Resting State and Task-related Brain Dynamics Supporting Insight

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Abstract— **Problems can be solved in a variety of ways. One might systematically evaluate a known space of possible solutions until the right one is found. Alternatively, it may prove necessary to enlarge or restructure the expected problem space – so called "thinking outside the box." This approach can yield an experience of unexpected insight or feeling of *Aha!*. Current challenges to understanding this phenomenon from a neurocognitive perspective include the vast diversity of problem domains and time scales for solutions. Whereas the subjective suddenness of an "Aha!" moment may lead to the impression that insight must be precipitated by a set of discrete, short-lived neural events, this report outlines research revealing that even before a problem is presented, scalp-recorded measures of resting or baseline brain states are linked with future performance and likelihood of experiencing insight during the search for a solution. Additionally, this study also shows that compared to more systematic problem solving approaches, insight is accompanied by differences in cortical and likely cognitive engagement that are detectable throughout much of the problem solving phase, rather than being confined to a distinct interval immediately preceding the dawn of a solution. These findings are important for the development of therapies targeting problem solving and reasoning skills, such as those used in cognitive training interventions to mitigate the effects of cognitive decline.**

I. Introduction

Insight involves enlarging or restructuring an expected problem space such that a previously inaccessible solution can emerge, often resulting in an "Aha!" experience [1]. Recent studies have revealed that brain activities during baseline rest or before problem presentation are linked to the occurrence of insight and other aspects of problem solving performance. For instance, Kounios et al [2] demonstrate that individuals who tend to experience insight more versus less frequently exhibit different patterns of EEG spectral activity during rest – particularly in the alpha and beta ranges – when solving anagrams. In a related vein, it has been shown that that solution times [3] and insight processes [4] are predicted by the magnitude of spectral power during the pre-stimulus baseline period, as well as during the solution-search phase.

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These findings are of particular relevance to the burgeoning field of cognitive training, which involves behavioral interventions targeting basic functions, such as attention, memory, and reasoning. In clinical settings, these interventions are administered with the overall objective of reducing or reversing the negative effects of cognitive decline (typically associated with aging) or other forms of impairment [5]. However, cognitive-training therapies are rapidly gaining traction among mainstream healthy populations as a means of maintaining mental acuity (http://www.lumosity.com/). It is possible that resting-state brain activity may impact the long- or short-term effects of cognitive training on outcome measures.

While this question remains to date unexplored, the present study centers on the relationship between resting-state EEG brain activities, on the one hand, and task performance, on the other, in healthy adults engaging in popular, challenging math puzzles analogous to those found in some "brain fitness" packages. We recorded high-density EEG during both rest and a subsequent one-hour period of work on puzzles. After completing each problem, participants rated on a five-point scale whether their solution was achieved through an Aha! experience. We then tested for correlations between individual participants' baseline spectral power and likelihood of experiencing insight. We also compared mean event-related spectral power derived from early portions of the solution search on trials yielding either strong or weak insight outcomes.

II. Methods

A. Participants

The Institutional Review Board of UCSD approved this experiment protocol. Fifteen volunteers were recompensed for their participation at a rate of $15.00 per hour. All were neurologically healthy university students who gave informed consent. Data from two individuals were excluded because ratings were limited to one end of the insight scale.

B. Materials

Math24 is a popular commercial game used in many schools to increase arithmetic problem-solving skills. Problems involve combining, as quickly as possible, four single-digit numbers (using each only once) with basic arithmetic operators (addition, subtraction, division, multiplication, grouping) to form an arithmetic expression whose value is 24. For example, the puzzle in Figure 1 could be correctly resolved through the following steps: $2 + 2 = 4$; $7 * 4 = 28$; $28 – 4 = 24$. Problems vary along three levels of difficulty, with harder items characterized by longer solution latencies [3, 6] and fewer possible and less typical solutions.

Figure 1. Sample Math24 problem.

In this study, all three difficulty levels were presented in a randomized, interleaved manner. After each trial, participants rated how they reached their solution on a scale of 1 (no insight whatsoever) to 5 (distinct feeling of Aha!), so that it was possible to differentiate solutions that individuals simply happened upon given their initial estimations of the problem space from those that required restructuring. Care was taken during the instruction phase of each experimental session to ensure that participants understood the definition of insight and how to use the five-point scale.

