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TRIANGULATING FRONT END ENGINEERING DESIGN ACTIVITIES WITH PHYSIOLOGY DATA AND PSYCHOLOGICAL PREFERENCES

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ABSTRACT
This paper presents the experimental foundation, methodology, and pilot data from an exploratory triangulation of front end engineering design activities with physiology data and psychological preferences. The aim is to gain more measurement control over engineering design activities by "opening the black box" of the designer's cognitive state (prevalent problem solving style and momentary cognitive load measured by means of physiology data) as he/she engages in different design activities (divergent engineering activity vs. convergent engineering activity). Ultimately, we intend to contribute to the design community's pressing need for design performance metrics that will allow the comparison of various engineering design activities.
The aim is to understand and model the relationships between engineering design behavior (actual engineering activity), problem solving preference (individual psychological predisposition), and real-time physiological data of engineers (EEG, ECG, and other physiological telemetry data).

Keywords: physiology sensors, electroencephalography (EEG), cognitive problem solving preference

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1 INTRODUCTION

This paper presents the experimental foundation, methodology, and pilot data from an exploratory triangulation of front end engineering design activities with physiology data and psychological preferences. The aim is to gain more measurement control over engineering design activities by "opening the black box" of the designer's cognitive state (prevalent problem solving style and momentary cognitive load measured by means of physiology data) as he/she engages in different design activities (divergent engineering activity vs. convergent engineering activity). Ultimately, we intend to contribute to the design community's pressing need for design performance metrics that will allow the comparison of various engineering design activities (Skogstad et al. 2009).

This research is the first part of an NSF-funded project (EAGER grant) that spans the boundaries between engineering design science and cognitive science. The aim is to understand and model the relationships between engineering design behavior (actual engineering activity), problem solving preference (individual psychological predisposition), and real-time physiological data of engineers (EEG, ECG, and other physiological telemetry data). This research focuses on the early stages of product design and development and engineering system design (ESD), with potential for expansion across the entire design process.

2 PROBLEM SETTING AND RESEARCH RATIONALE

Rather than modeling the activities of individual designers as an abstract "black box", we aim to create and calibrate an in-situ measurement system that will enable us to rigorously capture, record, and analyze actual design behavior (i.e., what engineers *do*). Rather than assuming an average, generalized human subject, we are focusing on simultaneously capturing design activities, physiological data, and psychological preferences to accommodate both behavioral and psychological individualism. With this research, we intend to support and enhance the long and successful engineering design research tradition which has, for the most part, focused on capturing and analyzing the inputs and outputs of the engineering design process. We hope to develop an engineering design measurement system that will help improve decision analysis models by reducing individual behavior-based uncertainty, as well as contributing data that will support the formation and optimization of teams and that allows us to gain novel insights into the interaction between engineering designers and their contextual environments (e.g., computational and collaborative tools, space, machines).

Specifically, the speed and the quality of engineering design activities are highly dependent on the capabilities of design team members (individually and as a whole) to pivot between divergent idea generation phases that produce new concepts and prototypes, and convergent deep reasoning phases that test and down-select the alternative space by means of analytical and optimization processes (Eris 2004)(L. J. Leifer & Steinert 2011). By combining insights, models, and instrumentation from both engineering design science and cognitive science, and by applying these in the context of actual engineering design challenges, we can gain significant insights into the underlying mechanisms at work. These insights will allow us to model and support engineering design activities to a much greater degree and on multiple levels (e.g., individuals and teams).

Our research reflects the current trend toward increased rigor in the empirical study of creativity, design, and problem solving. It complements the work of Shah (Shah et al. 2000) (Shah et al. 2003) and Vargas-Hernandez (Hernandez et al. 2010), which focuses on the development and application of validated outcome-based metrics to assess the effectiveness of design ideation methods. Our work, which is based on equally rigorous methodology, extends and complements these efforts in several ways: (1) by investigating the underlying cognitive processes of designers in depth as they apply design methods (including ideation techniques); (2) by correlating those cognitive processes with psychological preferences that are also expected to have an impact on design outcomes; and (3) by using the physiological responses of designers to track and model the interactions between preference, behavior, and cognition.

