NeuroImage 91 (2014) 84–90

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Resting-state cortical connectivity predicts motor skill acquisition

Jennifer Wu [a], Ramesh Srinivasan [b], Arshdeep Kaur [c], Steven C. Cramer [a,c,*]

[a] Department of Anatomy & Neurobiology, University of California, Irvine, CA, USA
[b] Department of Cognitive Sciences, University of California, Irvine, CA, USA
[c] Department of Neurology, University of California, Irvine, CA, USA

ARTICLE INFO

Article history:
Accepted 17 January 2014
Available online 25 January 2014

Keywords:
EEG
Motor learning
Coherence
PLS

ABSTRACT

Many studies have examined brain states in an effort to predict individual differences in the capacity for learning, with overall moderate results. The present study investigated how measures of cortical network function acquired at rest using dense-array EEG (256 leads) predict subsequent acquisition of a new motor skill. Brain activity was recorded in 17 healthy young subjects during 3 min of wakeful rest prior to a single motor skill training session on a digital version of the pursuit rotor task. Practice was associated with significant gains in task performance (% time on target increased from 24% to 41%, $p < 0.0001$). Using a partial least squares regression (PLS) model, coherence with the region of the left primary motor area (M1) in resting EEG data was a strong predictor of motor skill acquisition ($R^2 = 0.81$ in a leave-one-out cross-validation analysis), exceeding the information provided by baseline behavior and demographics. Within this PLS model, greater skill acquisition was predicted by higher connectivity between M1 and left parietal cortex, possibly reflecting greater capacity for visuomotor integration, and by lower connectivity between M1 and left frontal–premotor areas, possibly reflecting differences in motor planning strategies. EEG coherence, which reflects functional connectivity, predicts individual motor skill acquisition with a level of accuracy that is remarkably high compared to prior reports using EEG or fMRI measures.

Introduction

Individuals demonstrate significant variability in motor learning (Ackerman, 1987; King et al., 2012). The ability to predict an individual's learning skill could have utility in a number of settings, including clinical (Stinear, 2010). Previous studies have identified neural correlates of variability during motor learning (Tomassini et al., 2011), and both structural and functional neuroimaging methods have been evaluated as predictors of motor learning (Mathewson et al., 2012; Vo et al., 2011). However, the ability to accurately predict learning differences, in healthy or diseased populations, remains modest, for example, with fMRI-derived resting-state connectivity accounting for 35% (Wang et al., 2010) to 66% (Baldassarre et al., 2012) of inter-individual variability.

Recent resting-state studies have provided new inroads for measuring differences in brain function in relation to behavior across individual subjects (Deco et al., 2011). Markers of brain function at rest are influenced by experience (Lewis et al., 2009) and reflect the functional organization of brain networks that are selectively engaged during behavioral tasks. Organization of brain networks at rest has also been correlated with subsequent behavioral performance (Hampson et al., 2006; Tambini et al., 2010). However, there is limited study of how inter-individual heterogeneity in brain functional connectivity at rest relates to learning and plasticity.

Combined EEG and fMRI studies have reported that specific combinations of EEG rhythms correspond with low frequency activity of specific resting-state networks (Mantini et al., 2007). Thus, EEG metrics also may be useful for characterizing brain states and relating them to behavioral variance. One potential metric is spectral power, which measures synchronization *within* cortical regions (Nunez and Srinivasan, 2006). A recent EEG study found that a regional measure of spectral power in a frontal electrode (Fz) and a parietal electrode (Pz) obtained early during training predicted 53% of the variance in subsequent motor learning (Mathewson et al., 2012). An alternate EEG-based metric is spectral coherence, which measures synchronization *between* regions and thus can capture cortical connectivity. In various studies of motor function using EEG coherence, changes in brain connectivity have been observed in the β (20–30 Hz) frequency range (Deeny et al., 2009; Pfurtscheller et al., 1996; Tropini et al., 2011).

Measures of connectivity, as compared to assessments of focal brain regions, have an improved ability to represent complexity in human cortical processing and as a result have a stronger relationship with many types of behavior (Bullmore and Sporns, 2009). Therefore, the present study hypothesized that EEG coherence measures of motor network connectivity in the β band during wakeful rest would predict subsequent motor skill acquisition in a single motor skill training session. Secondarily, it was hypothesized that a PLS approach for deriving

Abbreviations: PLS, partial least squares; M1, primary motor area; PM, frontal–premotor; Pr, parietal.

* Corresponding author at: University of California, Irvine Medical Center, 200 S. Manchester Ave, Suite 206, Orange, CA 92868, USA.
E-mail address: scramer@uci.edu (S.C. Cramer).

1053-8119/$ – see front matter © 2014 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.neuroimage.2014.01.026

brain–behavior relationships would perform better than an ROI based approach. An additional secondary hypothesis was that β band coherence during movement (in the training session) would also be a predictor of subsequent motor skill learning.

Materials and methods

Experimental design

Healthy subjects, aged 18–30 years and right-handed (Edinburgh Handedness Inventory) were recruited. This study was approved by the University of California, Irvine Institutional Review Board. Each subject gave written informed consent.

The experiment took place across a single session. Participants sat in a chair facing a computer monitor atop a desk. In order to minimize variation across participants, awake resting-state EEG was acquired for 3 min (EEG-Rest) at 1000 Hz prior to any description or practice of the motor task. Next, each individual's maximum arm movement speed was measured, standardized instructions for the visuomotor skill task were provided, and a baseline assessment of the motor skill task was obtained (Test 1), during which EEG was again recorded (EEG-Test 1). Next, two blocks of practice and two additional blocks of motor skill task testing with EEG recording were completed in an interleaved manner (Fig. 1A), from which measures of motor skill learning were obtained. Arm movements were recorded by a USB 8″ × 6″ digitizing pen tablet (Genius MousePen, Taipei, Taiwan).

