic exercises were not. We expect that for these subjects, the isotonic exercises elicited a distribution of electrocortical activity that was different from that elicited by the isometric exercises. It would be interesting, in these cases, to allow the ICA algorithm to identify up to 4 mixture models (a task we leave for future work).

The locations of clusters of electrocortical sources in the primary motor cortex were consistent with the expected somatotopic distribution of the recruited muscles. We presume that the left and right lateral motor cortex clusters (brown and purple, Fig. 3) were the result of active trunk stabilization, which was required while sitting on the exercise bench. In addition, the medial motor cortex cluster (yellow, Fig. 3) for the knee model was located towards the top of the inter-hemispheric fissure in the left motor cortex, while the same cluster for the ankle model was located deeper in the inter-hemispheric fissure. These locations are consistent with the somatotopic arrangement of the right knee and the right ankle in the primary motor cortex.

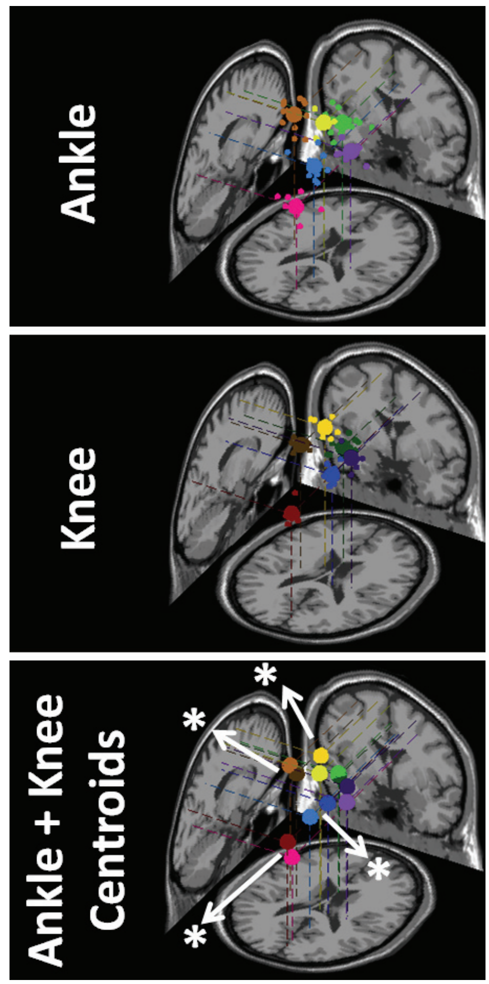

Fig. 3. Clusters of electrocortical source equivalent current dipoles localized to (green) anterior cingulate, (blue) posterior cingulate, (red) visual, (yellow) medial left motor, (brown) lateral left motor, and (purple) lateral right motor cortices. Two equivalent current dipole models are shown; (top) the model best fitting the EEG channel signals during ankle exercises and (middle) knee exercises. Small spheres indicate the equivalent current dipole locations for single electrocortical sources for single subjects; larger spheres indicate geometric cluster centroids. Clusters from the two models were paired by minimizing the Euclidean distance between cluster centroids (cluster pairs are shown in the same color; light shades represent the dipole model for ankle exercises and dark shades represent dipole model for knee exercises). (Bottom) geometric cluster centroids for both models are overlaid; clusters within the same pair that were significantly different from each other, in principle component analysis space (i.e., the space in which k-means clustering was performed), are indicated by * ($\alpha = 0.05$).

It is possible that certain sources of electromyographic or electroocular artifact were present during ankle and not knee exercises (or vice versa), even after removing artifacts using ICA. This would have positively influenced the prediction of knee vs. ankle action. To avoid this, subjects were seated in the same position for all experimental conditions and were instructed to keep their gaze forward. In addition, they were instructed to engage only the right leg during each exercise (i.e., subjects were not permitted to grab the exercise bench to generate more force).