2.1 Problem Setting

We place our research firmly within the classical engineering design process – see Figure 1 (Cross 2000) (Ulrich & Eppinger 2008) (Leifer & Steinert 2011). Of major importance in this process is the sequential alternating pattern of divergent and convergent phases; (Liu, Chakrabarti, & Bligh, 2003) this sequential pivoting between the two phases is the focal point of our research. Rather than depicting engineering design activities in a linear way, we may also represent the process as a series of repeating design cycles that iterate, spiral-like, through the generic prototyping phases of *design*, *build*, and *test* (see Figure 2) (Leifer & Steinert 2011). From this perspective, the pivoting between divergent and convergent phases emerges as a fundamental mechanism or building block of design.

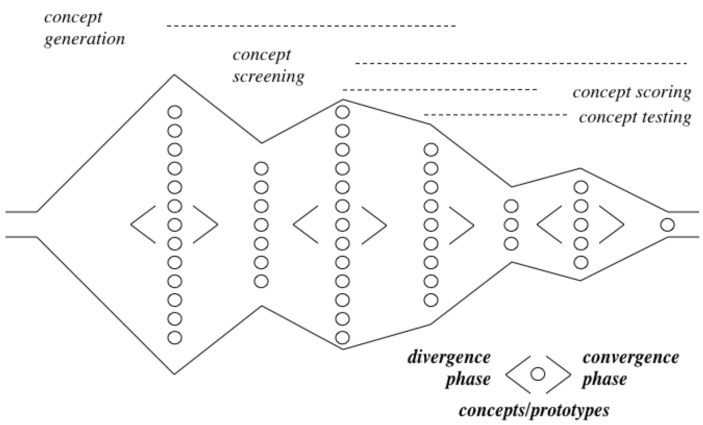


Figure 1. Engineering design process as a sequence of alternating divergent and convergent phases

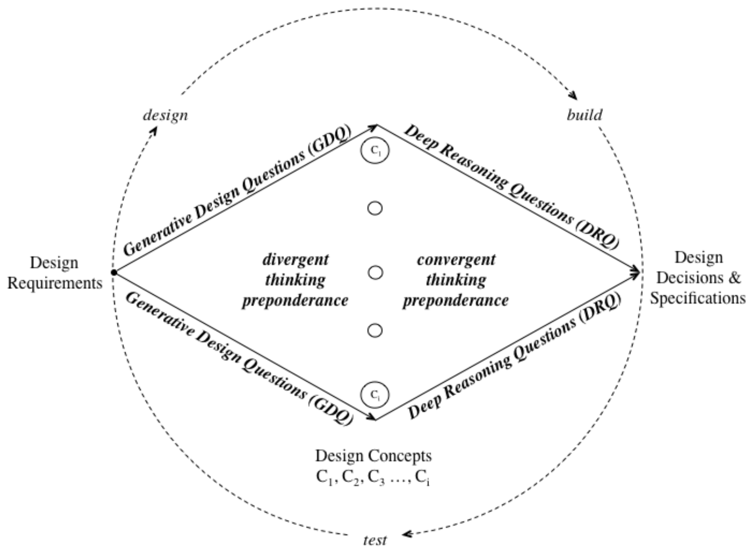


Figure 2. Pivoting between divergent and convergent engineering design activities

Through ample experience and with examples of more than 100 engineering projects gained in the last 30 years within ME310, Stanford's project-based mechanical engineering master course (Carleton & Leifer 2009), we observe (anecdotally, for the present) that individual engineers seem to favor one phase of design activity, divergent or convergent, over the other. In particular, some of the more structured and analytical engineers seem to favor the convergent phase, with its aim to systematically analyze and synthesize; in contrast, those engineers who prefer greater ambiguity, who like to explore and create "new" solutions, often seem to favor the divergent phase with its emphasis on creative generation. These observations need to be explored carefully to determine whether they reflect scientific truth or are a function of specific designer populations (for example).

