Phase to amplitude coupling as a potential biomarker for creative ideation: An EEG study

Mina Marmpena, Stavros I. Dimitriadis, Nitish Thakor, *Fellow, IEEE and* Anastasios Bezerianos, *Senior Member, IEEE*

***Abstract*— The most consistent finding of creative ideation in the neuroscientific study of creativity is the increment of EEG α power. However, the majority of existing studies focused only on ERP experimental paradigms while only a few analyzed time-related changes of EEG α power patterns during the time unlocked creation of ideas. Here, we designed an experimental paradigm where the participants were asked to generate alternative uses of everyday objects (AU task). For the control task, we adopted an Object Characteristics (OC) task, for which participants were asked to list typical characteristics or properties of an object. We estimated relative power spectrum, global efficiency from brain networks constructed with the imaginary part of coherence and phase-to-amplitude coupling (PAC) as potential biomarkers of creativity. Both relative power spectrum and nodal global efficiency failed to reach significant level by comparing AU with OC. In contrast, statistically significant differences between AU and OC were detected with PAC estimated within sensors in frequency pairs θ-γ and α2-γ. Our results can be the ground for both detecting and designing a connectomic biomarker of creativity.**

I. Introduction

Creativity is defined as the ability to produce ideas that are both novel and useful [1]. It is a crucial skill for effective problem-solving and decision-making, especially under extreme circumstances, in volatile, uncertain and increasingly complex environments. It constitutes an indispensable factor for the development of human civilization, and a driving force behind scientific, technological and cultural progress [2]. Understanding its neural mechanisms is of great importance but it comprises a considerable challenge.

Creativity as a cognitive function is not a homogeneous construct but rather a multifaceted mental ability [3] and a product of complex interplay between ordinary cognitive processes like memory, attention, executive function, and even emotion [4]. It occurs in different stages or phases and might thus considerably vary as a function of time [5]. The neural basis of creativity cannot be localized to one or a few brain regions, on the contrary, a multitude of brain regions becomes active during creative process [6]. Besides the challenges arising from the complexity of the neural process, an important drawback is the difficulty to develop experimental methodologies that can capture "real-life" creative achievement under tightly controlled laboratory conditions.

Many different experimental tasks and designs have been used to study creativity resulting in an admittedly large diversity of findings so far [2], [7]. One of the well-established approaches is based on divergent thinking tasks. Divergent thinking is defined as the ability to produce multiple solutions to an ill-defined problem, in contrast with convergent thinking where one has a well-defined problem, and logically deduces a well-established answer [8]. Divergent thinking tasks have significantly stronger relationship with creative achievement than scores on intelligence tests do [9], they are widely accepted as useful indicators of creative potential [10], and they represent the dominant approach in the psychometric assessment of creativity [11]. Off course, one cannot ignore the fact that although they show high reliability, evidence of their validity is rather inconsistent [3]. Nevertheless, divergent thinking tasks are currently considered to be the best option under laboratory conditions [12].

In the present study, we focused on the divergent thinking approach and we sought to examine the contrast in EEG brain signals between a divergent thinking task and a common intelligence task used as control task [13], [14]. More specifically for the divergent thinking, we have employed the Alternative Uses (AU) task [15], for which participants are asked to list as many possible uses for a common house hold item (such as s brick, a paperclip, a newspaper). For the control task we used Object Characteristics (OC) task, for which participants are asked to list typical characteristics or properties of an object (such as shape, material, size, color). OC was preferred as a control task since the form of its stimulus can be the same as the AU stimulus and allow for a strictly controlled design. For both tasks participants' responses are in spontaneous self-paced mode to better capture the free-flow manner in which ideas emerge during the thought process.

Previous EEG studies focused mainly on power spectrum analysis [3], [14], [16] while only a few analyzed time-related α power changes. Brain connectivity and also cross-frequency coupling are two important brain processes that support basic and higher cognitive functions [17]. γ band oscillations are involved in working-memory maintenance, α

M. Marmpena is with Biosignal Lab, Dept. of Medical Physics, School of Medicine, University of Patras, Greece (email: mina.marmpena@gmail.com).

