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# PHYSIOLOGICALLY BASED SEGMENTATION OF DESIGN PROTOCOL

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## Abstract

The measure of a design problem's hardness is a window into human intelligence. We propose a new measure of problem hardness based on the transient microstate percentage of EEG signals. Based on the heuristic that different segments of design protocol data have different perceived hardness, we use this transient microstate percentage to segment design protocol data into domain-valid segments. Currently, two main techniques exist to analyze design protocol data: simultaneous thinking aloud and retrospective protocol analysis. Our method based on physiological measurements (EEG) mitigates the strengths and weaknesses of both methods. It was able to classify some segments as expected and discover new segments. Using EEG to solve this problem is a typical inverse problem where a thought process is reconstructed from potential-valued signals of the brain. We discuss limitations and challenges of such an approach.

**Keywords**: Design cognition, Protocol data analysis, EEG based segmentation, Problem hardness

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# 1 INTRODUCTION AND BACKGROUND

In the movie HER (2013), Theodore is a lonely writer who develops an unlikely relationship with his operating system, Samantha. One of the scenes that impressed viewers occurs while Theodore is playing a next-generation immersive video game:

> THEODORE (*playing a video game*): I have been going in circles for an hour…
> SAMANTHA OPERATING SYSTEM (*giggles*): Ok… You have got… You are just not being very optimistic… You are being very stubborn right now… Stop walking the structure… It is the other way!
> THEODORE: Hum…
> SAMANTHA OPERATING SYSTEM: Thank you… thank you… The tunnel on the left is the only one we haven't tried…
> THEODORE: No, I think that's the one you sent me where I suddenly fell down the pit…
> SAMANTHA OPERATING SYSTEM: OK… I don't think so…
> THEODORE: Hum… Yeah… This is different…

What impressed most computer scientists, engineers and video game fans is the way the AI's in the movie were able to sense the emotions of their users and the environment they are evolving in. In the conversation above, the Samantha OS is clearly sensing Theodore's perception of the game's hardness and interacting with him based on this evoked hardness. One of the problems posed by the Samantha OS paradigm is the measurement of a problem's perceived hardness. Measuring a problem's perceived hardness is effectively a window into human intelligence and ability.

## 1.1 Design Protocol Data Analysis

Two techniques are known for the study of design protocol data: simultaneous thinking aloud and retrospective protocol analysis. In design, simultaneous thinking aloud is the most popular method to study design cognition. These techniques are discussed in Ullman, Stauffer & Dietterich (1987), Enis & Gyeszly (1991), Gero & McNeill (1998), McNeill, Gero & Warren (1998), Kan & Gero (2008). On one hand, simultaneous thinking aloud is good at characterizing temporal elements of the design process. However it may interfere with the design process itself. On the other hand, retrospective protocol analysis does not impact the design process itself but may suffer from imprecisions. Both methods aim at segmenting the design protocol data into *microstrategies* such as *problem analysis*, *solution synthesis* and *evaluation*. Physiological methods constitute a third option. Physiological methods are purely quantitative and may provide additional insight where investigative and descriptive techniques do not. They rely on metrics of the human mind and body and can provide a powerful retroactive analysis tool that is non-invasive to the design process while being precise if interpreted properly.

Recently, we have developed a hands-free purely telepathic measure of a problem's perceived hardness using electroencephalograms (EEG). We developed a measure called the *transient microstate percentage* and showed that it directly relates to the perceived hardness of design problems. Using this evoked hardness, we segmented the design protocol data accumulated by the Design Lab at the Concordia Institute for Information Systems Engineering in a series of experiments conducted to measure mental effort in the design process. These experiments are described in Nguyen (2013) and Xu *et al.* (2014). Subjects were asked to solve design problems of varying difficulty while having their EEG monitored and their solution recorded on a touchpad.

In the field of EEG data analysis, microstate segmentation is being increasingly discussed. Microstates are sub-second quasi-stable configurations in the EEG scalp field maps that rapidly change to another quasi-stable configuration. They are described in the literature as being the *atoms of thought*. Significant advances were made in the field through the work of Koenig *et al.* (1999,2002), Lehman *et al.* (1971,1987), Pascual-Marqui *et al.* (1995) and Blankertz *et al.* (2010).