As we know, radically new solutions and architectural product/system changes require an engineer to go through numerous iterations and to spend significant time in the divergent phases of design. These phases are, therefore, crucial for exploring, developing, and defining novel design requirements that solve design challenges in novel and elegant ways. Iterative cycles, rapid prototyping, creativity-based human-centered design, and "designerly" ways of thinking (Cross 1982)(Cross 2000) are the cornerstones of these activities (Dym & Little 2004) (Dym et al. 2005) (Steinert & Leifer 2012). Equally crucial, especially in the latter stages of development, is the time spent in convergent phases of design, as the analytical and structured work of those phases is critically important for creating a functional prototype and optimizing the final specifications. Besides traditional approaches like Design for X or Quality Function Deployment, methods such as TRIZ and CK-theory are currently used in these convergent phases (Altshuller 1999) (Altshuller 1999)(Altshuller & Rodman 1999)(Akao 2004) (Hatchuel & Weil 2009).

2.2 Research rationale

Based on the predominant teaching paradigm, the convergent or divergent approach tends to be favored at different academic institutions, sometimes to an extreme degree. Classically focused Mechanical Engineering Departments that have little or no exposure to designers or artists tend to focus on convergent activities, whereas places like Stanford, stimulated by the influence of its d.school (the Hasso Plattner Institute of Design) and its global ME310 course program, very actively promote divergent activities. In reality, engineers have to contribute in ***both ways*** – i.e., divergently and convergently. In essence, they are asked to behave schizophrenically by switching from an open and generative mindset that favors less structured, less constrained ideation to a highly structured and rigorous analytical mindset that favors prioritization and optimization – and vice versa.

In our educational settings, where we have spearheaded the implementation of a project-based teaching model that simulates real engineering design projects (we have real corporate sponsors, paying real money and expecting real prototypes), we can clearly identify problems within this divergent-convergent pivoting process. As a result of their individual mindsets and training, and based on the available support environment, not every student-engineer makes this switch easily. As noted earlier, we suspect that the majority of engineers may favor one phase or the other, but this link is not yet fully understood. As a result, in the better cases, engineers may abstain from participating in their respective "non-preferred" activities and not contribute; in the worst cases, they may obstruct their team when working in their "non-preferred" phase is required.

As a key to great engineering lies in accelerating the speed of iteration and prototype generation, and consequently, the pivoting between divergent and convergent design phases, we believe it is crucial to understand this pivoting mechanism better. In order to leverage the full spectrum of engineering capabilities within an individual engineer, as well as in the engineering team, we need to understand the fundamental relationships between:

1. The actual engineering design activity at hand (independent variable);
2. The general psychological mindset of the engineer (independent variable); and
3. The physiological parameters measured during engineering activity (dependent variable).

If we can clearly understand the relationships between the engineer's activity (divergent or convergent), his/her general psychological mindset (problem solving preference), and his/her actual physiological state, we will be able to identify and generate supportive tools, activities, and contextual environment settings, as well as guidelines for team composition, to enable the best possible performance from each individual. By combining the coded engineering activity, the psychological predisposition of the engineer, and real-time physiological telemetry data, we believe we will be able to open up the cognitive "black box" that has hampered prior research in this area. Ultimately, we aim to understand the pivoting mechanism between divergent and convergent engineering design activities, as we expect that controlling and leveraging this mechanism will allow us to introduce transformative design practices.

3 RESEARCH METHODOLOGY

The first phase of our research focuses on creating a proof-of-concept of the existence of a statistical relationship between *engineering design activities* (a) in the convergent phase (a_c) and in the divergent phase (a_d) and the *physiological responses of an engineer* (p) during convergent (p_c) and divergent (p_d) activity. Hypothesis H_1 (1) predicts that a shift between convergent and divergent activity can be detected and measured physiologically. Specifically, we predict that this shift will initiate a measurable change in the subject's physiological telemetry data:

$$Hypothesis\ H_1\colon \delta a_{d,c} \rightarrow \delta p_{d,c} \tag{1}$$

Additionally, based on an individual's *psychological predisposition* (b), as measured by established psychological instruments, engineers may be clustered (statistically) into homogeneous groups along a continuum/spectrum of cognitive preference. That is, we may group engineers into subjects with more or less preference for the activities typically associated with divergent or convergent thinking, respectively ($b_{d,c}$). We claim that these predispositions can be predicted based on the individuals' psychological profiles. We hypothesize that the relationship described under H_1 (1) is, in turn, significantly influenced by the psychological preference (b) of the engineer, thus creating H_2 (2):

$$Hypothesis\ H_2: \delta b_{d,c}(\delta a_{d,c} \rightarrow \delta p_{d,c}) \tag{2}$$