S. I. Dimitriadis is with Institute of Psychological Medicine and Clinical Neurosciences, Cardiff University School of Medicine and the Cardiff University Brain Research Imaging Center (CUBRIC), School of Psychology, Cardiff University, Cardiff, United Kingdom; AIIA Laboratory, Department of Informatics, and the NeuroInformatics Group, Aristotle University of Thessaloniki, Greece (email:dimitriadisS@cardiff.ac.uk / stidimitriadis@gmail.com).

N. Thakor and A. Bezerianos are with SINAPSE, National University of Singapore, 28 Medical Drive, 117456, Singapore (email: tassos.bezerianos@nus.edu.sg).

978-1-4577-0220-4/16/$31.00 ©2016 IEEE

band underlies the inhibition of task unrelated activity while θ frequency encapsulates the temporal organization of working memory task.

In the current study, we searched for potential biomarkers of creativity by adopting power spectrum analysis, network analysis and cross-frequency coupling namely phase-to-amplitude coupling [18]. We hypothesized that phase-to-amplitude coupling between the frequency pairs of θ - γ and $\alpha 2$ - γ will reveal the multifunctional process of creativity [17]. The experimental design is presented in Section II, the adopted methodology in Section III, the description of the results are demonstrated in Section IV, while Section V is devoted for discussion and conclusions.

II. EXPERIMENTAL DESIGN AND DATA COLLECTION

A. Participants

A total of 30 students were initially recruited from National University of Singapore to participate in this study. All participants were native speakers of English, right-handed, with normal or corrected-to-normal vision, and no reported history of CNS-affecting drugs, mental or neurological diseases. They all provided written informed consent and were reimbursed for their time. Three participants' data were excluded after data pre-processing stage due to excessive artifacts, resulting in a final sample of 27 subjects (14 females and 13 males, age range: 20-29, mean age: 23.11, std: 2.06). The study was approved by the Institutional Review Boards of the National University of Singapore.

B. Experimental task

Each task consists of 15 trials and each trial lasts for 60 s (Fig. 1). During a trial, the name of an everyday object is projected with white letters on a black screen and the participants are asked to generate multiple responses according to the task requirements (alternative uses for the AU task and object characteristics for the OC). The 30 object names used as stimuli were selected according to specifications: not to have multiple meanings and to be at once recognizable as names of everyday objects that people use very often. To further ensure optimum control for priming effects, the objects presented as stimulus during each task were randomly selected from the objects pool and then presented in randomized order. Every trial is preceded and followed by the presentation of a white fixation cross. Between the two tasks a short break takes place. The order in which the two tasks are completed is counterbalanced to neutralize possible order effects in the data.

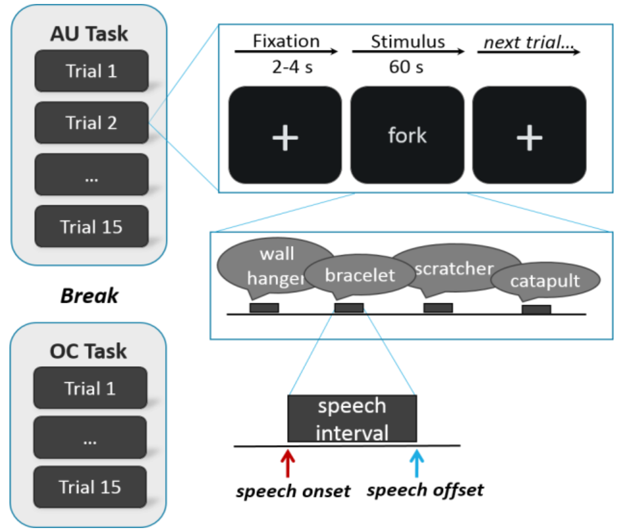

Fig. 1 Schematic representation of the tasks. Responses are sampled from the AU task.

