Characterization of Design Brain States Over Time When Using Morphological Analysis and TRIZ

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In this paper, we explored changes in brain states over time while designers were generating concepts. Participants either used morphological analysis or TRIZ to develop a design concept for two design tasks. While designing, participants' brain activation in their prefrontal cortex (PFC) was monitored with a functional Near Infrared Spectroscopy machine. To identify variation in brain states, we analyzed changes in brain networks. Using k-mean clustering to classify brain networks for each task revealed four brain network patterns. While using morphological analysis, the occurrence of each pattern was similar along the design steps. For TRIZ, some brain states dominated depending on the design step. Drain states changes suggests that designers alternate engaging certain subregions of the PFC. This approach to studying brain behavior provides a more granular understanding of the evolution of design brain states over time. Findings add to the growing body of research exploring design neurocognition.

Introduction

Characterizing the underlying patterns in the brain when engaged in designing [1] and creative thinking [2] offers new knowledge on design thinking and design processes. It also offers a potential to increase the efficiency and objectivity of methods used in design research to measure design cognition [3]. A deeper understanding of brain behavior while designing could lead to the development of a new family of design

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tools based on brain signals, for example, providing designers with neuro-cognitive feedback during design [4].

Prior studies in design neurocognition have tackled the differences between problem-solving and open-ended design tasks [5, 6], the effect of expertise in problem solving [7] and the effect of sketching on neurocognitive behavior [8]. Those studies suggest that problem-solving and open-ended tasks recruit different brain regions [5, 6]. Activation in parietal regions for experts and novices appeared different while design problem solving, that could be related to expertise [7]. Sketching tends to increase Alpha waves that suggests a more relaxed state after drawing [8]. Other research looked at brain activation when providing designers with an input for analogical reasoning by displaying visual stimuli [9]. Temporally, some brain regions are more engaged with inspirational stimuli than without [9]. In this paper, we focus on analyzing brain states over different steps of the design process.

In our prior work, we analyzed designers brain activation using three design techniques while designers ideated [10, 11] and explored changes in brain network over time [12]. The research reported in these previous papers focused on the ideation phase only. They did not include brain behavior analysis of problem identification and analysis, which is an important step of the design process. In a recent paper, we inquired about brain behavior changes during other phases of design like problem identification [13]. The findings from this prior study suggested that the prefrontal cortex was recruited differently depending on the design phase, either concept generation or problem identification.

In the present paper, we build on these prior findings to explore the dynamic functional connectivity of designers' brains while generating concepts with morphological analysis or TRIZ. The motivation for this research was to examine whether specific brain states characterize design cognition processes such as problem identification or ideation. We studied morphological analysis and TRIZ because they induce a structured approach to designing. This way, we could identify design phases and track their related brain behavior. Functional connectivity in the brain was assessed by identifying brain regions that synchronize, meaning that they activate and deactivate concurrently [14]. Co-activation of brain regions could imply information transfer between those regions [15]. Dynamic functional connectivity focuses on analyzing changes in brain states of synchronization over time [16]. The implications of the findings presented in this paper are two-fold: providing new insights about whether the cognitive processes that occur in design can be mapped to brain behaviors, and subsequently, further developing new methods to study design neurocognition.

Background

Two Approaches to Concept Generation: Characteristics of Morphological Analysis and TRIZ

Designers rely on a variety of techniques to assist them in their design process, for instance brainstorming or concept maps. The type of technique influences how designers advance in the design process [17]. In this study we focused on two techniques, morphological analysis and TRIZ. Morphological analysis relies on a two-step process starting with an analytic strategy to decompose the problem followed by a systematic association of partial solutions to sub-problems to stimulate unconscious thoughts [18]. An example of morphological analysis provided by Alexander [19] was a kettle to boil water. The kettle's requirements could be subdivided into design problems related to safety (e.g., able to withstand the temperature of boiling water), use (e.g., easy to grasp when it is hot, easy to store), or maintenance (e.g., easy to clean) [19]. Each sub-problem can be addressed by a sub-solution, for example a plastic handle will solve the 'easy to grasp when it is hot' sub-problem. Each sub-solution is then synthesized into an overall design solution.

