Measuring State and Trait Attention Control Using Mouse Movements

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***Abstract* - Attention is a scarce resource in an increasingly distracting world. Although computing devices might well be blamed for much of the distraction we experience, these devices also afford an opportunity for feedback and improvement, as seen in a variety of contexts. This paper provides initial evidence that mouse movement data can be used to measure users' attention control. Attention control refers to the ability to maintain top-down attention to goal-relevant stimuli and resist the distracting influence of irrelevant stimuli competing for attention. During a controlled experiment with conditions of varying levels of distraction, we captured participants' mouse movements to determine whether mouse movement data can be used to detect both state and trait attention control. We discuss various applications of this approach as a feedback mechanism in situations where maintaining focus is an important determinant of system success, such as in online learning or training scenarios.**

Keywords – attention, distraction, mouse tracking, behavior analysis, human-computer interaction

I. Introduction

Attention is a scarce resource in the modern economy [1], becoming scarcer all the time as devices, feeds, and notifications compete for attention in an increasingly crowded technological landscape [2]. Among other effects, the proliferation of these technologies has had a general impact on many users' ability to manage and focus their attention [3], driven mainly by a near-constant barrage of distractions [4].

Even without an array of distractions vying for attention, our species' inability to sustain focused attention is well documented across a broad range of stimuli and environments [5]. Maintaining focus on a particular goal is effortful, requiring executive functions that consume cognitive resources such as working memory [6]. When those resources are depleted—because of distractions or from frequent task switching—cognitive performance suffers [7, 8].

Although technology certainly plays a role in this attention problem, it may also be part of the solution. Research has demonstrated that real-time feedback about whether one is becoming distracted can help focus a wandering mind [9] and attention feedback systems have been studied in a variety of contexts, from distracted driving [10] to the workplace [11, 12].

A key drawback of existing attention feedback systems is their reliance on dedicated sensors to detect and monitor attention or focus. These include eye tracking [12, 13], functional magnetic resonance imaging (fMRI) [9, 14], or electroencephalogram (EEG) devices [15]. Although effective in providing real-time monitoring of attention, these technologies may not be practical for more general use, particularly in everyday web contexts.

This paper describes an alternative approach to real-time attention monitoring using mouse movements and describes the results of an initial test of the approach in a web-based setting. Based on the concept of attention control (AC) [16] and drawing on dual-process theory [17], we hypothesize that mouse movement data can be used to measure trait AC (i.e., an individual's general propensity to maintain attention during goal-directed tasks) and to detect changes in state AC (i.e., to determine when an individual has become distracted during a given task).

In summary, the research question that guides this research is:

Can mouse-cursor movements be used to measure both trait and state attention control during a goal-directed task?

We address this research question by first summarizing prior research on attention feedback systems and related applications of mouse movement data. We then use dual-process theory and the response activation model to explain how and why mouse cursor movements can serve as a proxy for attention control. We summarize a controlled experiment that evaluates our hypotheses and conclude with a discussion of the results of our study and implications for future research.

II. Previous Research

Dual-process theories divide mental processing into two broad systems or types [18]: one that is reflexive, automatic, impulsive, and habit-driven, and another that is rational, logical, controlled, and cognitive [19]. Higher cognition—referred to as *executive control* [20]—results from the second system directing attention to the task at hand and, when necessary, intervening to override irrelevant distractions that activate the lower-level, automatic system [21, 22].

Based on this dual-process view, many attention monitoring systems measure neurological activity, watching for signs that mental processing has shifted from the higher-level system to the reflexive, automatic system, indicating that the individual has become distracted. For example, EEG devices can detect sustained attention and provide real-time feedback to the wearer, significantly increasing focused attention [15]. Similar EEG monitoring and feedback systems have shown promise in improving outcomes in real-world scenarios, including therapeutic settings [23] and in the workplace [11].