## 1.2 Measuring the Hardness of Design Problems

Next generation CAD/E systems are being studied and aim at incorporating new dimensions such as *collaboration, conceptualism, creativity, cognitivity* and *environment-awareness*. These are discussed in Goel *et al.* (2012) and Zeng & Horváth (2012).

A fundamental aspect of this endeavor is to be able to measure the hardness of a design problem, whether it be perceived or evoked. The perceived hardness of a design problem is effectively a window into human ability. As a parameter in a Human-Computer Interface (HCI), it becomes a key component of a subsystem's interactivity. As subsystems become more collaborative, measuring design task hardness becomes a recurrent problem.

The traditional computational approach to measure the hardness of a problem is to measure the complexity of the underlying algorithm used to solve the problem. In the context of design, the notions of hardness and creativity are also related. Nagai & Noguchi (2003) report a set of experiments that link the difficulty of keywords describing design problems to the perceived hardness of the problem. An assumption about cognitive loads and their impact on creativity was proposed in Zeng (2005) and was studied by Sun & Yao (2012). On the other hand, Dinar *et al.* (2014) propose an extensive survey of methods used to analyze design protocol data. Concepts such as problem iteration, the role of sketches, protocol data encoding, fixation, mimetism and the usage of fMRI technology are surveyed.

At least four approaches to measuring the hardness of design problems can be found: the axiomatic approach, the conceptual approach, empirical approaches and the physiological approach. Axiomatic approaches such as those based on Design Axioms have been proposed and are being studied by Suh (1990) in the context of functional requirements and systems design processes. Following Suh's design axioms, *bad* designs do not maintain the independence of the functional requirements and do not minimize the information content of the design. The *hardness* of a design task specification can then be understood in terms of the two axioms. Conceptual approaches such as those based on the Recursive Object Model (ROM) have been proposed by Zhu et al. (2007) and Zeng (2008) to measure mental effort and stress. Experiments show that information encoded using a ROM diagram is more effective than natural language. Other conceptual methods surveyed in Dinar *et al.* (2014) are based on P-Map and the FBS model (Function-Behavior-Structure). Empirical approaches are based on direct experimentation and observation. They typically observe sequences of events and interaction. The physiological approach is an emerging method (cf. Nguyen & Zeng (2010-14)).

### 1.3 Physiological Methods

Recently, physiological approaches have been devised to study the hardness of design problems. Heart-rate variability and task hardness have been experimented with by Moriguchi *et al.* (1992) in the context of medical research and Nguyen & Zeng (2014) in the context of design sciences. Tang & Zeng (2009) propose to measure movements (kinesics) to parameterize problem hardness and mental effort. The approach taken in this paper follows the momentum gained in Nguyen & Zeng (2010, 2012, 2014). Kakizaki (1984) showed that the amplitude of EEG alpha and beta bands increased when subjects were performing *hard* subjectively rated tasks. Quantitatively, the next step was to use microstate analysis to measure physiological phenomena that occur when solving design problems of varying hardness. Physiological methods have the benefit of being hands-free and purely quantitative. They lend themselves to be utilized in engineering systems and devices.

Immersive Brain-Computer Interfaces (BCI) are not pure science-fiction and they have been well-studied in the past decades in the context of not only next-generation immersive video games, but also medical devices, smart home design, CAD/E systems and design sciences. Such applications can be found in Graimann *et al.* (2010), Carabalona *et al.* (2012) and Nguyen & Zeng (2010-14). The importance of measuring environment-based parameters as discussed in Zeng (2004, 2011) for the development of these next-generation smart systems is non-negligible. The idea is to layer traditional AI and machine-learning techniques with human-centric dimensions such as *collaboration*, *conceptualism*, *creativity* and *cognition* stated in Goel *et al.* (2012). It can be noted that current commercially available BCI headsets are able to measure mental stress and strain in addition to eye and head movements using built-in accelerometers and algorithms.