To measure maximum arm movement speed, two 20-pixel target circles were displayed on the monitor, 1300 pixels apart. Participants were instructed to make horizontal movements between the centers of each circle, as rapidly as possible. The maximum number of targets hit during a 10 s period was recorded, and a maximum movement speed was calculated. The speed test was repeated three times, and the maximum was used to determine the speed that motor task target moved for each individual participant.

The motor skill task used in the current study was a digital version of the classic pursuit rotor task motor learning paradigm (Adams, 1952; Grafton et al., 1994). Subjects viewed a computer monitor on which a target (a 20-pixel diameter red circle) moved, back and forth, along a fixed arc (yellow, spanning a 450-pixel wide and 200-pixel long path), at 50% of each individual's maximum movement speed. A cursor (15-pixel diameter white circle) was also present, the position of which was controlled by subjects using the digitizing tablet pen held by the right hand (Fig. 1B). Subjects were instructed to keep the cursor on the target as the target moved along the arc (Fig. 1C).

Participants directed cursor movement by moving the pen tip across the surface of the USB digitizing tablet, maintaining contact of the pen tip on the tablet surface at all times during task performance. To ensure arm movements were standardized across participants and were restricted to right shoulder internal/external rotation only, a soft strap was placed on the distal part of the right forearm, minimizing shoulder abduction, and a wrist brace was placed across the distal right arm, minimizing wrist flexion/extension (Fig. 1B). Subjects sat with both feet flat on the floor and were not permitted to move at other body joints.

Performance was quantified as percent time that the cursor position was >50% overlapping with target position (*% on Target*, Fig. 1C). A total of three test blocks and two interleaved practice blocks were completed (Fig. 1A). Each test block consisted of a 50 s rest period followed by an 80 s task period. Each practice block consisted of four 20-s task periods interleaved with three 50-s rest periods. Degree of motor skill acquisition was calculated from absolute change in *% on Target* from Test 1 to Test 3 (% Improvement).

EEG acquisition

Dense-array surface EEG was acquired using a 256-lead Hydrocel net (Electrical Geodesics, Inc., Eugene, OR). Awake resting-state EEG was acquired for 3 min. EEG signal was referenced to Cz during recording and re-referenced to the average of all leads for analysis; an advantage of this approach is that it minimizes common reference effects. A ground electrode was not used. EEG signal was recorded raw with no bandpass filter used.

During EEG-Rest, participants were asked to hold still with the forearms resting on the anterior thigh and to direct their gaze at a fixation cross displayed on the computer monitor. During EEG-Test 1, and subsequent recordings (EEG-Test 2 and EEG-Test 3), participants used their right hand to keep the cursor on the target, as above. Data were collected at 1000 Hz using a high input impedance Net Amp 300 amplifier (Electrical Geodesics) and Net Station 4.5.3 software (Electrical Geodesics).

EEG preprocessing

EEG data were exported to Matlab (7.8.0, MathWorks, Inc., Natick, MA) for preprocessing. The continuous EEG signal was low-pass filtered at 50 Hz, segmented into non-overlapping 1-s epochs, and detrended.

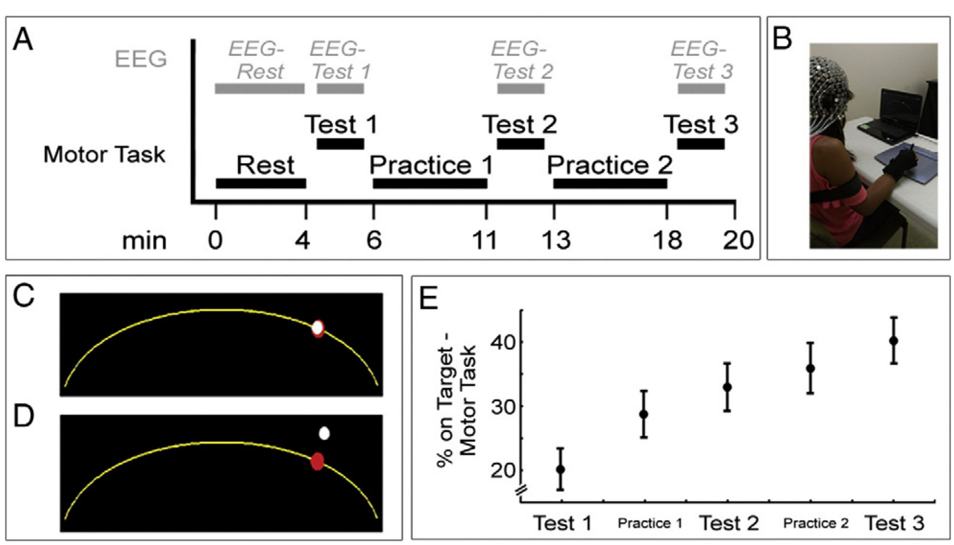

Fig. 1. Experimental setup. A. Experiment timeline. B. Digitizing pen tablet and presentation laptop. C. Example of cursor *on target*. D. Example of cursor *off target*. E. The % Improvement (Test 3 − Test 1) on the motor task with practice was statistically significant (mean ± S.E.; repeated measures ANOVA, $F(2,15) = 5.05$, $p < 0.0001$).