TRIZ, or the Theory of Inventive Principles, provides even more structure to the concept generation process, with a set of procedures to generate inventive solutions by defining the problem and looking at existing solution principles, before developing a solution [20, 21]. Using TRIZ, designers first identify contradictions in a design problem, solve the problem at a conceptual level then adapt it to a solution within the context of their specific constraints. The most popular TRIZ tools include the use of the contradiction table to identify contradictions in the design problem. Once contradictions are defined, designers will search for existing principles to address contradictions at a conceptual level. The inventive principles list was built from recurring patterns observed by Altshuller in patented technologies [20]. TRIZ's inventive principles are a set of conceptual solutions for technical problems that drive the process of problem solving and innovation. These inventive principles offer conceptual solutions to conceptual problems defined by the contradiction matrix. With TRIZ, designers seek a match between the problem and the solution at the conceptual level [20, 21]. The last step in TRIZ consists of transforming the conceptual solution into a solution that adapts to the real context of the design brief. In practice, TRIZ is used by professionals to promote innovation rapidly, increase the competitiveness of a company using this approach and adapt to new regulations [22].

In general, more structuredness in the concept generation technique, as in morphological analysis and TRIZ, leads to more reasoning on the design problem [17]. Using one technique or the other has an effect on cognitive processes [17, 23]. Recent studies highlight that concept generation technique implementation also alter brain behaviors [10, 12] that could be related to cognitive processes designers engaged in [13].

Design processes can be analyze by design researchers through a multitude of methods like protocol analysis [24], direct observations or retrospective interviews [25]. In this study, we explored the potential of analyzing brain states to inform our understanding of the design processes.

Using Dynamic Functional Connectivity to Identify Brain States

Higher order cognitive tasks like designing can involve multiple brain regions. Functional connectivity in the brain is assessed by identifying several brain regions that synchronize, meaning that they activate and deactivate concurrently [14]. In other words, two regions can be functionally connected if they have coherent and synchronized dynamics. Brain networks are representations of functional connectivity and stand as useful tools to study complementary characteristics of brain activation during a task [14, 26, 27]. Analyzing static functional connectivity in design tasks provides insights into patterns of brain region synchronization that could be related to specific cognitive tasks [12]. Research in creative cognition studying the whole brain points toward a coordination of two types of networks to generate creative ideas, the default mode network and the executive network [28, 29]. Both networks are associated with creative tasks like ideation: the default network is recruited for mind wandering and imagination while the executive network is engaged during goal directed tasks like problem solving [29].

Recently, the use of functional connectivity over time has provided a new method to describe the fundamental properties of how the brain functions [16]. Using a sliding window approach, the functional connectivity can be measured over time. By applying clustering methods to correlation matrices of brain regions, connectivity states or recurring patterns of region-to-region correlations can describe brain functions and the effect of morphological analysis and TRIZ [16]. Interestingly, the dominance of some brain states, like a cooperation between the default and executive network, correlate with creative personality traits [30].

For design research, an interest in dynamic functional connectivity is twofold. First, such techniques help associate brains states and cognitive function. It provides new knowledge, mapping brain activity and design cognition. Second, it can provide an alternative method to studying design tasks. Instead of solely relying on protocol analysis or direct observations methods to study design cognition [25], brain behavior, for instance EEG microstates, or fNIRS network analysis, might be useful to identify design processes in protocols [3].

Methodology

Experiment Design

Thirty graduate engineering students (all right-handed, 22–26 years old) were recruited to participate in the study. All participants had taken courses in engineering design. None were familiar with TRIZ or morphological analysis so they were given instructions on using these techniques in their design course. Participants were presented with the task and equipped with the fNIRS cap in the lab's experiment room. Each participant generated concepts for the following design tasks: designing an alarm clock for the hearing impaired, and designing a kitchen measuring tool for the blind. They were randomly assigned one design technique to engage in each concept generation task. The order in which design tasks were presented was random. No time limit was given to participants. Students were encouraged to draw their design on paper or write their ideas (Fig. 2). The fNIRS cap is suitable for such tasks thanks to its robustness to movement [31].

Morphological analysis and TRIZ are structured in phases that were tracked during the experiment. For morphological analysis, three phases were monitored. The first phase was for participants to define and decompose the problem. The second phase was to generate multiple sub-solutions to each sub-problem. Participants were invited to generate a morphological chart where sub-functions are associated to a sub-solution. For example, sub-functions of an alarm clock could be to provide a signal to users, adapt to sleeping cycles, or providing time. Examples of sub-solutions that fit those subfunctions, respectively, were to vibrate or emit smell as a signal, identify the users' sleep cycle through heart rate monitoring, and display time through a visual display. The final step was the ideation phase where participants integrated all of the sub-solutions into a coherent final design.