The rest of this paper is organized as follows: Section 2 briefly reviews EEG data analysis and microstate segmentation. Section 3 discusses the segmentation of design data protocol data using the transient microstate percentage as a discerning metric. Section 4 discusses experiments that were performed to measure a problem's perceived hardness and its application to design protocol segmentation. Section 5 proposes a discussion and Section 6 concludes and proposes future work venues.

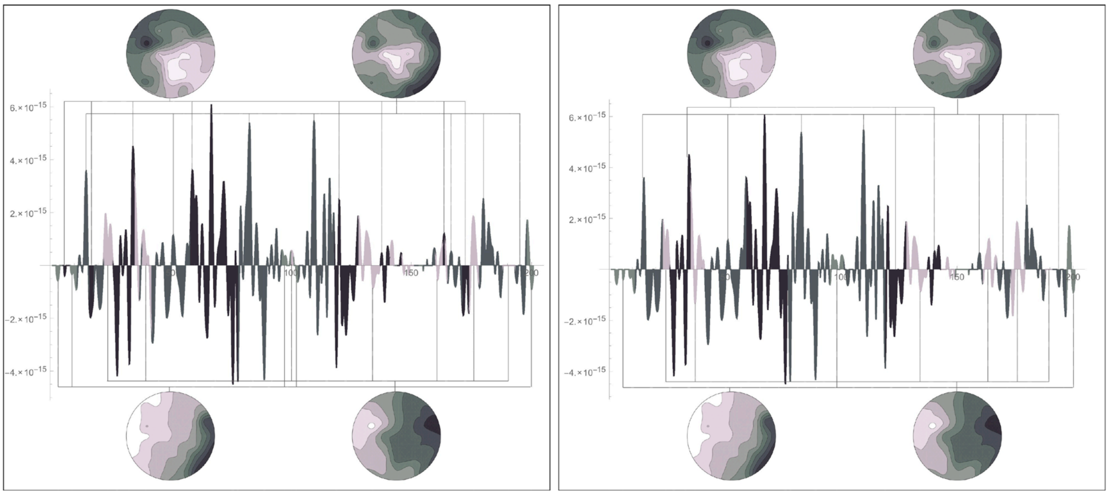


*Figure 1. Segmentation of an EEG signal using the P2ML algorithm (left) and smoothed segmentation using the regularized P2ML algorithm (right). The microstates to which each segment is related are shown above and below*

## 2 MICROSTATE SEGMENTATION AND REGULARIZATION

Electroencephalograms are a sequence of potential values measured at different electrode positions (*cf.* Michel *et al.* (2009)). At a given time *t*, the number of potentials corresponds to the number of electrodes used in the EEG apparatus. The mean-normalized average of these electrode values is called the global field power, a set of which yields a global field power curve.

Another important feature of EEG signals are the microstates (*cf.* Michel *et al.* (2009)). Microstates are sub-second quasi-stable patterns in the scalp field potential values of an EEG. An EEG typically alternates between different microstates. The P2ML algorithm proposed by Pascual-Marqui, Michel and Lehman (1995) algorithm is a popular method used to compute these microstates and to find a segmentation of an EEG according to the computed microstates.

For some EEG potential values at time *t*, $V_t \in \boldsymbol{V}$ and the $k^{th}$ candidate microstates $M_k \in \boldsymbol{M}$, the P2ML algorithm optimizes the following objective function:

$$\arg\max_k\{(V_t^T \cdot M_k)^2\} \tag{1}$$

The objective function effectively clusters scalp field potentials into K clusters with centroids given by their corresponding microstates. Finding the microstates amounts to iterating the objective function. The result of the P2ML microstate segmentation algorithm is a sequence of labels corresponding to the microstate labels. For example, if 4 microstates are used, the result could be a sequence S=(1,1,1,1,2,3,3,3,3,4,4,4,1,1,1,1,…). It can be noted that the 5th value of the sequence is a 2 and corresponds to a low-duration flashing microstate. Such low duration microstates have been shown to have significant physiological meaning by Koenig et al. (1999) and Koenig et al. (2002). To address the smoothness of the microstate segmentation, Pascual-Marqui et al. (1995) developed a regularized P2ML microstate algorithm by introducing a smoothness penalty factor in the objective function of P2ML. The smoothness penalty factor is defined as:

$$E_t = \sum_{i=t-w}^{t+w} \delta\,(S_i, n), \quad n = 1, \dots, K \tag{2}$$

where δ is the (0,1)-Dirac delta function and *w* is a sliding window length defining a window of length 2*w.* The regularized P2ML objective function is then given by:

$$\arg\min_k \left\{ \frac{\left(V_t^T \cdot V_t - \left(M_k^T \cdot V_t\right)^2\right)}{2e(N-1)} - \lambda E_t \right\} \tag{3}$$