C. Procedure

Participants received oral and written instructions regarding the Math24 task and insight scale. They were given the opportunity to ask questions and completed a practice set. Data acquisition began with a five-minute recording of EEG at rest with eyes open, followed by a one-hour session of Math24. The opportunity was given to go on to the next trial if a particular problem was proving difficult after two minutes. Trials "timed out" after three minutes, and a new puzzle was presented when the participant signaled readiness with a mouse click.

Immediately upon arriving at a solution, participants clicked the mouse and shared their answer via intercom with an experimenter in the adjacent control room. The experimenter evaluated responses online and registered their accuracy with a mouse click. The Math24 portion of the experimental session lasted one hour. Afterwards, participants completed a basic addition task. Either the same or similar puzzles were presented over again with the requirement that participants simply sum the four numbers. Importantly, this task involved perceptual and arithmetic features that closely resembled the experimental task for baseline subtraction purposes.

D. Data Acquisition

High-density EEG data were recorded over 128 scalp locations and amplified using a BioSemi ActiveTwo EEG system with a CMS-DRL ground. The sampling rate was 512 Hz. The onset of Math24 puzzles, as well as participants' and experimenters' behavioral responses were recorded and synchronized using Lab Streaming Layer (https://code.google.com/p/labstreaminglayer/).

E. Behavioral Data Analysis

Only trials involving correctly solved puzzles were analyzed. Solution latencies (SLs) were determined by measuring the time between the stimulus onset and the mouse click indicating solution readiness. SL values were sorted into three categories, depending on the insight rating of their associated trial: low insight (rated as one or two), medium insight (three), or high insight (four or five). SLs were then averaged within each category for each participant, and then averaged again across participants. Reliability of differences in response times between levels of insight was tested with repeated-measures ANOVA. Pre-planned post hoc contrasts were conducted with t-tests.

F. EEG Analysis

1) Preprocessing: EEG time series was inspected to remove poor-quality channels and segments of data heavily contaminated by movement and other non-brain artifacts. The remaining signals underwent Independent Component Analysis (ICA, [7, 8]) for the purpose of artifact correction. ICA is now a widely-used statistical technique to find linear projections of the EEG data that maximize the mutual independences of estimated components, and has been proven as an effective technique to remove EEG artifacts arising from eye blinks, eye movement and muscle activities [9]. EEG signals were analyzed using MATLAB (The Mathworks, Inc.) and the open source toolbox, EEGLAB (Swartz Center for Computational Neuroscience, University of California San Diego, La Jolla, CA; http://www.sccn.ucsd.edu/eeglab).

2) Baseline Rest: For each participant, an insight index was derived according to (1).

$$\frac{\sum X(\mathrm{i, H}) - \sum X(\mathrm{i, L})}{\sum X(\mathrm{i, H}) + \sum X(\mathrm{i, L})} \qquad (1)$$

Here, X(i, H) denotes the quantity of trials receiving high insight ratings (4 or higher), and X(i, L), the quantity of low insight ones (2 or lower).

Twelve representative channels distributed over the right, left, and midline axes along four evenly spaced points extending from the front to the back of the were selected for further analysis scalp (F3, F4, C3, C4, P3, P4, O3, O4, Fz, Cz, Pz, Oz). (Exploratory tests conducted over nearby sites yielded similar results.) Estimates of power spectral density were computed from ICA-corrected baseline rest EEG (3 to 50 Hz) using wavelet-based discrete Fourier transforms (3 cycles with linearly tapered windows). Correlation tests were conducted between insight indices and power estimates across a range of frequencies implicated in cognitive processing, including theta (θ: 5-8 Hz), alpha (α: 8-13 Hz), beta (β: 14-30 Hz), and gamma (γ: 30-50 Hz).