For example, our research aims to measure the level of anxiety or stress of individuals when they operate in their preferred and non-preferred activity states, respectively. Equipped with this measurement framework, we will be able to generate and test collaboration tools and environmental conditions that will facilitate individual team members to actively support the entire engineering endeavor (and team), even when they are in a state of heightened anxiety and coping. As a final goal, we should then be able to significantly improve design team performance by facilitating the pivoting of all team members between convergent and divergent engineering design activities by allowing each engineer to maximize her or his contribution in each phase.

3.1 Experimental Set-Up

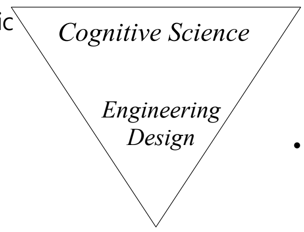
As illustrated in Figure 3, our first aim is to prove the relationships described above and to identify and iteratively improve the corresponding conceptual framework and measurement system.

psychology – cognitive problem solving preference
independent variables ***b***

- KAI (Kirton Adaption-Innovation inventory)
- Other established psychometric measures

physiology – physiological telemetry data recorded during engineering design activity
dependent variables ***p***

- EEG, ECG,
- Breathing wave amplitude, RR Interval, Heart Rate, Respiration Rate, Skin Temperature, Posture, Vector Magnitude
- All wireless using rugged measurement systems deployable in the field



behavior - engineering design activity
independent variables ***a***

- 1st year (EAGER): in situ, controlled single subject engineering design challenge:
    - Video observation and recording

Figure 3. Proposed components of the research framework

As a starting point for the engineering design activity (independent variable a), a controlled, single-subject, in-situ experiment was designed. Subjects were tasked with two independent exercises, which intentionally stressed divergent and convergent thinking practices (see Table 1).

Table 1. Experimental design activities – divergent and convergent tasks

Divergent Task: Alternate Designs	**Convergent Task: Pugh Comparison**
Each subject is given a design scenario in which they work for a popular soup manufacturer. They are told that they must redesign the packaging of their soup products to create an edge over the competition. Subject is tasked with drawing or describing new options or solutions in 15 minutes.	Each subject is given eight alternative designs that include criteria for a car horn. The subject is then tasked with selecting the optimal solution based on the given decision matrix and their own reasoning.

We video-recorded the activities of each individual designer, enabling us to code all activities on a timeline with high inter-coder reliability. The video coding primarily serves to capture *a*, the design activity, and to separate its divergent and convergent phases. Hence, the actual engineering design activity and the pivoting it requires between convergent and divergent phases become the foundation of our framework.

In order to monitor physiological responses (dependent variable *p*), subjects were connected to Biopac's B-alert X10 wireless EEG/ECG headset, as shown in Figure 4. This unit returns 9 channels of real time EEG PSD data (F3, FZ, F4, C3, CZ, C4, P3, POz, P4), heart rate data, cognitive state classification, and workload monitoring. Data collection included an initial 15-minute baseline data acquisition process in which individualized EEG profiles were created.

Finally, each subject was aligned along a spectrum according to their psychological preference for structure (independent variable *b*) via the Kirton Adaption-Innovation inventory or KAI® (Kirton 1976). This well-established and rigorously vetted psychometric instrument (Kirton 2011) assesses an individual's innate style of problem solving and creativity (i.e., cognitive style). The KAI has been used successfully in assessing these individual differences among engineers in both industrial and academic settings (Jablokow & Booth 2006) (Jablokow 2008) (Samuel & Jablokow 2011).