Another application of attention monitoring and feedback uses fMRI to provide real-time feedback that indicates when someone has lost focus—a phenomenon known as mind wandering [24]. Researchers monitored brain-imaging data in real time and intervened when lapses in attention were detected, improving the focus and performance of study participants who received this "neurofeedback" [14].

Although these monitoring techniques provide relatively direct measurement of attention and focus, they are not practical for many everyday situations, despite the increasing availability of more wearable EEG sensors [e.g., 25]. By contrast, mouse movement data is ubiquitous in desktop computing situations and requires no specialized hardware. Mouse data has been used to infer attention in web-based settings [e.g., 26, 27], though much of this prior work has used mousing data as a way to measure and improve search engine results [e.g., 28, 29] or has been exploratory in nature without incorporating a theoretical lens to understand the mechanisms through which attention and distraction affect mouse movements [30, 31].

However, prior research has demonstrated that mouse movement data also reveals dynamic cognitive processes [32, 33], based on the notion that cognitive demands compromise motor function. Thus, mouse movements can detect deception [34], frustration [35], or fraud [36], using methods compatible with real-time monitoring that can detect state changes [37]. As dual-process theory argues, maintaining attention during goal-directed behavior is a process that evolves over time, whether because of a wind-wandering loss of focus or because of distractions. Thus, the present research explores whether mouse movements could be used to detect differences in attention, as informed by the cognitive resource perspective detailed in the next section.

III. Theory and Hypotheses

Dual-process theory explains that goal-directed behavior is guided by the intentional application of attention to a given task [20]. This process of *attention control*—defined as maintaining focus on goal-relevant information, particularly in the face of distraction [16]—requires cognitive effort and is compromised when cognitive resources are strained [38-40].

Individuals differ in their capacity for sustaining the cognitive resources AC demands [41]. Those who measure higher in this individual trait are less susceptible to distraction [42] and tend to perform better in, for example, academic settings [43]. Individuals can also improve their trait AC through practice or training, becoming less susceptible to distractions and better able to sustain focus over time [44, 45].

Distinct from trait AC, state AC is a measure of an individual's ability to maintain attention during a given task and can be influenced by various aspects that influence the cognitive demands of the task. For example, a perceived threat [46] or other negative emotion [38] will decrease state AC, and distractions or other sources of cognitive burden during a task will temporarily deplete an individual's AC [40, 47]. As prior research has shown that trait and state AC are distinct concepts [45], we treat them separately in this work, exploring whether mouse movement data can serve as a proxy measure for one's trait AC (see H1) as well as measure differences in state AC resulting from experimentally induced distraction (see H2).

Dual-process theory is used to explain the underlying mechanisms linking attention and distraction to motor movements, most notably in the Response Activation Model (RAM) [48]. The RAM argues that as a person interacts with the surrounding environment, stimuli with actionable potential are evaluated and selectively inhibited as movement toward goal-relevant stimuli is ultimately accomplished. Thus, the attention and movement systems are intimately linked [48]—perhaps resulting from their co-evolutionary roots [49]—and monitoring hand movements can reliably reveal many different attention-related processes [50].

A growing body of prior mousing research has demonstrated that cognitive demands result in slower, more deviant, inefficient mouse movements, whether because of negative emotions [35], deception [34], or various forms of cognitive conflict [33]. Following this prior work and the dual-process RAM [48], we argue that a mouse user's ability to maintain focus—both in general and in the face of temporary distractions—can be inferred from that user's mouse movement patterns. Specifically, we hypothesize that higher AC will be characterized by faster, more efficient (i.e., with shorter distances), while low AC will be associated with slow, distracted, inefficient mousing patterns. These assumptions are incorporated for trait and state AC separately in the following hypotheses:

H1: Mouse movements of individuals with low trait AC will be (a) slower and (b) cover more distance than individuals with high trait AC.

H2: Mouse movements of individuals in a distracted state will be (a) slower and (b) cover more distance than individuals who are not in a distracted state.

IV. Methodology

We tested our hypotheses using a within-subjects experiment in which participants completed a simple mouse-clicking task on a website created by the research team.