To our knowledge, this work is the first to establish that ICA-based mixture models can distinguish underlying motor tasks that have different somatotopic arrangements, even within the same hemisphere. Future work will attempt to decode exercise type (isometric/isotonic, flexion/extension, high/low joint torque) from the spectro-temporal features of the electrocortical IC processes.

V. Conclusion

An adaptive mixture ICA algorithm generated two distinct mixture models from a set of EEG signals recorded during knee and ankle actions, without prior knowledge of the underlying exercise. The fit of the models to single trial EEG distinguished knee exercises from ankle exercises. We believe that combining spatial characteristics derived from ICA with classifiers based on spectro-temporal properties of electrocortical processes may be beneficial for non-invasive BCI. In addition, because ICA has enabled EEG-based electrical neuroimaging during locomotion, we believe that the above approach may be applicable to neurorehabilitation of gait, including monitoring cortical plasticity and controlling robotic lower-limb exoskeletons.

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References

[1] J.R. Wolpaw, N. Birbaumer, D.J.McFarland, G. Pfurtscheller, T. Vaughan. "Brain-computer interfaces for communication and control," *Clin Neurophysiol*, vol. 113, pp. 767-791, 2002.
[2] A. Kubler, B. Kotchoubey, J. Kaiser, J.R. Wolpaw, N. Birbaumer. "Brain-computer communication: unlocking the locked in," *Psychol Bull*, vol. 127(3), pp. 358-375, 2001.
[3] W. Wang, et al. "Neural interface technology for rehabilitation: exploiting and promoting neuroplasticity," *Phys Med Rehabil Clin N Am*, vol. 21, pp. 157-178, 2010.
[4] J.J Daly and J.R. Wolpaw. "Brain-computer interfaces in neurological rehabilitation," *Lancet Neurol*, vol 7, pp. 1032-1043, 2008.
[5] S. Makeig, A.J. Bell, T.P. Jung, T.J. Sejnowski. "Independent component analysis of electroencephalographic data," *Advances in Neural Information Processing Systems*, vol. 8, pp. 145-151, 1996.
[6] T.P. Jung, et al. "Removing electroencephalographic artifacts by blind source separation," *Psychophysiology*, vol. 37, pp. 163-178, 2000.
[7] T.P. Jung, et al. "Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects," *Clin Neurophysiol*, vol. 111, pp. 1745-1758, 2000.
[8] A. Delorme and S. Makeig. "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *J Neurosci Methods*, vol. 134, pp. 9-21, 2004.
[9] A. Delorme, T. Sejnowski, S. Makeig. "Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis," *Neuroimage*, vol. 34, pp. 1443-1449, 2007.
[10] J. Onton, M. Westerfield, J. Townsend, S. Makeig. "Imaging human EEG dynamics using independent component analysis," *Neuroscience and Biobehavioral Reviews*, vol. 30, pp. 808-822, 2006.
[11] S. Makeig, K. Gramann, T.P. Jung, T. J. Sejnowski, H. Poizner. "Linking brain, mind and behavior," *International Journal of Psychophysiology*, vol. 73, pp. 95-100, 2009.
[12] J.T. Gwin, K. Gramann, S. Makeig, D.P. Ferris. "Electrocortical activity is coupled to gait cycle phase during treadmill walking," *Neuroimage*, vol. 54, pp. 1289-1296, 2010.
[13] J.T. Gwin, K. Gramann, S. Makeig, D.P. Ferris. "Removal of movement artifact from high-density EEG recorded during walking and running," *J Neurophysiol*, vol. 103, pp. 3526-3534, 2010.