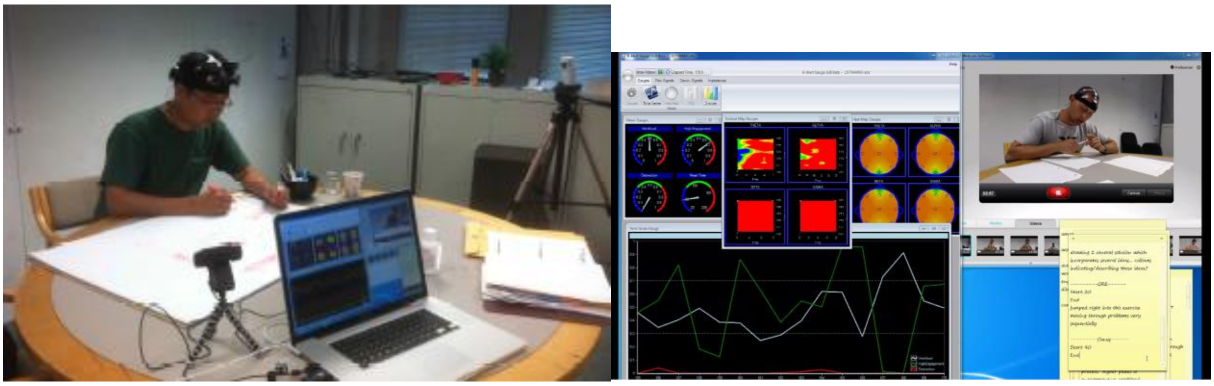


Figure 4. Subject completing design exercises with EEG, ECG, and video monitoring; Biopac GUI of real time EEG/ECG monitoring

3.2 Preliminary Findings

The first phase of this research focused on the physiological responses of the subjects depending on the engineering design activities in which they were engaged (i.e., *Hypothesis* H_1). Average power spectral densities (PSD) were calculated across 9 EEG channels for each subject and each task (divergent and convergent). Figure 5 illustrates the varying patterns for a single subject across tasks.

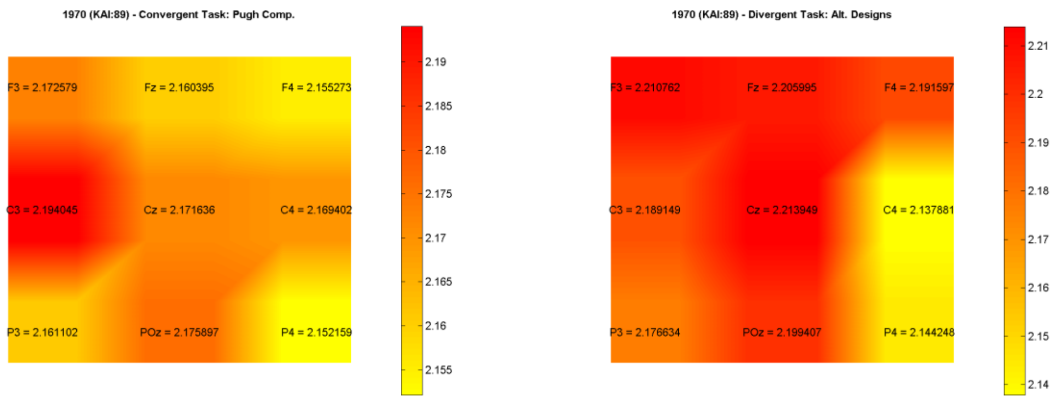
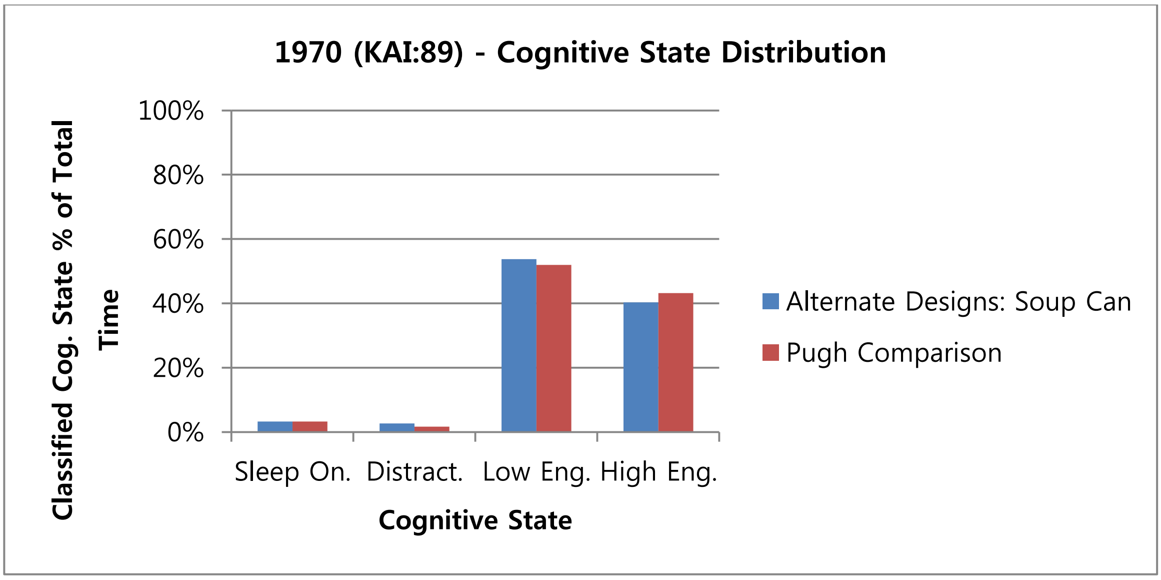