A. *Procedure*

The task was adapted from a common experimental task in the attention research literature in which participants perform a visual search to identify a single target among several distractors [51]. A typical mousing–attention study uses highly controlled tasks with a single movement path from a starting location to a target [52]. We expanded and adapted the task to allow for more extensive mousing behavior that more closely approximates real-world web environments. Specifically, each trial asked the participant to click on a series of four numbered targets in sequential order. While the participant clicked the targets, the interface either displayed the numbered targets alone (high attention control) or also displayed four distractor targets and a distractor image to the right of the target area (low attention control). The distractor targets were visually identical to the numbered targets except that they contained letters. (The interfaces for the low AC and high AC treatments are shown in Figures 1 and 2.) The order of the conditions was randomly counterbalanced across the participants.

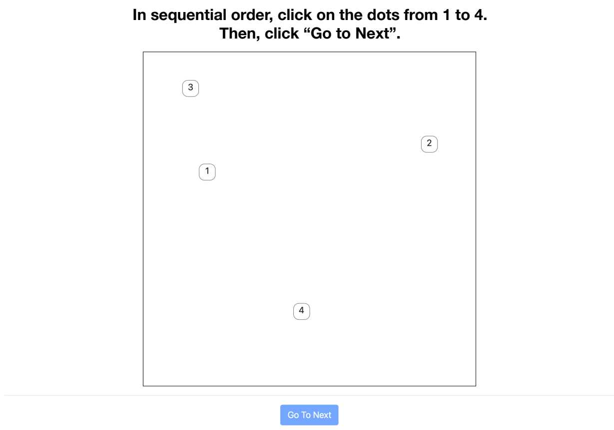

Figure 1. High Attention Control Task.

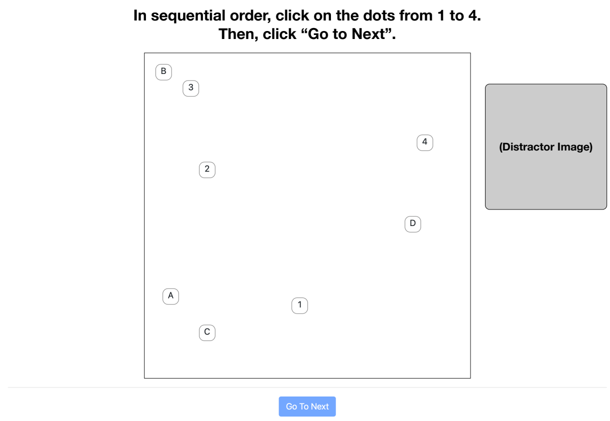

Figure 2. Low Attention Control Task.

After completing the clicking task, participants were presented with a concluding survey. As a manipulation check, the survey displayed screenshots of the interfaces used in each condition and asked the participants to rate them in terms of how distracting the interface was. The post-survey also collected the *attentional control scale* (ACS) [53], a widely used survey measure of trait AC, as well as demographic information.

B. *Participants*

A total of 223 students from a large, private university participated in the study in exchange for 0.25% extra credit applied to a participating management course of their choice. Approximately 49% of the participants were male, 85% were from the USA, and the average age was 21.8.

C. *Mouse Movement Data*

The web interface contained embedded JavaScript that captured mouse movement data during each trial. The library captured the x- and y-location of mouse movements, along with timestamps, which were then sent to a server to calculate speed and distance features.

We calculated the total distance for each trial by summing the Euclidean distances between each pair of x-y positions a_i and a_{i+1}, given by the following equation: $d(a_i, a_{i+1}) = \sqrt{(a_i^{(x)} - a_{i+1}^{(x)})^2 + (a_i^{(y)} - a_{i+1}^{(y)})^2}$. This translates to a total distance of $D = \sum_{i=1}^{n-1} d(a_i, a_{i+1})$ between the recorded points a_1, a_2, …, a_n. Speed was then calculated as a function of cursor distance D and trial time t, and is thus measured in pixels per second: $v = D / t$.