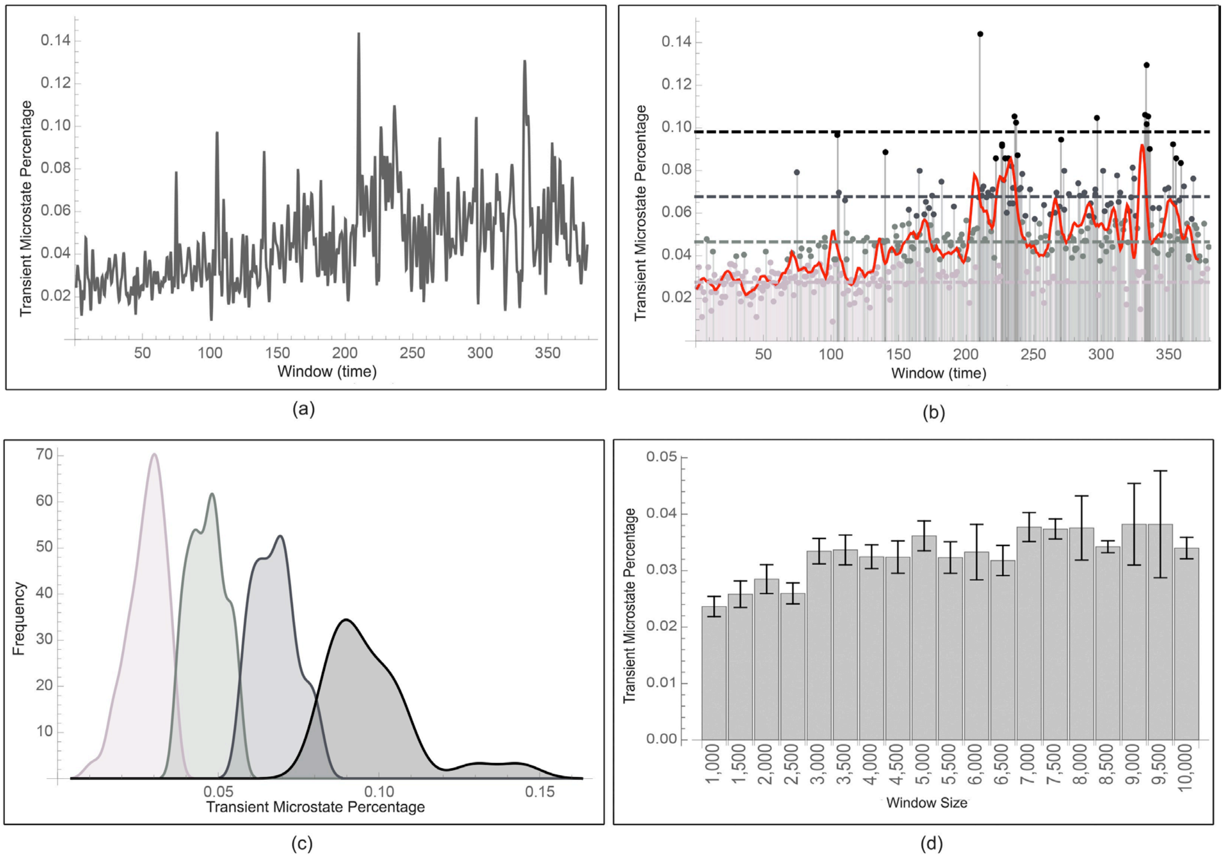


*Figure 2. (a) shows the time-varying transient microstate percentage of EEG signals of a subject who was asked to perform a set of tasks over 30 minutes. In (b), the transient microstate percentage curve was classified into eyes-closed/very easy segments (lighter gray) easy segments (light gray), average segments (gray) and hard segments (black). A trending curve was added. In (c), histograms were computed. Lower microstate percentages correlated with easier tasks while higher microstate percentages correlated with harder tasks. In (d), the transient microstate percentage was computed on a subject with eyes closed using different window sizes. The percentage shows stability with respect to window size*