Figure 5. Average PSD for all 9 EEG channels: (Left) Convergent task (Pugh comparison); (Right) Divergent task (alternate designs). Both figures illustrate results for Subject 1970, KAI = 89.

Based on visual comparison and shifting activity centroids, we were successful in showing symmetric differences in the EEG responses of individual subjects, depending on whether they were engaged in a divergent or convergent task. While additional data collection and analysis will be needed to confirm the full support of Hypothesis 1, our preliminary results in this direction are promising. A detailed statistical analysis is currently underway.

If we look at the *psychological predisposition* (*cognitive style*) of each subject and its influence on EEG activity by comparing the distribution of cognitive states (i.e., *Hypothesis* H_2), differences may also be detected. Figure 6 illustrates the results for two different subjects (#1970: KAI=89 and #1950: KAI=114). Again, a pattern begins to emerge depending on the design tasks and cognitive style (KAI). Among other results, the more innovative subjects (higher KAI) may experience more stress during convergent tasks, while the more adaptive (lower KAI) may experience more stress during divergent tasks, as measured by higher engagement and more phases of distraction in both cases. Further analysis of these data is also underway.



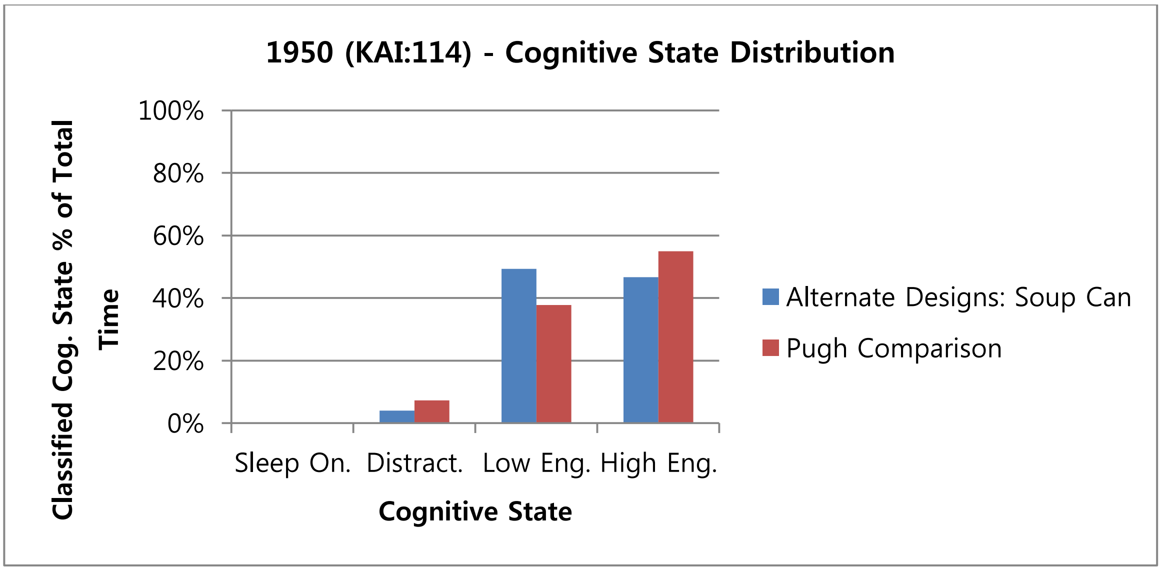


Figure 6. Distribution of primary cognitive state classifications for two subjects & both tasks: (Top) Subject 1970, KAI = 89; (Bottom) Subject 1950, KAI = 114.

3.3 Challenges and Limitations – Next Steps

Our first pilot runs were aimed at demonstrating the existence of the principal relationships proposed and testing/calibrating our measurement tools and experimental set-up; these were successful, although our results are not yet statistically significant due to the small sample size. We also encountered several problems related to using physiology data in design research. Physiological data are “messy” by nature, depending on a complex system of vastly different input conditions and including “noise” from other than the experimental controls (such as the external environment and the internal state of the subjects). In particular, we observe:

– *Internally induced “noise”:* No subject can concentrate entirely and earnestly onto the given task without occasional distraction. Our attention span is limited, and the cognitive load is never totally focused onto the primary task.
– *Externally induced “noise”:* Also, many kinds of external stimuli can and will lead to a physiological reaction.

Individual reactions to these stimuli are subject-specific and context-dependent. As a result, we had to learn (through many testing iterations) that it is of the utmost importance to control the experimental environment as much as possible. Even a small mirror left in a corner of the lab can and did induce significant distraction in one subject. Also, due to the fact that we used design tasks which needed to be understood, reflected upon, iterated, prototyped, and displayed, each physiological reaction was not uniform over the duration of the exercise. Hence, an averaging of (for example) the theta band EEG activity of a subject over the course of one entire exercise is not only unsatisfactory but not conclusive for our hypotheses testing.