[14] K. Gramann, J.T. Gwin, N. Bigdely-Shamlo, D.P. Ferris, S. Makeig. "Visual evoked responses during standing and walking," *Front Hum Neurosci*, vol. 4, pp. 202, 2011.
[15] P.S. Hammon, S. Makeig, H. Poizner, E. Todorov, V.R. de Sa. "Predicting reaching targets from human EEG," *IEEE Signal Processing Magazine*, vol. 25, pp. 69-77, 2008.
[16] A. Kachenoura, L. Albera, L. Senhadji, P. Comon. "ICA: A potential tool for BCI systems," *IEEE Sig. Proc. Mag.*, vol.25, pp.57-68, 2008.
[17] S. Lew, C.H. Wolters, A. Anwander, S. Makeig, R.S. MacLeod. "Improved EEG Source Analysis Using Low-Resolution Conductivity Estimation in a Four-Compartment Finite Element Head Model," *Hum Brain Mapping*, vol. 30, pp. 2862-2878, 2009.
[18] R. Oostenveld and T.F. Oostendorp. "Validating the boundary element method for forward and inverse EEG computations in the presence of a hole in the skull," *Hum Brain Mapping*, vol. 17, pp. 179-192, 2002.
[19] M.G. Wentrup, K. Gramann, E. Wascher, M. Buss. "EEG Source Localization for Brain Computer Interfaces," in *Proc. 2nd Int. IEEE EMBS Conf. Neural Engineering,* Arlington, Virginia, 2005.
[20] Z.C. Chao, Y. Nagasaka, N. Fujii. "Long-term asynchronous decoding of arm motion using electrocorticographic signals in monkeys," *Front Neuroengineering*, vol. 3, pp. 3, 2010.
[21] M. Besserve, J. Martinerie, L. Garnero. "Improving quantification of functional networks with EEG inverse problem: Evidence from a decoding point of view," *Neuroimage*, to be published.
[22] L. Qin, L. Ding, B. He. "Motor imagery classification by means of source analysis for brain-computer interface applications," *J Neural Eng*, vol. 1, pp. 135-41, 2004.
[23] H. Ramoser, J. Muller-Gerking, G. Pfurtscheller. "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans Rehabil Eng*, vol. 8, pp. 441-446, 2000.
[24] H. Zhang, C. Wang, C. Guan. "Time-variant spatial filtering for motor imagery classification," in *Proc. IEEE EMBS*, pp. 3124-3127, 2007.
[25] J. Muller-Gerking, G. Pfurtscheller, H. Flyvbjerg. "Designing optimal spatial filters for single-trial EEG classification in a movement task," *Clin Neurophysiol*, vol. 110, pp. 787-798, 1999.
[26] J.A. Palmer, K. Kreutz-Delgado, S. Makeig. "Super-Gaussian Mixture Source Model for ICA," in *Lecture Notes in Computer Science*, J. Rosca, et al., Eds., Springer, Berlin, pp. 854-861, 2006.
[27] J.A. Palmer, S. Makeig, K. Kreutz-Delgado, B.D. Rao. "Newton Method for the ICA Mixture Model," in *33rd IEEE Int. Conf. on Acoustics and Signal Processing,* Las Vegas, Nevada, 2008.
[28] A.J. Bell and T.J. Sejnowski. "An information-maximization approach to blind separation and blind deconvolution," *Neural Comput*, vol. 7, pp 1129-1159, 1995.
[29] T.W. Lee, M. Girolami, T.J. Sejnowski. "Independent component analysis using an extended infomax algorithm for mixed subgaussian and supergaussian sources," *Neural Comput*, vol.11, pp.417-441, 1999
[30] T.W. Lee, M.S. Lewicki, M. Girolami, T.J. Sejnowski. "Blind source separation of more sources than mixtures using overcomplete representations," *IEEE Sig Proc Letter*, vol. 6, pp. 87-90, 1999.
[31] M.S. Lewicki and T.J. Sejnowski. "Learning overcomplete representations," *Neural Comput*, vol. 12, pp. 337-365, 2000.
[32] M. Scherg. "Fundamentals of dipole source potential analysis," in *Advances in Audiology: Auditory Evoked Magnetic Fields and Electrical Potentials*, 6th ed. Vol. 6, F. Grandori, M. Hoke, and G.L. Romani, Eds. Basel: S. Karger, 1990, pp. 40-69.