C. Procedure

Participants were seated comfortably in an armchair in front of a screen and a keyboard. The experimenters explained to them the two tasks with appropriate examples and asked them to press a response key every time they would come up with an idea and then announce it. After vocalizing their idea, they had to go back into generating more ideas for as long as the name of the object appeared on the screen. An experimenter had to press a key whenever the participants had concluded with the vocalization of their responses, so that the speech offset (Fig. 1) was also marked (speech onset was marked when the participants press the key after the idea had emerged in their mind). This set up allowed to discriminate the periods that capture the thinking process from the speaking intervals and to avoid intervals contaminated with artifacts caused by speech activity [3].

D. Data acquisition and pre-processing

EEG data were collected using a Refa TMSi amplifier (TMSI B.V., Netherlands) and a WaveguardTM cap (CA-142; ANT Neuro, Netherlands) with 64 sintered Ag/AgCl electrodes and 10kΩ built in resistor. The electrodes were placed in accordance with the International 10-20 system. Two of the auxiliary inputs were used for collecting horizontal and vertical electrooculogram (hEOG and vEOG). The EEG data were recorded using the data acquisition software ASA-LabTM v4.7.12 (ANT Neuro, Netherlands), with a sampling rate of 256 Hz, referenced to the common average. Offline, the EEG data were band-pass filtered at 0.5-40 Hz and epochs were extracted from -2 to 0 s relative to the response button click. All epochs were visually inspected and the ones contaminated with excessive artifacts were rejected. Independent components analysis was applied with AMICA algorithm [19] to detect EOG and other artifact related components and remove them from the data. Finally a surface Laplacian algorithm based on spherical splines [20] was applied on the data to increase topographical localization and facilitate electrode-level connectivity analysis.

III. DATA ANALYSIS

A. Time-frequency decomposition

The power spectrum of the single trials was derived with fast-Fourier-transform and then multiplied by the power spectrum of complex Morlet wavelets $\exp(-t^2/2s^2)\exp(i2\pi f)$, where t is time, f is frequency (increasing from 4 to 40 Hz, in 37 linearly spaced steps) and s is the standard deviation that defines the width of the wavelet (equal to $n/2\pi f$ where n is the number of wavelet cycles, increasing from 4 to 10 cycles spaced in as many values as the frequencies; for balancing the trade-off between temporal and frequency precision; [21]). Subsequently, the inverse fast-Fourier-transform of the product which is a complex number for each time point and frequency was used to derive time-frequency power (squared magnitude). Finally, the initial epochs from -2.5 to 0 s were trimmed (from -2.3 to 0.3 s) to avoid edge artifacts caused by the wavelet convolution.

B. Relative power

We estimated the relative power spectrum for each sensor, trial and separately for each condition within the predefined frequencies of θ (4-8 Hz), α1 (8-10 Hz), α2 (10-13 Hz), β1 (13-20 Hz), β2 (20-30 Hz) and γ (30-40 Hz).

C. Brain Connectivity and Network Analysis

Using the imaginary part of coherence [22], we constructed weighted graphs called hereafter functional connectivity graphs (FCGs) within the same frequencies as used in power analysis and via wavelet decomposition. The whole analysis was repeated on a single-trial basis and for each condition.

In order to preserve the most informative links from the full-weighted network and reveal the backbone of the brain network, we adopted a data-drive thresholding scheme based on the maximization of global cost efficiency. This technique was already used in previous studies [23], [24]. The code can be downloaded from author's website: http://users.auth.gr/~stdimitr/software.html

As a next step in our analysis, we estimated a well-known network metric called global efficiency for each sensor, trial and condition [24], [25].

D. Phase-to-amplitude (PAC) coupling

Phase-to-amplitude (PAC) coupling was adopted as a within sensor CFC estimator. PAC was estimated within sensors X_i (i=1…62) between the frequency pairs θ-γ and α2-γ. The PAC was computed via phase locking value (PLV) [18].