Using TRIZ, participants engaged in four distinct phases. First, participants were asked to read the brief and to define the problem. Then, they used Altshuller's 39 engineering parameters to search for a physical contradiction and well-solved problems that correspond to their specific problem [20]. In this phase, the design problem was set up through parameters such as "the weight of the object", its "shape", "strength" or its "convenience of use". In that stage, the task was to identify physical contradiction related to the function of the object. For example, when designing an umbrella, a bigger size would protect the user better but also make it cumbersome to carry around [21]. Therefore, the size of the object is a physical contradiction.

The third step consisted of adapting some of the 40 inventive principles to solve the current problem. The contradiction matrix provided a list of relevant inventive principles to resolve the contradictions formulated in the previous step, based on the specific parameters selected. These inventive principles provided conceptual solutions. For example, principle 23 about feedback, refers to introducing feedback to improve a process or adapt the feedback according to operating conditions. This principle is found at the intersection of the parameter "productivity" (improving feature) and "loss of information" (worsening feature) in the contradiction matrix.

The final step of the task was the ideation phase where participants generated a solution based on the principle from the contradiction matrix. In the case of the alarm clock, the feedback principle could be applied to the current problem as one could imagine a tactile signal indicating the time to wake up. For both TRIZ and morphological analysis, participants moved through the steps linearly without iteration revisiting previous steps.

Data Collection

Participants were equipped with a function Near Infrared Spectroscopy (fNIRS) cap from the LIGHTNIRS system (Shimadzu Co., Japan Kyoto) with a sampling frequency of 4.44 Hz (Fig. 1a). fNIRS is a tool to measure brain activation by monitoring metabolic demands (oxygen consumption) of active neurons [32, 33], with a penetration depth of about three centimeters. In the fNIRS cap, light is emitted from sources at specific wavelengths (between 700 and 900 nm) into the scalp. The light scatters, before reflecting back to the light receivers. The oxy-hemoglobin (oxy-Hb) and deoxy-hemoglobin (deoxy-Hb) absorb more light than water and other tissue in the brain. The change in the difference between the emitted light and reflected light is used to calculate the change in oxygenated blood using a Modified Beer-Lambert Law.

fNIRS is suited for naturalistic environments. Participants can perform the design task in an upright sitting position [4–6]. Three wavelengths of near-infrared light (780, 805, and 830 nm respectively) were used by this fNIRS system to record a change in participants' oxy-Hb. We only report oxy-Hb due to its relatively higher amplitudes and sensitivity to cognitive activities than deoxy-Hb.

The sensor placement on the fNIRS cap is illustrated in Fig. 1b. We used 16 sensors (eight emitters and eight detectors) located using the 10/20 international systems. The 16 sensors covered the frontal part of the 10/20 system. The eight emitters and eight detectors formed a total of 22 channels. A channel (grey lines in Fig. 1b) is the combination of a light source (red squares in Fig. 1b) and a nearby light receiver (blue squares in Fig. 1b). The 22 channels capture the change in oxygenated cortical blood in the PFC. Multiple sub-regions in the PFC are covered: the dorsolateral prefrontal cortex (DLPFC: channels 1, 2, 3, 9, 10 in the right hemisphere, and channels 5, 6, 7, 13, and 14 in the left hemisphere), the ventrolateral prefrontal cortex (VLPFC: channels 16 and 17 in the right hemisphere, and channels 21 and 22 in the left hemisphere), the orbitofrontal cortex (OFC: channel 18 in the right hemisphere, and channel 20 in the left hemisphere), and medial prefrontal cortex (mPFC: channels 4, 11, 12 and 19) in both hemispheres.