where $e$ is an error value and $\lambda$ a smoothness penalty parameter. Given some appropriate regularization parameters, the resulting smoothed segmentation could then be (1,1,1,1,1,3,3,3,3,4,4,4,1,1,1,1,…). The low-duration *flashing* microstate is then effectively replaced by the microstate that incurs the smallest smoothness and distance penalty. Examples of microstates are computed using the regularized and non-regularized P2ML algorithm in Figure 1.

## 3 PHYSIOLOGICALLY BASED SEGMENTATION

While microstate segmentation effectively segments an EEG, the problem of segmenting design protocol data stems from another application domain. The heuristic we use to perform the segmentation of design protocol data is that the expected perceived hardness of two different subtasks is different. We therefore segment the protocol data into windows of a given time length and aim at measuring the hardness of these subtasks to distinguish them. Adjacent segments of similar measured hardness are then considered to be part of the same subtask. Obviously, this is a necessary condition to make a proper segmentation, which may result in a segment consisting of different types of activities. Sufficient conditions for the proper segmentation will be studied in our further research.

We propose a physiological approach to measuring this perceived hardness, based on which the hardness of a task is given by the transient microstate percentage. The transient microstate percentage is given by:

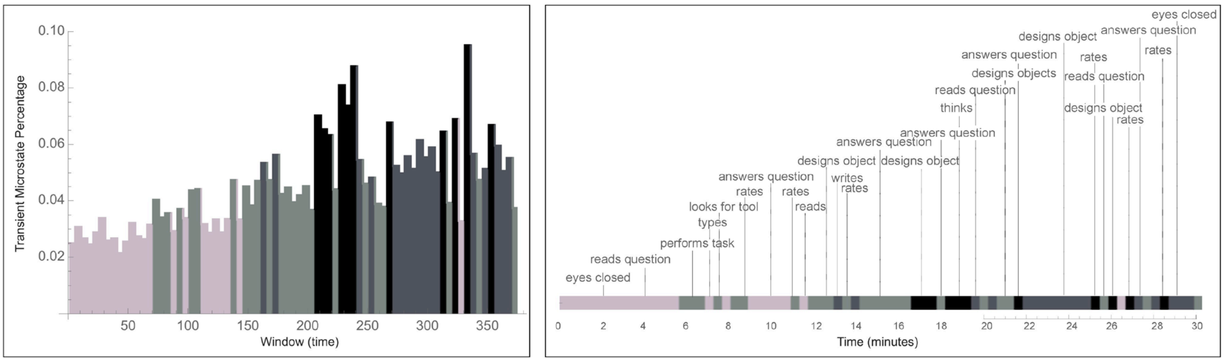


*Figure 3. Segmentation of design protocol video based on the transient microstate percentage. A window size of 5 (25 seconds) was chosen. Values in the window were averaged. The resulting values were clustered into 4 clusters*

$$H(V_1, \dots, V_N) = \frac{numSegments - numSmoothSegments}{N} \quad (4)$$

The number of segments is given by the number of discontinuous segments obtained using the P2ML algorithm while the number of smooth segments is given by the number of segments obtained using the regularized P2ML algorithm. For example, the segmentation (1,1,1,2,2,3,4,1) has 5 discontinuous segments. In Figure 1, the P2ML segmentation has 37 discontinuous segments while the regularized P2ML segmentation has 22 discontinuous segments.

The transient microstate percentage effectively measures the number of short duration *flashing* microstates. These microstates were determined in the related literature to be significant physiologically and were characterized as being the *atoms of thought*. This number is always positive and can be shown experimentally to camp between 1% and 20% on average. A clear gap can be found between the transient microstate percentage of a subject who was asked to keep his eyes closed and a subject who was asked to solve a design problem. We posit that tasks perceived to be easy are shown to have a lower transient microstate percentage than tasks perceived to be hard.