We have, therefore, devised a more complex test scenario with four activity rounds for each subject that include ideation, paper-based and physical prototyping, testing, comparing, and ranking of design concepts for a planetary landing system. Each of the four activities has clearly identifiable (triggered) convergent and divergent phases. Our EEG/ECG measurement is consequently now focused on those peak phases where we specifically analyze and compare thin data slices of 5 minutes each. This generates four data sets per subject. We are currently recruiting an initial sample of 40-60 subjects from two self-selecting pools of Mechanical Engineering design students at Stanford University. The first pool targets product design engineers, while the second pool targets engineers from mechanics, flow physics, and computational engineering. We will assess both pools and their distinct KAI classification patterns to eliminate self-selection bias. Data collection will be finished during winter quarter 2013; we hope to present the first comparative results at ICED13 in Korea.

4 CONCLUSIONS AND FUTURE WORK

The experimentation thus far has served as a successful exploration and pilot study of the originally proposed project framework (Figure 3). While the small initial sample size limits our ability to make statistically significant conclusions at this time, the chosen exercises have clearly resulted in differing data sets. For many subjects, the differences in the distribution of cognitive state classifications (Figure 6) are quite pronounced between tasks. Similarly, different subjects have varying power spectral density profiles (Figure 5). These and other results give us confidence that our hypotheses will be fully supported through larger samples. Perhaps most importantly, we have identified the general approach of using physiological data capturing as worthwhile within design research.

Going forward, we will continue to calibrate the design exercises and the subjects’ physiological and behavioral monitoring, while moving to full sample data collection and analysis. At a larger scale, we hope to see statistically relevant trends in the data, which are supportive and indicative of Hypotheses 1 and 2. In the longer term, we will shift towards in-situ measurement of individuals working alone and in teams. Special attention will be given to wearable and robust physiological data loggers that record the required data with the required precision, while reducing the interference to the designer as much as possible. Similarly, we envision a shift from capturing design activity through video observation and coding alone to capturing digital activity data directly via more advanced 3D spatial movement recording.

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