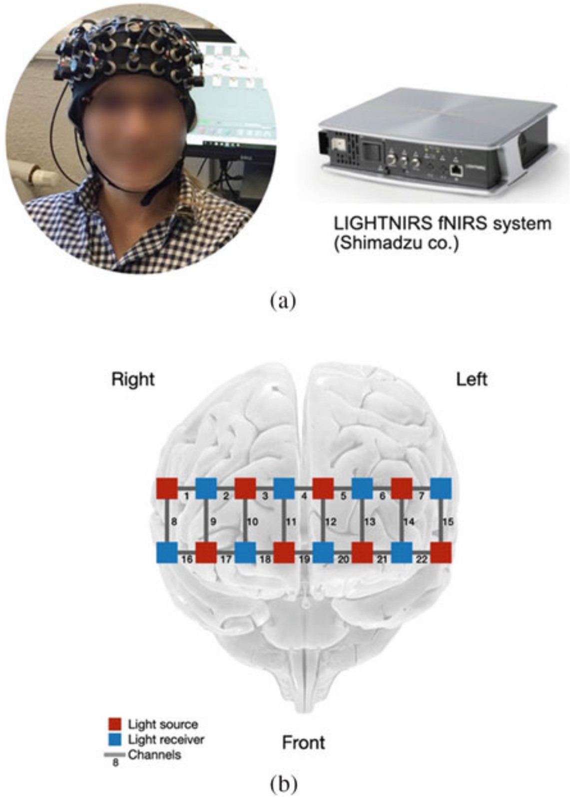

Fig. 1 **a** Participant set up for the experiment. **b** Placement of the fNIRS cap sensors on the prefrontal cortex

Data Analysis

To pre-process the raw fNIRS data, the steps taken were based on previous fNIRS studies [34–36]. Out of the 30 participants, three subjects were removed from the analysis due to bad signals. The remaining fNIRS raw data were processed using a bandpass filter (frequency ranging between 0.01 and 0.1 Hz, third-order Butterworth filter) to remove high-frequency instrumental and low-frequency psychological noise [37]. To remove motion artifacts, ICA (independent component analysis) with a coefficient of spatial uniformity (CSU) of 0.5 was applied. The filtering process was done with Shimadzu fNIRS software. The analysis was based on filtered oxy-Hb, which aligns with previous studies [38, 39]. Oxy-Hb signals were z transformed to normalize the data across subjects before conducting further analysis.

The following steps of the methodology are presented in Fig. 2. After pre-processing the data, each subject data was segmented into a window of 5 s. Functional connectivity was assessed for each window. Functional connectivity is defined as a statistical dependence between the time series of measured neurophysiological signals [14]. In this study, a Pearson correlation matrix between variations in oxy-Hb