Once the transient microstate percentage curve is computed on an EEG signal (typically a signal of a given sample size such as 2,500 samples), these values are aggregated into groups of windows (e.g. 5 windows) and the data is clustered. Since the clustering algorithm is evaluating single values, no significant performance penalty is incurred. Different segments are then defined as clusters with different cluster neighbors.

## 4 EXPERIMENT AND ANALYSES

The data that was used in this study contained video sequences of a subject who was asked to perform a set of design tasks on a touchpad while having his/her EEG monitored. After each task, the subject was asked to grade the level of difficulty of the task. The experiment lasted around 30 minutes. Details of experimental setting and experimental tasks can be found in Nguyen (2013) and Xu *et al.* (2014). In summary, the subjects were asked to alternate between 2 types of tasks: answering multiple choice questions on design problems that presented different alternatives to solve a given problem and designing a solution to a design problem by drawing a sketch. After each tasks, the subjects were asked to rate the hardness of the problem as they perceived it.

In a first set of analyses, we computed the transient microstate percentage of longer EEG epochs by using the P2ML and regularized P2ML algorithms for the subject. Figure 2(a) shows these percentages. The transient microstate percentage is a stronger figure than the number of transient microstates because it can be used when two sequences do not match in length and it can be shown to not be sensible to sequence length.

In a second set of analyses, the time-varying transient microstate percentages of the EEG sequence was used to segment the task execution video obtained on a touchpad into subtasks. The dataset used in Figure 2(a) is the same as the dataset used in Figure 2(b) and was obtained by measuring the EEG of a subject who was asked to perform various tasks for a duration of about 30 minutes. The epoch of 30 minutes was then divided into windows of 2,500 samples at a sample rate of 500 samples per

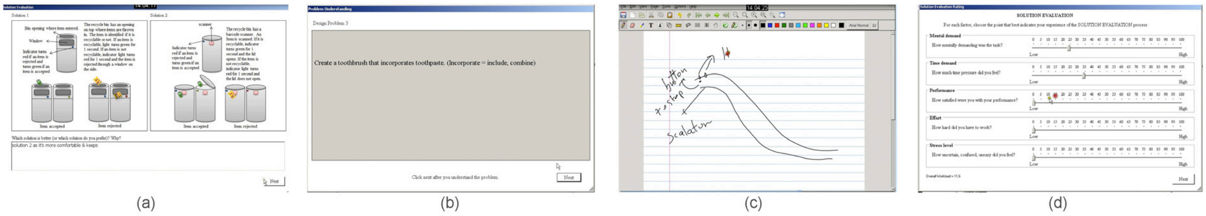

*Figure 4. (a) displays a typical answer question segment, (b) a read question segment, (c) a design object segment and (d) a rate problem segment*

second and the transient microstate percentage of each window of about 2.5 seconds was computed. The transient microstate percentage curve was segmented into four categories: resting/very easy, easy, average and hard. Figure 2(c) shows that the very easy category peeks at a transient microstate percentage value of 0.025, the easy category at 0.045, the medium category at 0.065 and the hard category at 0.10.

In a third set of analyses, we tested the stability of the transient microstate percentage with respect to the window size. We computed the transient microstate percentage of a subject with eyes closed over different window sizes. We expected that the transient microstate percentage remain within the same range. Figure 2(d) illustrates this analysis.

In a fourth and last set of analyses, we compared the segmentation of the design protocol data obtained using transient microstate percentages with the actual video of the protocol data. These experiments are illustrated in Figure 3.

## 5 DISCUSSION

Our design protocol data was a set of videos taken from the touchpad on which subjects were asked to perform various design tasks of varying hardness. Screenshots of the experiment are shown in Figure 4. The EEG of the subjects was monitored and, after each task, a short questionnaire on the perceived hardness of the task was handed.

Such design protocols were a sequence of segments where the subjects were asked to keep their eyes closed and segments where the subjects were asked to perform tasks.