D. *Analysis*

We first used the manipulation check data to ensure that our experimental design reduced state AC as intended. A Wilcoxon rank sum test indicated that participants ranked the interface from the low AC condition significantly higher in terms of how distracting the interface was during the task.

To test whether our two mouse movement measures could be used to effectively differentiate between different levels of trait AC, we used the ACS survey items. The ACS contains two subscale scores that represent different aspects of trait AC—*focusing* and *shifting* [54]. Thus, we first performed a basic factor analysis to evaluate the factor structure of the items, eliminating items that loaded poorly on their intended factor or that significantly cross-loaded on both factors. The remaining items were then averaged to derive a single, continuous measure of trait AC that could be included in subsequent analyses.

We first tested the first-order correlations among trait AC and our measures of speed and distance. The results revealed significant correlation between speed and distance (r = *.65*), but nonsignificant correlations close to zero between trait AC and speed (r = *.04*), and trait AC and distance (r = *.03*). Two additional tests for a possible relationship between trait AC and the two mouse movement measures were performed to further confirm the lack of results. First, to eliminate possible noise from the distractors used in the low AC condition, we performed the same correlation analysis using only mousing data from each participant's high AC trial. Second, we categorized each participant's trait AC score into one of four quartiles, comparing those individuals in the bottom quartile with those in the top quartile. Both of these additional tests revealed no significant relationship between trait AC and the mousing measures (i.e., H1 was not supported). Thus, the trait AC measures were excluded from subsequent analysis. (These nonsignificant results are discussed further in the discussion section.)

Next, we tested whether the mouse movement data could effectively differentiate between state AC, comparing each participant's mousing data from the two experimental conditions in a mixed-effects linear regression analysis. Mixed-effects models use random effects to account for individual differences in repeated observations [55]—including differences in natural computing ability or, importantly, trait AC that may not be well captured by the ACS measures—and fixed effects to model the treatment effects—in our case, the high versus low AC manipulation. (Table 1 provides the descriptive statistics for the two conditions.)

We specified one model with mousing speed as the dependent variable and a second with mousing distance as the dependent variable, allowing a random intercept for each participant and specifying the AC manipulation as a fixed effect. The regression model results are summarized in Table 2. Both models revealed significant effects resulting from the AC manipulation, providing initial evidence that mouse movements may be used as a proxy measurement for state AC. Thus, H2 was supported. The implications of our results and plans for future follow-up work are detailed in the next section.

TABLE I. MEAN (SD) OF MOUSING MEASURES BY CONDITION

Trial Condition	*Speed (px/s)*	*Distance (px)*
High AC (no distractions)	460 (130)	3,180 (926)
Low AC (with distractions)	427 (135)	3,550 (1,086)

TABLE II. MIXED-EFFECTS MODEL RESULTS

Fixed Effect	*Estimate*	*Std. Err.*	*df*	*t-value*
DV: Speed (px/s)				
(Intercept)	459.6	8.9	331.9	51.8^{***}
Low AC	-32.3	8.1	222	-4.0^{***}
DV: Distance (px)				
(Intercept)	3179.7	67.6	381.2	41.1^{***}
Low AC	370.8	73.7	222	5.0^{***}

V. DISCUSSION AND FUTURE RESEARCH

The goal of this research was to investigate whether mouse movement data can be used as a proxy measure for the attention (or, conversely, distraction) of the user in a web-based setting. The dual-process view explains how attention is managed by two different systems, with distractions adding additional cognitive burden during goal-directed tasks [20]. Prior research has demonstrated that dynamic feedback about individuals' level of sustained attention can significantly improve their focus and other related outcomes [14, 15], but cumbersome brain monitoring technologies are not well suited to web-based administration. Based on this same dual-process view of attention, we explored whether mousing behaviors could be used to identify both trait and state AC. Using a controlled, within-subjects experiment, we captured mousing behaviors during one high-AC and one low-AC task, hypothesizing that the depleted AC caused by visual distractions would cause systematic differences in mousing speed and distance. We also measured trait AC using the ACS [53], allowing us to test whether those same mouse movement features could reliably reveal individual differences in trait AC.