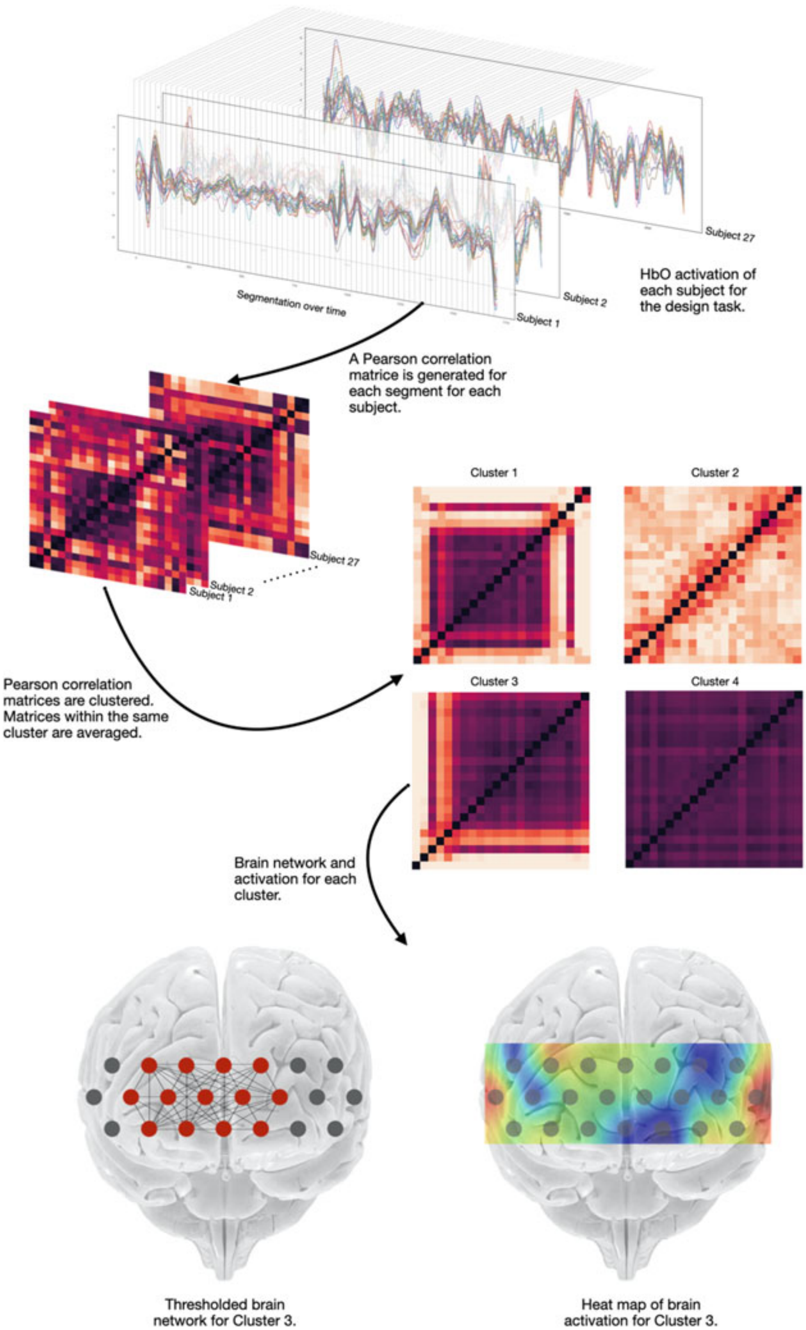

Fig. 2 Steps of the analysis. The brain signals are segmented. For each segment, a Pearson correlation matrix is generated. Matrices are clustered to define brain states. From the average matrix for each state, the network represents coactivation patterns and the activation heatmap inform on higher activation regions

processed signal channels provided an indicator of similarity activation between two channels. It follows methods from prior studies [40–42]. The time window value was selected because it allowed sufficient data points per window to obtain a reliable measure of the Pearson correlation while having enough windows for each morphological analysis or TRIZ phase. Multiple time window durations were tested (including 10 and 15 s) that provided similar results.

For each technique, the matrices capturing coactivation between channels for each participant were generated. Correlation values for two channels range from -1 to $+1$. A value of -1 signified that both channels followed opposite behaviors and $+1$ implies that the channels displayed the exact same behavior. The correlation of activation was evaluated using the segment time of 5 s. In total, 3,862 matrices were produced for the TRIZ dataset and 3,249 matrices were generated for the morphological analysis dataset. The matrices were then clustered using k-means clustering (Scikit-Learn package in Python). The matrices were classified within four clusters that subsequently defined four types of brain networks occurring while designing. We used the Elbow method to define the appropriate number of clusters [43]. Using a threshold on the correlation matrix, a network of the most correlated nodes was generated, i.e., nodes that undergo a similar trend of activation across time. There is no consensus on the particular value for the threshold to be used [14]. A range of plausible global threshold coefficients (incrementally from 0.6 to 0.7) was used in prior studies [15, 44]. In this study, a correlation coefficient of 0.7 was used.

The networks that met the threshold represented potential functional relationships between synchronized activation in different brain regions for each brain state. For each state, we generated a heatmap of the activation of channels to better define each brain state. This part of the analysis was conducted using Python libraries (Numpy, Pandas, and Networkx) (see Fig. 2). To test whether some clusters were particular to one phase in the design process, we compared the distribution of each cluster for each phase. The statistical difference in the distribution of each type of brain state for each phase was compared using t-tests. The data was tested for normality (Shapiro–Wilk test) and variance (using the SciPy package in Python).

Results

Identification of Brain States When Generating Concepts with Morphological Analysis

Students took on average 11 min for the design task using morphological analysis. On average, they spent a few seconds to define the problem, 5 and half minutes to generate multiple sub-solutions and 4 min to generate a final idea.

The cluster analysis identified four brain states during concept generation with morphological analysis. Each state describes a certain degree of synchronization of the PFC sub-regions. The distribution of the four brain states was similar for each of the three design phases of morphological analysis (problem decomposition phase, generation of sub-solution phase and the ideation phase).

The most frequent state was defined by a high coordination of sub-regions within the PFC (see brain network for Cluster 3_{MA} in Fig. 3a). On average, participants entered that brain state for 34.2–37.2% of the time during the design task (Table 1). All the nodes from this brain network state were connected to each other. Most regions within the PFC were activated when designers experienced that state (see brain activation for Cluster 3_{MA} in Fig. 3a).

In one of the states, the channels were not synchronized which implies that sub-regions of the PFC activated in different ways (see brain network for Cluster 1MA in Fig. 3a). In this state, the highest activation occurred in the right part of the DLPFC (dorsolateral PFC) and VLPFC (ventrolateral PFC) as well as in the lower part of the medial PFC (see brain activation for Cluster 1_{MA} in Fig. 3a). This state was the second most frequent state within all three design steps of morphological analysis. It occurred for 36.8% of the time during the problem decomposition phase, 34.5% of the time during the generation of sub-solution and 32.7% of the time during the