IV. RESULTS

A. Condition-related changes based on relative spectrum

No statistical differences were detected based on relative power spectrum on a sensor level between AU and OC conditions ($p < 0.05$). On Fig. 2, increased power activity was demonstrated over frontal brain sites in θ /α1, over parietal brain sites in α1/α2 /β1 and bilaterally over temporal-parietal brain sites in β1/ β2 / γ frequencies.

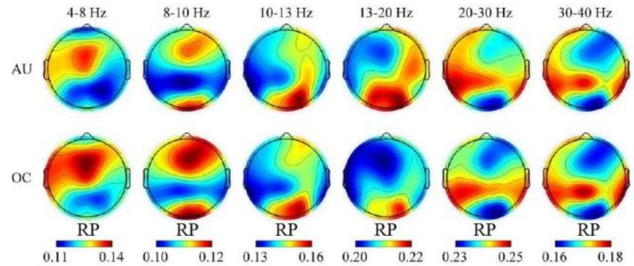

Fig.2 Group-averaged relative power (RP) spectrum for both conditions AU and OC from θ to γ.

B. Nodal global efficiency estimated over imaginary part of coherence

No statistical differences were detected based on global efficiency on a sensor level between AU and OC tasks ($p < 0.05$). On Fig. 3, increased global efficiency was demonstrated over frontal brain sites and bilaterally over occipital brain areas in all the frequency bands.

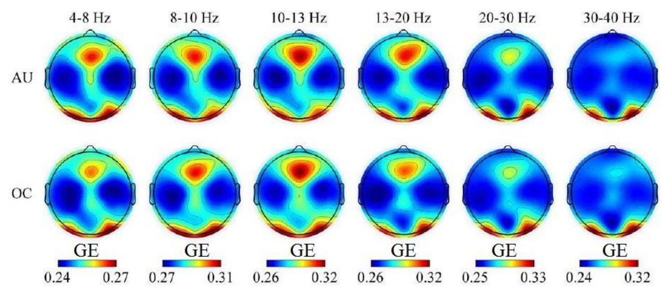

Fig.3 Group-averaged nodal global efficiency (GE) for both conditions AU and OC from θ to γ.

C. PAC estimates within sensors

Statistical differences were detected based on PAC on a sensor level between AU and OC tasks ($p < 0.05$; Wilcoxon Rank-Sum Test; Bonferroni Corrected). Specifically, in θ-γ, higher PAC was revealed for AU condition over CP4 and CP6 brain sites while in α2-γ, higher PAC was demonstrated in FC1 and CZ for AU condition compared to OC (Fig.4).

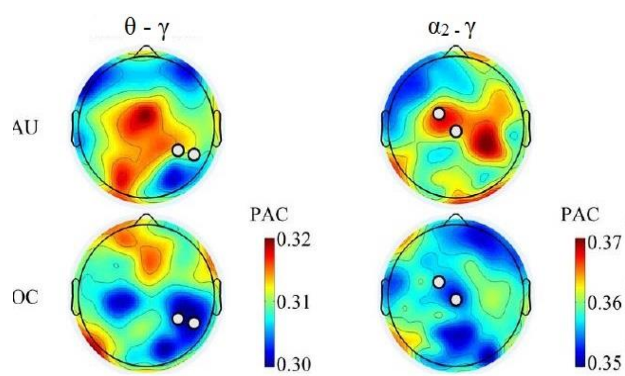

Fig.4 Group-averaged nodal Phase-to-Amplitude Coupling (PAC) for both conditions AU and OC and within frequency pairs θ–γ and α_2-γ. White circles denotes statistical significant differences of PAC on sensor level between the two conditions.

V. CONCLUSION

In the present study, we analyzed power spectrum, brain networks and phase-to-amplitude coupling from an AU experimental paradigms based on EEG recordings from 27 participants. Power spectrum (Fig.2), global efficiency (Fig.3) didn't succeed to reveal any significant trend. In contrast, PAC succeeded to unfold statistically significant increment in θ-γ, higher PAC over CP4 and CP6 brain sites for AU compared to OC condition and in α2-γ, higher PAC was demonstrated over FC1 and CZ brain areas for AU compared to control OC condition (Fig.4).