3) Solution Search: Twelve regions of interest (ROIs) were defined along left, right, and central axes encompassing frontal, central, parietal, and occipital recording cites (Figure 2). Because solution times varied considerably, we analyzed high- and low-insight single trial data epochs within these 7 s time windows: 1) extending forward from puzzle onset, 2) centered on the mid-point of each trial, and 3) extending back from the button press to signal readiness. Data epochs associated with recording sites within each ROI were first averaged, then transformed into spectrographic images by computing power spectral density estimates (3 to 50 Hz) across 200 equally spaced time points. Mean Event-related Spectral Perturbation (ERSP, [10]) plots were derived from

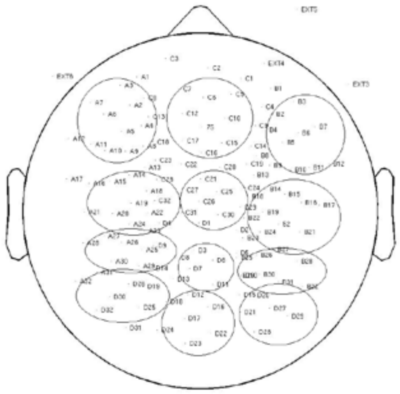

Figure 2. Map of ROIs created from channel montage.

single-trial spectrographic images by converting to log power, averaging across trials, and subtracting the mean log power derived from the baseline addition task (Fig. 5A). Mean power spectra for each interval were computed by averaging across the time window within theta, alpha, beta, and gamma frequency ranges. Reliability of spectral power differences between high and low insight trials was tested with repeated-measures ANOVA.

III. Results

A. Solution Times

Mean solution times to puzzles involving low, medium, and high insight ratings are plotted in Figure 3. A main effect of insight rating ($F(2,12) = 4.14$, $p < 0.05$) motivated follow-up contrasts between the three levels. Low insight problems were solved substantially faster than medium insight ones ($t(12) = -2.27$, $p < 0.05$). However, medium versus high insight solutions did not reliably differ in the amount of time that they elicited ($t(12) = -1.6$, n.s.).

B. Resting-state Dynamics

Figure 4 plots mean spectral power derived from left occipital EEG (measured over O3) during rest from the four participants with the highest versus lowest insight index scores. Scores ranged from -0.94 to +0.92, with negative numbers indicating less frequent occurrence of insight, and positive numbers, the opposite). Reliable correlations between all participants' power estimates and insight scores ($r = 0.54$ to 0.77) were found in the high alpha (11.5 to 13 Hz) and beta ranges (14 to 24 Hz) (demarcated within the grey box). Increased activities in these ranges were associated with increased occurrence of insight.

C. Solution Search

During the middle portions of solution searches, trials involving high versus low insight were reliably differentiated in the theta range (Figure 5) over the central midline ROI. High insight trials were characterized by substantially greater theta activities throughout the entire seven-second period ($F(1,13) = 8.05$, $p < 0.05$). No other consistent insight effects were detected in other frequency bands or time windows. Figure 6 plots the topographic distribution of spectral fluctuations for the full seven seconds.

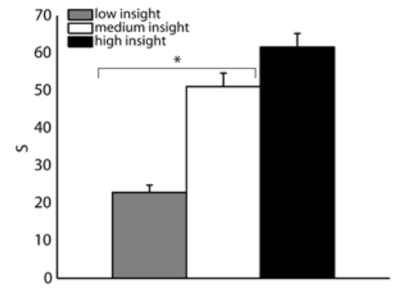

Figure 3. Mean solution times associated with low, medium, and high

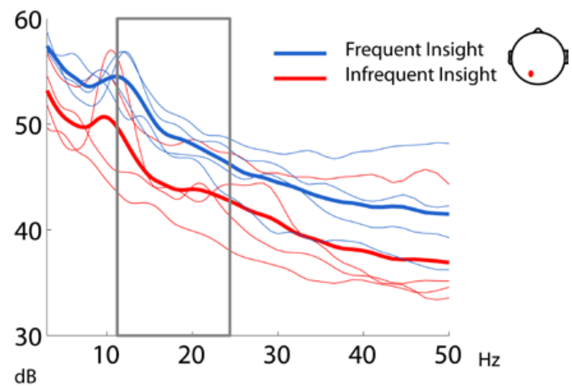

Figure 4. Power spectra during rest from individuals with the lowest (red) and highest (blue) insight scores. Thick lines indicate mean spectra for each group. The grey box delineates the frequency range in which insight scores reliably correlated with power across all participants