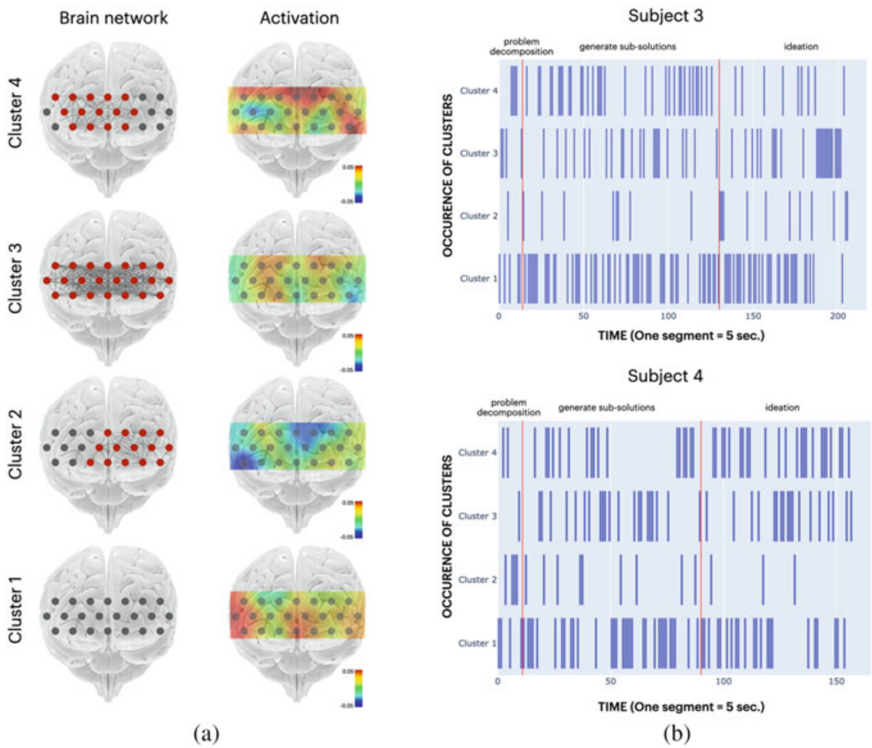

Fig. 3 **a** Representation of the brain network and brain activation in the PFC for each cluster of the morphological analysis concept generation. **b** Example of the occurrence of brain states over time for two subjects

Table 1 Distribution of brain state per phases of morphological analysis

	Problem decomposition %, (SD)	Generate sub-solutions %, (SD)	Ideation %, (SD)
Cluster 1_{MA}	36.8 (31.0)	34.5 (21.0)	32.7 (17.3)
Cluster 2_{MA}	15.8 (16.5)	16.1 (12.8)	18.0 (13.7)
Cluster 3_{MA}	34.3 (34.2)	34.2 (18.7)	37.2 (17.8)
Cluster 4_{MA}	13.1 (15.4)	15.1 (11.6)	12.1 (11.3)

ideation phase (Table 1). Figure 3b provides an example of the occurrence of this state over time for two subjects.

The other two states were characterized by a brain network that connected sub-regions within the medial and the right part of the PFC (see brain network for Cluster 4_{MA} in Fig. 3a) or that connected sub-regions within the medial and left part of the PFC (see brain activation for Cluster 2_{MA} in Fig. 3a). Brain activation for the Cluster 2_{MA} state was mainly in the left DLPFC and VLPFC (see brain activation for Cluster 2_{MA} in Fig. 3a) while the brain activation for the Cluster 3_{MA} state was in the medial part of the PFC.

The occurrence of the identified states over time varied for each subject as exemplified in the timeline represented in Fig. 3b.

Identification of Brain States When Generating Concepts with TRIZ

Students spent 13 min on average generating a concept using TRIZ. They spent about 57 s reading the task and defining the problem, 3 min searching for engineering parameters, 5 and a half minutes searching for inventive principles to adapt to their design problem and 4 min to generate a solution.

Four brain states were identified through the cluster analysis when participants used TRIZ to generate concepts. Cluster 1_{TRIZ} state was one of the most frequent states during the design activity. It occurred between 28.0 and 37.3% of the time depending on the phase (Table 2). This state was characterized by a synchronization of each channel activation, represented by a highly connected brain network (see brain network for Cluster 1_{TRIZ} in Fig. 4a). The highest activation appeared in the medial part of the PFC (see activation heatmap for Cluster 2_{TRIZ} in Fig. 4a). This state was the most frequent in the ideation phase. The occurrence of this state during ideation was significantly higher than during the problem decomposition phase ($t(52) = 2.33$, $p = 0.03$), while searching for parameters ($t(52) = 2.54$, $p = 0.02$) and selecting an inventive principal ($t(52) = 2.05$, $p = 0.049$).