In previous studies, EEG creative oriented studies focused on power spectrum in α frequency band [3], [14] which was the most representative biomarker of creative ideation. Our results illustrated task-relevant inhibition in FC1 and CZ (α2-γ) brain sites while active creative retrieval (θ-γ) over right centro-parietal brain areas [17].

We successfully addressed the contribution of different aspects of brain activity in relationship with creativity ideation. Further study should analyze the experimental paradigm via dynamic functional connectivity using both intra and inter-frequency coupling to reveal dynamic connectomic biomarkers that will reveal the creative ideation [18], [25]–[28].

ACKNOWLEDGMENT

The authors would like to thank the National University of Singapore for supporting the Cognitive Engineering Group at the Singapore Institute for Neurotechnology (SINAPSE) under grant number R-719-001 -102-232, and Ministry of Education of Singapore, for funding support under the grant number MOE2014-T2-1 -115.

REFERENCES

[1] R. J. Sternberg, *Handbook of Creativity*. Cambridge University Press, 1999.

[2] A. Dietrich and R. Kanso, "A review of EEG, ERP, and neuroimaging studies of creativity and insight," *Psychol. Bull.*, vol. 136, no. 5, pp. 822–848, 2010.

[3] A. Fink and M. Benedek, "EEG alpha power and creative ideation," *Neurosci. Biobehav. Rev.*, vol. 0, pp. 111–123, Jul. 2014.

[4] R. W. Weisberg, *Creativity: Understanding Innovation in Problem Solving, Science, Invention, and the Arts*. John Wiley & Sons, 2006.

[5] R. A. Finke, T. B. Ward, and S. M. Smith, "Creative approaches to cognition. Creative cognition: Theory, research and applications." *Appl. Cogn. Psychol.*, vol. 8, no. 5, pp. 528–529, Oct. 1994.

[6] G. A. Wiggins and J. Bhattacharya, "Mind the gap: an attempt to bridge computational and neuroscientific approaches to study creativity," *Front. Hum. Neurosci.*, vol. 8, p. 540, 2014.

[7] R. Arden, R. S. Chavez, R. Grazioplene, and R. E. Jung, "Neuroimaging creativity: a psychometric view," *Behav. Brain Res.*, vol. 214, no. 2, pp. 143–156, Dec. 2010.

[8] A. Cropley, "In Praise of Convergent Thinking," *Creat. Res. J.*, vol. 18, no. 3, pp. 391–404, Jul. 2006.

[9] K. H. Kim, "Meta-Analyses of the Relationship of Creative Achievement to Both IQ and Divergent Thinking Test Scores," *J. Creat. Behav.*, vol. 42, no. 2, pp. 106–130, Jun. 2008.

[10] M. A. Runco and S. Acar, "Divergent Thinking as an Indicator of Creative Potential," *Creat. Res. J.*, vol. 24, no. 1, pp. 66–75, Jan. 2012.

[11] J. C. Kaufman, J. A. Plucker, and J. Baer, *Essentials of Creativity Assessment*. John Wiley & Sons, 2008.

[12] H. Takeuchi, Y. Taki, H. Hashizume, Y. Sassa, T. Nagase, R. Nouchi, and R. Kawashima, "The Association between Resting Functional Connectivity and Creativity," *Cereb. Cortex*, vol. 22, no. 12, pp. 2921–2929, Dec. 2012.

[13] R. E. Beaty, M. Benedek, S. B. Kaufman, and P. J. Silvia, "Default and Executive Network Coupling Supports Creative Idea Production," *Sci. Rep.*, 2015.

[14] A. Fink, R. H. Grabner, D. Gebauer, G. Reishofer, K. Koschutnig, and F. Ebner, "Enhancing creativity by means of cognitive stimulation: Evidence from an fMRI study," *NeuroImage*, vol. 52, no. 4, pp. 1687–1695, Oct. 2010.

[15] J. P. Guilford, *The nature of human intelligence*. New York, NY, US: McGraw-Hill, 1967.