IV. Discussion and Conclusions

This study yielded two noteworthy findings. First, we uncovered a link between occurrence of insight and resting-state EEG power between 11 and 24 Hz centered over the left occipital region of the scalp. Higher spectral power within this bandwidth was positively correlated with individual insight index scores, which are a measure of the relative frequency of high to low insight solutions. This outcome is consistent with [2], who also reported that individuals who experienced insight more (HI group) versus less frequently (LI group) exhibit differences in high alpha and beta EEG activities over the back of the head. However, in [2], the HI group was associated with *lower* resting alpha and beta power relative to the LI group. Further, the HI group exhibited greater right relative to left hemisphere activity in these ranges, whereas the LI group demonstrated the opposite pattern of asymmetry. Kounios et al suggest that heightened occipital beta activities in the LI group reflect more focused attention.

Outcomes in [2] are directly the opposite from those observed here. Notably, though, [2] administered an anagram task, whereas the present work involved arithmetic and quantitative reasoning. Given the tendency toward left hemisphere lateralization of arithmetic abilities in right-handers [11], the left posterior focus of the correlations found here is unsurprising. Further, it is likely that the mental restructuring precipitating an Aha! experience would require more focused attention – and hence higher beta band power – in the case of the challenging math puzzles administered here (requiring on average between 20 s and 1 minute to solve) relative to anagrams (which were solved within 16 s or less).

This study also uncovered the novel finding that during problem solving, the magnitude of theta activities in the middle portion of trials differentiates high versus low insight performance outcomes. Trials that receive high insight ratings tend to involve much higher theta power during this time window than trials receiving low insight ratings. Frontal and frontal midline theta activity have been extensively implicated in tasks requiring attentional control, such as error monitoring [12] or maintenance of verbal and visuo-spatial information in immediate memory [13-21]. Thus, greater mental effort in the middle of problem solving tends to result in greater subjective experiences of insight at the time of solution. This finding is remarkable, as it reveals that well before the actual Aha! moment, insight problems elicit different patterns of neurocognitive engagement than counterpart problems solved more straightforwardly. Next, we plant to analyze causal connectivity between frontal midline and left posterior source contributions to the surface EEG.

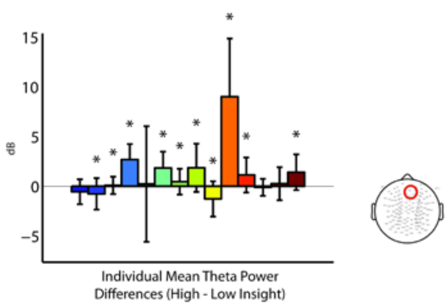

Figure 5. Differences obtained by subtracting mean theta power on low from high insight trials over central midline electrodes for each participant. Positive values reflect greater power on high versus low insight trials; negative values, the reciprocal. Asterisks indicate reliable differences from zero.

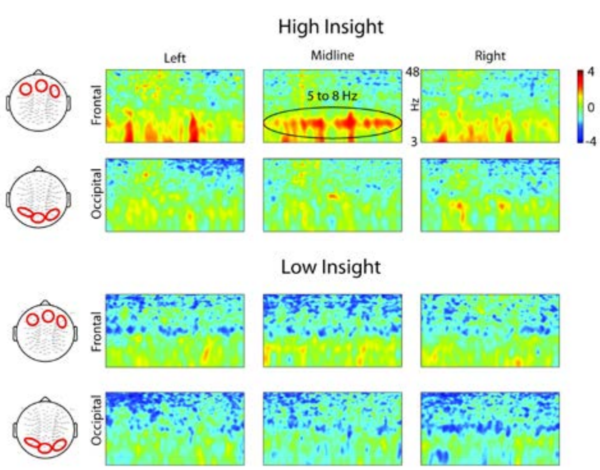

Figure 6. ERSP plots derived from frontal and occipital ROI's reflecting mean spectral modulations during the middle seven seconds of trials involving high versus low insight.

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