Cluster 2_{TRIZ} state was characterized by a high desynchronization of the PFC sub-regions. The correlation of activation for channels in this cluster was below the network threshold of 0.7 (no edges appear in the brain network for Cluster 2_{TRIZ}, see

Table 2 Distribution of brain state per phases of TRIZ averaged across participants

	Problem definition %, (SD)	Search parameters %, (SD)	Select inventive principles %, (SD)	Ideation %, (SD)
Cluster 1_{TRIZ}	28.0 (21.5)	30.4 (16.2)	32.0 (16.1)	37.3 (20.0)*
Cluster 2_{TRIZ}	40.8 (27.3)	38.8 (21.1)	37.8 (19.6)	35.0 (21.9)
Cluster 3_{TRIZ}	16.8 (17.4)	16.6 (13.5)	16.2 (13.5)	12.6 (10.8)
Cluster 4_{TRIZ}	13.8 (15.2)	14.5 (19.0)	14.2 (17.8)	15.3 (13.6)

* Distribution of cluster 1_{TRIZ} for ideation is significantly higher than for the other phases

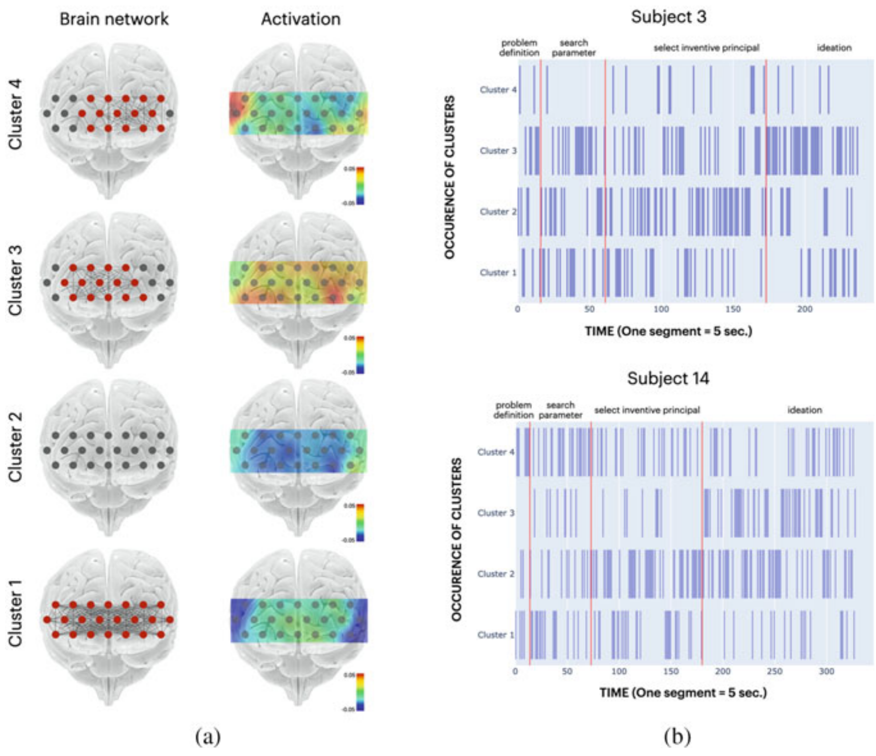

Fig. 4 **a** Representation of the brain network and brain activation in the PFC for each cluster of the TRIZ concept generation. **b** Example of the occurrence of brain states over time for two subjects

Fig. 4a). During this state of desynchronization in the PFC, the PFC was deactivated compared to other states (see activation heatmap for Cluster 2_{TRIZ} in Fig. 4a). On average, participants experienced this brain state between 35.0 and 40.8% of the time (Table 2).

The last two states represented less than 17% of brain states during any phases of TRIZ. Cluster 3_{TRIZ} was characterized by a higher synchronization of the medial and right part of the PFC (see brain network for Cluster 3_{TRIZ} in Fig. 4a). The activation for this state was higher in two channels in the right and left VLPFC (see activation heatmap for Cluster 2_{TRIZ} in Fig. 4a). This state was less frequent during the ideation phase of TRIZ.

The brain state defined by Cluster 4_{TRIZ} was characterized by a higher synchronization of the medial and left part of the PFC (see brain network for Cluster 4_{TRIZ} in Fig. 4a). In this state, higher activation occurred in the left VLPFC and the lateral part of the right DLPFC (see heatmap for Cluster 4_{TRIZ} in Fig. 4a). This state was more frequent in the ideation phase than in any other phase of TRIZ.