By characterizing a segment of a design protocol dataset by its perceived hardness, we have effectively introduced a metric to perform the segmentation of these protocols using monitored EEG signals. Harder tasks have harder levels of transient microstate and easier tasks have lower levels of transient microstate.

The transient microstate percentage of a subject with eyes closed typically ranges from near 0% to 4% while the transient microstate percentage of a subject who is asked to perform tasks ranges from 5% to 18%. Easy tasks range in the lower spectrum while harder tasks range in the higher spectrum.

When using the transient microstate percentage to segment design protocol videos, the accuracy was surprisingly high in detecting, within a given range, segments such as *read question, rate question, design object* and *answer question*. The *think* segment in the experiment was defined as a sequence in the video where the subject paused while designing an object or answering a question. More specifically, we noticed that the *rate* segments were classified as having high transient microstate percentage. Furthermore, *design* segments were classified on average as having larger transient microstate percentages. The design protocol data started and ended with an *eyes closed* segment. The first *eyes closed* segment was detected as having a low transient microstate percentage while the second segment had a mid- transient microstate percentage. This may be due to the fact that, following the 30 minutes experiment, the subject was not thoroughly resting. It was however properly segmented. Some expected segments were properly classified while others were not, which may be resulted from the fact that the proposed segmentation criterion (hardness) is only a necessary condition for a proper segmentation. Furthermore, unexpected segments were discovered, which may be because in conducting a design activity a designer may experience different levels of difficulty for the activity period. Like in most data mining approaches, false positives are to be expected. Table 1 summarizes the results of the design protocol segmentation for a series of experiments.

*Table 1. Design protocol data segmentation results of a task lasting around 30 minutes. Bolded events were the events discovered by the segmentation algorithm while non-bolded events were expected. Segments marked with an asterisk were unexpected but made sense in the design protocol. 33 segments were discovered using the EEG-based method. 32 segments were expected from a post-protocol analysis. EEG-based methods excel at discovering internal articulations in expected events. For example, after writing a solution, the subject decided to consult the experiment instructions and this segment was discovered. Furthermore, while designing particular objects, sub-object design was often discovered*

| | | | | |
|---|---|---|---|---|
| 0:00 - Eyes closed | 11:30 - Reads question | 17:43 - Rates | 21:40 - Reads | 26:55 - Designs object |
| 4:20 - Reads question | 11:55 - Reads (cont.)* | 18:00 - Reads | 22:20 - Answers question | 27:20 - Designs object (cont.)* |
| 4:41 - Designs object | 12:20 - Designs object | 18:35 - Answers question | 22:45 - Answers (cont.)* | 27:45 - Rates |
| 6:05 - Adds object* | 13:35 - Rates | 19:00 - Answers (cont.)* | 23:12 - Rates | 28:10 – Reads question |
| 7:20 – Writes* | 14:00 - Reads question | 19:26 - Rates | 23:30 - Reads question | 28:35 – Answers question |
| 7:45 - Consults instructions* | 14:25 - Answers question | 19:39 - Reads | 23:46 - Design object | 28:30 - Rates |
| 8:10 – Rates | 14:50 - Answers (cont.)* | 20:15 - Designs object | 25:17 - Rates | 29:00 - Eyes closed |
| 8:35 - Reads question | 15:43 - Rates | 20:40 - Designs (cont.)* | 25:30 - Answers question | 29:25 |
| 9:25 - Answers question | 16:30 - Reads | 21:05 - Designs (cont.)* | 26:05 - Rates | 29:50 |
| 9:55 - Evaluates | 17:20 - Designs object | 21:30 - Rates | 26:30 – Reads question | 31:05 |

## 6 CONCLUSION

In this paper, the transient microstate percentage is introduced as a new measure to assess problem hardness. Based on the heuristic that different tasks have different perceived hardness, we have effectively segmented design protocol datasets. These protocol datasets were segmented into eyes closed, easy, average and hard subtasks. Compared to traditional segmentation which depends on subjective judgment, the proposed EEG based method is more objective and less labor-intensive. Future work would involve alleviating our experimental dependency on subjective ratings.

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