[16] D. Schwab, M. Benedek, I. Papousek, E. M. Weiss, and A. Fink, "The time-course of EEG alpha power changes in creative ideation," *Front. Hum. Neurosci.*, vol. 8, p. 310, 2014.

[17] F. Roux and P. J. Uhlhaas, "Working memory and neural oscillations: α-γ versus θ-γ codes for distinct WM information?," *Trends Cogn. Sci.*, vol. 18, no. 1, pp. 16–25, Jan. 2014.

[18] S. I. Dimitriadis, N. A. Laskaris, M. P. Bitzidou, I. Tarnanas, and M. N. Tsolaki, "A novel biomarker of amnestic MCI based on dynamic cross-frequency coupling patterns during cognitive brain responses," *Front. Neurosci.*, vol. 9, p. 350, 2015.

[19] J. A. Palmer, K. Kreutz-delgado, and S. Makeig, "AMICA: An Adaptive Mixture of Independent Component Analyzers with Shared Components," *Swartz Cent. Comput. Neursoscience Univ. Calif. San Diego Tech Rep*, 2012.

[20] F. Perrin, J. Pernier, O. Bertrand, and J. F. Echallier, "Spherical splines for scalp potential and current density mapping," *Electroencephalogr. Clin. Neurophysiol.*, vol. 72, no. 2, pp. 184–187, Feb. 1989.

[21] M. X. Cohen, *Analyzing Neural Time Series Data: Theory and Practice*, 1 edition. Cambridge, Massachusetts: The MIT Press, 2014.

[22] G. Nolte, O. Bai, L. Wheaton, Z. Mari, S. Vorbach, and M. Hallett, "Identifying true brain interaction from EEG data using the imaginary part of coherency," *Clin. Neurophysiol. Off. J. Int. Fed. Clin. Neurophysiol.*, vol. 115, no. 10, pp. 2292–2307, Oct. 2004.

[23] S. I. Dimitriadis, G. Zouridakis, R. Rezaie, A. Babajani-Feremi, and A. C. Papanicolaou, "Functional connectivity changes detected with magnetoencephalography after mild traumatic brain injury," *NeuroImage Clin.*, vol. 9, pp. 519–531, 2015.

[24] M. Antonakakis, S. I. Dimitriadis, M. Zervakis, S. Micheloyannis, R. Rezaie, A. Babajani-Feremi, G. Zouridakis, and A. C. Papanicolaou, "Altered cross-frequency coupling in resting-state MEG after mild traumatic brain injury," *Int. J. Psychophysiol. Off. J. Int. Organ. Psychophysiol.*, Feb. 2016.

[25] S. I. Dimitriadis, N. A. Laskaris, and S. Micheloyannis, "Transition dynamics of EEG-based network microstates during mental arithmetic and resting wakefulness reflects task-related modulations and developmental changes," *Cogn. Neurodyn.*, vol. 9, no. 4, pp. 371–387, Aug. 2015.

[26] S. I. Dimitriadis, N. A. Laskaris, V. Tsirka, M. Vourkas, S. Micheloyannis, and S. Fotopoulos, "Tracking brain dynamics via time-dependent network analysis," *J. Neurosci. Methods*, vol. 193, no. 1, pp. 145–155, Oct. 2010.

[27] S. I. Dimitriadis, N. A. Laskaris, P. G. Simos, S. Micheloyannis, J. M. Fletcher, R. Rezaie, and A. C. Papanicolaou, "Altered temporal correlations in resting-state connectivity fluctuations in children with reading difficulties detected via MEG," *NeuroImage*, vol. 83, pp. 307–317, Dec. 2013.

[28] S. I. Dimitriadis, N. A. Laskaris, and A. Tzelepi, "On the quantization of time-varying phase synchrony patterns into distinct functional connectivity microstates (FCμstates) in a multi-trial visual ERP paradigm," *Brain Topogr.*, vol. 26, no. 3, pp. 397–409, Jul. 2013.