For each participant, the four brain states occurred with different frequency and organization within phases. For example, in the timeline representing the occurrence of brain states for two participants (Fig. 4b), we see that subject 3 experienced Cluster 4_{TRIZ} brain state much more frequently than subject 14.

Discussion and Limitations

The analysis of dynamic functional connectivity in the brain of designers provides new insight into the brain states need for generating concepts. Two parallel analyses were carried out to assess brain states when using two different techniques, morphological analysis and TRIZ. The four states that occurred when using each technique are similar. This agrees with our expectations based on cognitive studies that identify similar general cognitive actions in designing [45, 46]. One brain state was characterized by a desynchronization of the PFC (Cluster 1_{MA} state when using morphological analysis and Cluster 2_{TRIZ} state when using TRIZ). It implies that the activation of sub-regions of the PFC were not following similar trends of activation over the time window. This state was the most frequent when using both types of techniques. The average pattern of activation for both states was different between techniques: in morphological analysis, higher activation occurred in the left and medial on the PFC while for TRIZ, we observed a deactivation of the PFC with bilateral activation in the lateral part of the PFC.

Another dominant brain state was characterized by a synchronization of all the sub-regions in the PFC (Cluster 3_{MA} state when using morphological analysis and Cluster 1_{TRIZ} state when using TRIZ). This state corresponds to an activation of the whole PFC in both cases. Only for TRIZ was this state significantly more frequent in the ideation phase compared to the other phase.

The other two states suggest a synchronization of the medial and left part of the PFC (cluster 2 state when using morphological analysis and cluster 4 state when using TRIZ) or the medial and right part of the PFC (cluster 4 state when using morphological analysis and cluster 3 state when using TRIZ).

In design cognition studies, concept generation phases are qualified by similar yet different cognitive effort [17]. Therefore, we expected brain state dominance to better characterize the concept generation phase, as previously demonstrated in an EEG study that analyzed microstates [3]. The results from the study presented here clearly demonstrate a variation of brain state over time, but falls short in relying on those states to inform cognitive processes. These results could imply that although cognitive processes are different over time when designing (focusing on problem identification versus ideation), brain functional connectivities are alike. This does not directly align with previous findings in design neurocognition that suggest a change in behavior depending on the phase of a concept generation tasks [5, 13].

These results could also be a consequence of limitations of the experimental setting. In a recent study on identifying microstates while designing [3], the EEG microstate dominance over time accounted for the switch in cognitive tasks. In this previous study, cognitive tasks were analyzed based on video protocol analysis while in our study, the phases were preset and tracked during the task. This could have led to an inaccurate segmentation of the design task into phases that do not correspond to cognitive tasks. To lift that limitation, future work should measure protocol analysis and brain state analysis concurrently.

Only the PFC was monitored during our tasks. Brain networks are usually assessed at the whole brain level (see default mode network and the executive network [28, 29]). In [3], the microstates were found based on the whole brain electrical behavior. This could provide an explanation for our results: brain activation in the PFC could be similar for each phase of the concept generation process but its functional connectivity to other regions of the brain could differ. In an ongoing study, we are collecting designers' brain behavior for the whole brain. Our future work will focus on applying a similar methodology to whole brain activation data to overcome the current limitation of the study presented here.

Conclusion

In this paper, we explored the dynamic functional connectivity of the brains of designers (engineering students) while generating concepts to two different design tasks: designing an alarm clock for the hearing impaired, and designing a kitchen measuring tool for the blind. For each task, participant used a design technique to help them with concept generation. For one of the tasks, they applied morphological analysis while for the other they developed a solution following the TRIZ approach. Each technique is structured in phases such as problem identification, generating sub-solutions or ideation. Brain behaviors was monitored to assess activation patterns over time. Functional connectivity explores whether two distinct brain regions synchronize (activate/deactivate in similar patterns). Our results highlighted four similar brain states that designers experienced when generating concepts with morphological analysis and TRIZ. Contrary to our expectations, each brain states occurred in each phase of the concept generation process. Nonetheless, analyzing the dynamic functional connectivity of designers' brain behavior while designing offers a potential better understanding of design neurocognition. Our study was limited to the PFC, which could explain the lack of correlation between brain states and design cognition phases. The findings from this study will serve as inputs for future research in that direction. Better understanding of design neurocognition provides the foundation for design tools based on neurofeedback [4], a direction worth exploring in the future [47].

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