The analysis revealed no significant relationships between trait AC and the mouse movement features. There are several plausible explanations for these nonsignificant results. First, this preliminary study design was a first attempt at investigating a potential link between trait AC and mousing behaviors and should not be considered comprehensive evidence for or against an observable relationship between the two. Prior research has demonstrated that individual differences in working memory capacity—closely related to trait attention control [41]—influence one's susceptibility to distraction, observable in hand movements such as while using a handheld touchscreen pen [56]. The link between these individual differences and attention-related performance may also only apply to longer tasks [57] or in situations of real-world pressure like when an audience is watching [58]. Our preliminary experimental design is not likely to create those nuanced effects, and a more refined study design may produce the conditions necessary to observe the hypothesized effects.

Another likely explanation for the nonsignificant trait AC results is the scale chosen to measure the construct. Although the ACS [53] is arguably the most widely used survey measure of trait AC, recent research has provided convincing evidence that the ACS may not correlate well with objective measures of AC [59, 60]. Thus, using a trait AC score derived from the ACS may be an inaccurate way to measure the construct and test the relationship. An improved study design could use a more objective measure of trait AC to afford a more reliable test of the hypothesize relationships between trait AC and mouse movements.

However, our analysis provided evidence in support of H2, namely, that mouse movement data show promise as a method for identifying if a web user has become distracted. The state AC manipulation (in which various distractors were displayed among the goal-relevant targets) produced significant fixed effects in both the mousing speed and mousing distance models. This provides initial evidence that mouse movement data may be used in a web-based setting to detect when a user has become distracted. These findings have important implications for future research.

First, state AC can be influenced by various internal and external factors, including stress, fatigue, and distraction. Having a way to measure the momentary AC in real-time could therefore provide insight into these cognitive states, which could be used to inform the design and delivery of related interventions.

Relatedly, research has shown that feedback interventions that are tailored to individuals' cognitive states can be more effective than interventions that are not tailored [61]. Thus, a measurement technique such as that suggested by our results could be used in a range of different customized feedback loops to enhance outcomes in situations where user attention is crucial—most notably, perhaps, in the context of online learning.

A final potential application for our preliminary findings further investigation is in helping users develop metacognitive skills, such as self-awareness and self-regulation. Metacognitive skills are important for learning and cognitive performance, as they allow individuals to monitor and adjust their cognitive processes to meet the demands of the task [24]. Systems that provide real-time information on users' attention states can help users develop metacognitive skills by increasing their awareness of their own cognitive processes.

Despite these promising findings, the preliminary study reported here leaves room for further refinement and improvement. The mousing measures evaluated constitute a high-level representation of what is likely a complex cognitive process. Alternative explanations for the observed effects—such as frustration or task complexity—need to be ruled out. Moreover, expanding the approach to test the method's validity during more complex and varied attention-related tasks will be required before a real-time attention feedback system based on this technology could be used reliably. Despite these limitations, however, the results reported here provide initial evidence that mouse movement data may contain signals that, with proper refinement and isolation, may prove valuable in detecting and promoting more focused attention.

VI. Conclusion

This research applied mouse movement data to a unique but promising area of potential application—monitoring users' attention in real-time. Based on dual-process theory and aligned with attention feedback systems in offline settings, we developed hypotheses predicting how mouse movements will differ based on differences in attention control. A controlled experiment provided initial evidence that attention control impacts a user's mousing behavior while also suggesting several promising opportunities for further development and refinement of the theory and approach used. With further exploration and additional empirical evidence, using this approach to monitor and respond in real time to users' cognitive states could produce significant value in web-based contexts where attention is a crucial resource relevant to system success.

VII. References

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